Neural Nonlinear Autoregressive Model with Exogenous Input (NARX) for Turboshaft Aeroengine Fuel Control Unit Model

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ABSTRACT

One of the most important part of a turboshaft engine, which has direct impact on the performance of the engine and, as a result, on the performance of the propulsion system, is the engine fuel control system.
The traditional engine control system is a sensor-based control method, which uses measurable parameters to control engine performance. In this context engine component degradation leads to a change in the relationship between the measurable parameters and the engine performance parameters, so an increase of control errors. In this work a nonlinear model predictive control method for turboshaft direct fuel control is implemented to improve engine response ability also in presence of degraded conditions.
The control objective of the proposed model is the prediction of the specific fuel consumption directly instead of the measurable parameters. In this way is possible decentralize controller functions and realize an intelligent engine with the development of a distributed control system. Artificial Neural Network (ANN) are widely used as data-driven model for modelling of complex systems such as aeroengine performance. In this paper two Nonlinear Autoregressive Neural Networks have been trained to predict the specific fuel consumption for several transient flight manoeuvres. The data used for the ANN predictions have been estimated through the Gas Turbine Simulation Program. In particular the first ANN predicts the state variables based on flight conditions and the second one predicts the performance parameter based on the previous predicted variables. The results show a good approximation of the studied variables also in degraded conditions.

1.0 INTRODUCTION

An Aero-engine is a multi-parameter, non-linear and very complex thermodynamics system, operating in a highly variable environment. Additionally, the performance of its components is typically subjected to deterioration during its entire life. Therefore, it is of great importance to accurately model the behaviour of the engine in its whole flight envelope. Finally, it is still more essential to implement an on-board model embedded in Full Authority Digital Electronics Control (FADEC) in order to track in real-time information the engine performance [1]. But this centralized control system is found to be complex since it receives information from all the sensors installed on the engine, and it requires a complex architecture to meet the complex control requirements [2]. To reduce the degree of complexity of the system, and improve its potential, the centralized control system is transformed into a distributed control system [3] and decentralize the control system into multiple data management systems network. The benefits of this system can be many:

- Increased performance with the reduction in engine weight due to digital signalling, lower wire/connector count, reduced cooling need. 5% increase in thrust-to-weight ratio.
- Improved Mission Success: System availability improvement due to automated fault isolation,

reduced maintenance time, modular line-replaceable unit (LRU). 10% increase in system availability.

- Lower Life Cycle Cost: Reduced cycle time for design, manufacture; Reduced component and maintenance costs

In a distributed environment, intelligent control system platforms can play the role of key differentiator in terms of system and software architecture development approach, safety, performance, system integration, engine maintenance, obsolescence management, upgradeability, system reuse and other lifecycle costs. Turbine engines of the future are more complex and require smart sensors, smart actuators, constant monitoring and require capability for rapidly processing many parameters. The analysis of the applicability of the distributed architecture in terms of the controls and communication issues and examination of the potential benefits and challenges for implementing distributed FADEC systems.

The control design of aero-engine systems has been investigated in [4] by using distributed architecture and its delay due to the network transmission. The results showed that the designed controller is stable and ensure the desired performance of the aero-engine in the presence of persistent delay.

In order to obtain and analyse as much data as possible, the engine performance simulations have been widely used in gas turbine designs; in this way is possible to decrease design and development costs [5]-[7]. These types of simulations can be classified into design point, off-design steady state, and transient performance simulations based on the engine's operation. Transient performance simulations are very useful in the initial stage of engine design. For example, with transient data it is possible to establish the safety of new engines, including accelerations and decelerations, and to provide a numerical test-bed for the development of control systems including the examination of the dynamics behaviour and the coupling between engines and control systems. Moreover, during transient operations the engine experiences overloads and over-temperature, therefore these simulations are vital for diagnostic and prognostic of the health state of the system.

Furthermore, novel control systems will incorporate real-time prognostics and health monitors to detect degradation of engine performance and failures of its components.

Advanced aircraft control systems will integrate more versatile controllers which will accomplish the complex task of real-time engine supervision and control combined with engine health management models. The main issue of these intelligent systems is to improve the efficiency of engine components through active control, advanced diagnostics, and prognostics to enhance component performance and life.

Performance simulations and prognostic methods can be classified into two main categories: model-based and data-driven-based approaches. Model-based methods need the mathematical and physical model of the engine, while data-driven-based methods are based on recorded or real-time data from sensors measurements for the prediction of the future state of the engine's components. Due to the difficulties in the development of a detailed and accurate mathematical model of an aeroengine, data-driven methods are now of great interest in the aereo engine community. They use real or estimated data to represent and model the performance of the components and predict the transient behaviour of the system. [8] In the recent past, machine learning techniques strongly entered the aerospace field due to their flexibility and capacity to analyse and generalize huge amounts of data. If one thinks to the massive number of parameters and variables that can be measured during the operation of an aircraft engine, it is clear how these techniques can be useful in the analysis of such complex systems. Artificial Neural Networks (ANN) have been widely used as data-driven model for modelling and simulation of aeroengine performance. ANN itself includes different approaches such as Function Fitting, Nonlinear Input-Output (NIO), Nonlinear AutoRegressive eXogenous (NARX), Long Short-Term Memory (LSTM), Adaptive Network-based Fuzzy Inference System (ANFIS), Feedforward Multi-Layer Perceptron (MLP), Backpropagation Neural Networks (BPNN) and Radial Basis Function (RBF). In [9] the authors have proven to have an excellent ability of capturing the dynamics of complicated systems such as gas turbines. In addition to neural networks, new techniques of Genetic Programming (GP) are also starting to be used in the aerospace sector.

These machine learning techniques will be treated and used in this work to calculate and predict the evolution of the engine status, in particular the Specific Fuel Consumption (SFC). In this way is possible to find a correlation between each input and output as the Aero-engine is a typical multi-variable model and it is possible to improve the stability of control system.

2.0 GAS TURBINE MODELLING

The propulsion system, PW200 Pratt & Whitney Canada, is a family two spool turboshaft engines developed specifically for helicopter applications. This propulsion is a lightweight turboshaft engine with a free turbine (Low Pressure Turbine (LPT)), connected to the rotor shaft with a nominal speed of 6000 rpm, and a single stage centrifugal compressor driven by a single stage turbine (High Pressure Turbine (HPT)). This engine is installed on one of Airbus' most successful light aircraft, the H135 is known for its endurance, compact build, low sound levels, reliability, versatility, and cost-competitiveness.

Table 1: Specifications and configuration for the PW200.

Description	Value
Power	200-400 [kW]
Weight	110 [kg]
Pressure Ratio	8:1
Turbine Inlet Temp	1173.15 [K]
SFC (Specific Fuel Consumption)	0.426-0.33 [kg/kWh]
Compressor Configuration	1 centrifugal
Turbine Configuration	1 HPT, 1 LPT

The data used for this work have been estimated through the Gas Turbine Simulation Program (GSP) and, due to the lack of experimental data, it was not possible to validate accurately the model. GSP is an off-line component-based modelling environment for both aircraft and industrial gas turbines. Gas turbine performance calculations are nowadays performed using computer software and advanced model-based diagnostic techniques which enable component condition estimation without the need for engine disassembly. Both transient and steady state simulation of any kind of gas turbine configuration can be achieved by establishing a specific arrangement of engine component models.

2.1 Design Point

GSP is a powerful tool for performance prediction, emissions calculation, control system design, diagnostics and off-design analysis. It is especially suitable for sensitivity analysis of some variables such as ambient conditions, component deterioration and exhaust gas emissions. More information on this software can be found in the GSP11 user manual [10].

The first step in developing an engine model is to study and research its design point. The model built in GSP for the PW200 engine series is shown in Figure 1. In addition to the classic components (such as turbomachinery, combustion chamber and nozzles), two new components called Duct are visible. They are used in transient models to introduce dynamics and volumetric effects, in order to perform the mass balance (ICV-Intercomponent Volume method [11]-[14]). In the case of steady operating conditions, they have no influence on engine performance and operating parameters.

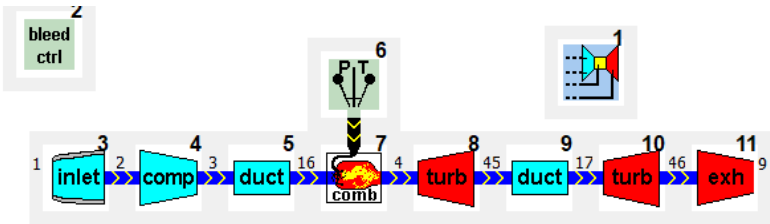


Figure 1: Turboshaft engine model in GSP.

The design point is given by sea level condition (altitude of 0 m and temperature of 288,15 K), so it is possible to obtain the maximum power. Iterative modifications were made to the air flow rate and the fuel flow rate injected into the combustion chamber in order to obtain the same power indicated on the specifications. The default compressor and turbine maps were scaled according to a set of input parameters taken from the database of the reference engine. The iteration allowed a prediction of the design take-off power with an accuracy of 1% with respect of the reference engine.

Table 2: Design parameters for the PW200.

Description	Value	Unit
Power (*POW*)	266	[kW]
Intake Pressure ratio (*PR*)	0,988	[-]
Air Flow rate ($\dot{m}_a$)	2	[kg/s]
Combustion efficiency (η_b)	0.99	[-]
Fuel Flow rate ($\dot{m}_f$)	0.0315	[kg/s]
Compressor Rotor Speed (n_1)	40891	[rpm]
Compressor Efficiency (η_c)	0.99	[-]
LPT Rotor Speed (n_2)	6000	[rpm]
Turbine efficiency (η_t)	0.88	[-]
Spool Mechanical Efficiency (η_m)	0.99	[-]

2.2 Transient simulations

Under steady conditions all engine parameters are balanced, and no change occurs over time, either in flow properties at any point in space or in engine parameters (speed, temperatures and compression and expansion ratios). However for real engines, a steady state is only theoretically possible because, during their operation, they experience significant variations in operating conditions. All these changes shift the engine operating point from its original equilibrium to another operating point at which the engine parameters reach a new state of equilibrium [12]. This process, in which the operating point of the engine moves from one thermodynamic equilibrium condition to another one, is called dynamic response and the engine performance is transient.

The software GSP is able to perform also transient simulations, allowing the user to take into account dynamic effects such as spool inertia, heat exchange in turbomachinery and volumetric effects.

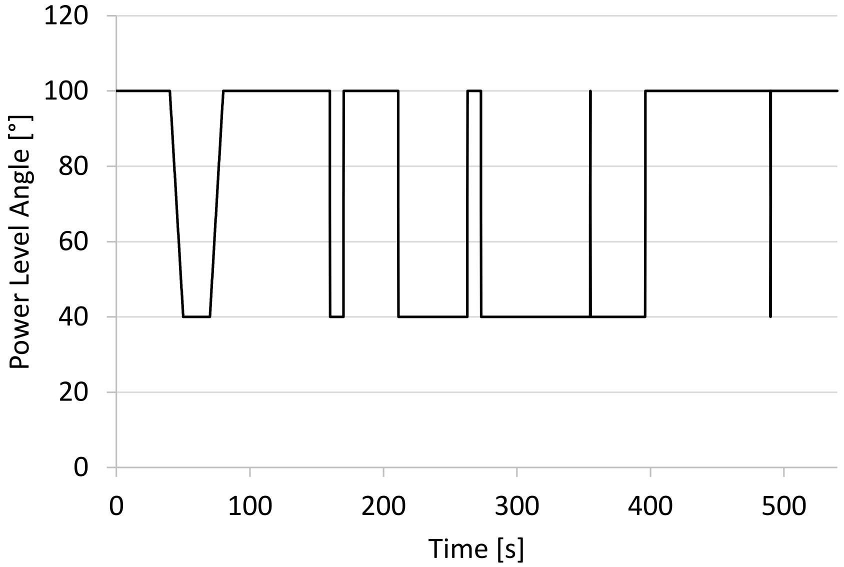


Figure 2: PLA signal.

To describe the dynamic behaviour of the system, power level angle (PLA) changes are performed with standard step, ramp and pulse signals in different flight conditions from idle to full and vice-versa (Figure 2 and Table 3).

So, the data sets used in this work have been simulated during several manoeuvres and cover the whole operating range of the engine.

Table 3: Flight conditions.

	h **[m]**	***Mach number***
TO (Take-Off)	0	0
CR1 (Cruise1)	313.5	0.45
CR2 (Cruise2)	400	0.12
CR3 (Cruise3)	800	0.09
CR4 (Cruise4)	313.5	0.21

The time series data sets considered are compressor pressure ratio, compressor rotational speed, inlet turbine temperature, fuel flow rate and specific fuel consumption, based on flight altitude, Mach and the PLA.

2.3 Deteriorated model

During its life cycle, the engine can suffer several issues due to over-temperatures, erosion of compressor and turbine blades, fouling, bird strike, for example.

Typically, any fault in a single component or inconsistency in the performance of a group of components can increase machine degradation. To perform fault identification or to create a model for simulating faults, the relationship between physical faults and component deterioration must be determined.

In the fault identification process, it is useful to find a relationship between the faults and their corresponding effects on the engine performance. Table 4 summarizes some of the issues that it is possible to find in the compressor and the turbine and their related effects, where $\dot{m}_c$ is the compressor mass flow rate, η_c is the compressor efficiency, $\dot{m}_t$ is the turbine mass flow rate, and η_t is the turbine efficiency.

Table 4: Effects of various faults on component degradation.

Physical Fault	Flow Capacity Change	Isentropic Efficiency Change
Compressor Fouling	$\dot{m}_c \downarrow$	$\eta_c \downarrow$
Compressor Erosion	$\dot{m}_c \downarrow$	$\eta_c \downarrow$
Compressor Corrosion	$\dot{m}_c \downarrow$	$\eta_c \downarrow$
Compressor Blade Rubbing	$\dot{m}_c \downarrow$	$\eta_c \downarrow$
Turbine Fouling	$\dot{m}_t \downarrow$	$\eta_t \downarrow$
Turbine Erosion	$\dot{m}_t \uparrow$	$\eta_t \downarrow$
Turbine Corrosion	$\dot{m}_t \downarrow$	$\eta_t \downarrow$
Turbine Blade Rubbing	$\dot{m}_t \uparrow$	$\eta_t \downarrow$
Thermal Distortion	$\dot{m}_t \uparrow$	$\eta_t \downarrow$
FOD (Foreign Object Damage)	$\dot{m}_c \downarrow \& \dot{m}_t \downarrow$	$\eta_c \downarrow \& \eta_t \downarrow$

An issue in the study of engine component degradation is to select the appropriate measured parameters that can reflect the performance degradation of aeroengine to realize its performance degradation forecast [12]-[14]. Thus, exhaust gas temperature (*EGT*) is often used for engine control, condition monitoring, fault diagnosis, and maintenance decisions. When other conditions remain the same, the higher the EGT is, the more serious the performance degradation of aeroengine is [12]-[14]. But in this work specific fuel consumption (*SFC*), compressor pressure ratio, compressor rotational speed, fuel flow, turbine inlet temperature have been compared with the corresponding clean and healthy parameters.

GSP allows us to represent the deterioration of the engine in a number of ways. The most used is to run a simulation with a constant degree of deterioration i.e. a constant decrease of the efficiency and mass flow rate in the case of the compressor. As seen before this can be represented by the fouling index or the erosion index. Obviously, it is implied that, in this case, the engine considered is already damaged by some of the phenomena seen before. But in order to make the study as general as possible, a step change has been considered, represented as a variation of the only compressor efficiency. It has been decreased of the 10% with respect to the healthy condition.

3.0 NEURAL NETWORK APPLICATION TO TRANSIENT SIMULATIONS

A neural network is a system inspired by the architecture of biological nervous systems. It consists of interconnected neurons which are organized in a sequence of layers including an input layer, one or more intermediate hidden layers, and an output layer. An example of a feed-forward neural network with one hidden layer is shown in Figure 3. In general, there can be multiple hidden layers. Each node in the layer is a Neuron, which can be thought of as the basic processing unit of a neural network.

The input layer is used to provide the input data, with different intensity and strength. The input signal enters the input neurons and combines to form a net input into another neuron. The output layer, with a number of neurons equal to the number of expected outputs, is calculated by weight and bias associated with connections among neurons. This is the layer that gives out the predictions. The inter-mediate layers are connected to the input and output layers. Each neuron in the hidden and output layers receives the signals from all the neurons of the previous layer and then performs a weighted sum on inputs.

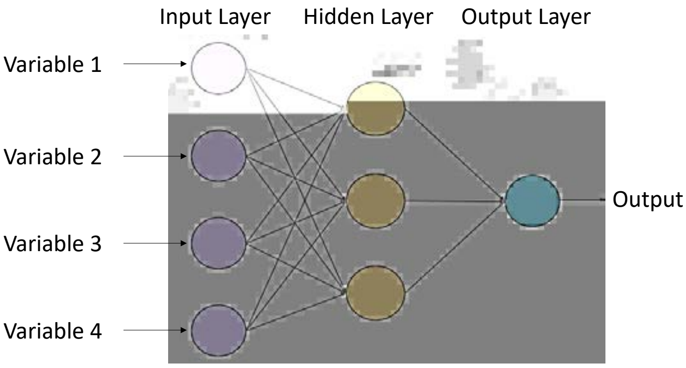


Figure 3: Example of a feed-forward artificial neural network.

An Artificial Neuron is the basic unit of a neural network. It calculates the weighted sum of its inputs and then applies an activation function to normalize the sum. The activation functions can be linear or nonlinear. Also, there are weights associated with each input of a neuron. These are the parameters that the network has to learn during the training phase. A schematic diagram if a neuron is shown in Figure 4.

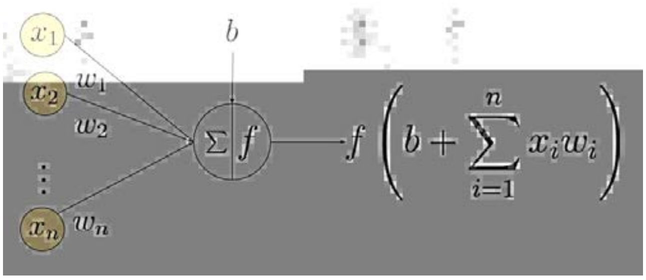


Figure 4: Schematic diagram of a neuron.

3.1 NARX Neural Network

Among ANNs based models, the most promising approach for the prediction of transient behaviour of aero-engine is given by NARX. These neural networks are suitable for capturing dynamics of complicated systems such as gas turbines, so it can be applied for design optimization of gas turbines, as well as of the whole operation and maintenance activity of the aero-engine.

A good approach to dealing with chaotic time series with a large amount of data is one based upon "Nonlinear Autoregressive models with eXogenous input (NARX model)". The structure of the neural network can be assumed as a "black-box" with the *x(t)* series at the input and the *y(t)* series at the output, which is the variable that ANN should predict. This is a powerful class of models which has been demonstrated that they are well suited for modelling nonlinear systems and specially time series but also the values of the series in the past time.

Learning of NARX networks is more effective than in other neural network and these networks converge much faster and generalize better than other networks. NARX are recurrent dynamic network that correlate the current value assumed by an output parameters *y(t)* in a time series to the past values of the same parameters and of the driving parameters. So, this network allows to use as input not only the series *x(t)* but also the values of the series *y(t)* in the past times. The fundamental equation of the NARX model is as follows:

$$y(t) = f\,(x(t-1),...,x(t-d\,), y(t-1),..., y(t-d\,)) \tag{1}$$

where *d* is a parameter called delay.

Neurons number in the hidden layer and the delay *d* can greatly influence both the network training time and its accuracy. The training samples are passed through the network and the output obtained from the network is compared with the actual output. This error is used to change the weights of the neurons such that the error decreases gradually. This is done using the Backpropagation algorithm, also called *backprop*. Iteratively passing batches of data through the network and updating the weights, so that the error is decreased, is known as Stochastic Gradient Descent (SGD). The amount by which the weights are changed is determined by a parameter called Learning rate.

In this work, the MATLAB Neural Network tool has been used to build the NARX models for a combination of the simulated time-series data sets of the several flight conditions. The aim of this study is not only to predict the output variables value in future instants of time, but to derive a relationship between the inputs provided to the neural network and the desired output. The Closed-loop structure of the NARX model is showed in Figure 5.

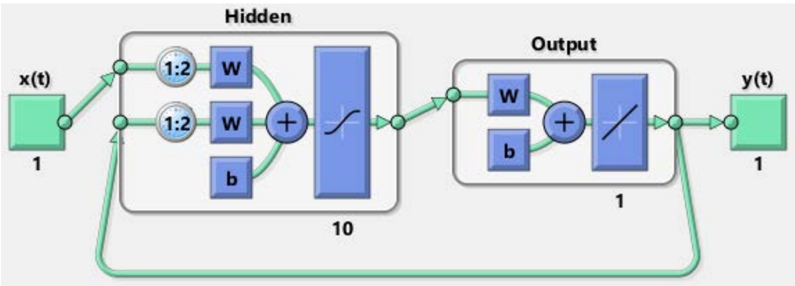


Figure 5: NARX neural network.

In this work two neural networks have been applied. The first one uses as input ambient conditions (P_1, T_1), Mach number (*M*) and power level angle (PLA) and gives as output a prediction of fuel flow rate, compressor speed, turbine inlet temperature and compressor pressure ratio. Then these variables are used in the second network as an input, together again with ambient condition and Mach number, in order to predict engine performance parameters, i.e. specific fuel consumption (Figure 6).

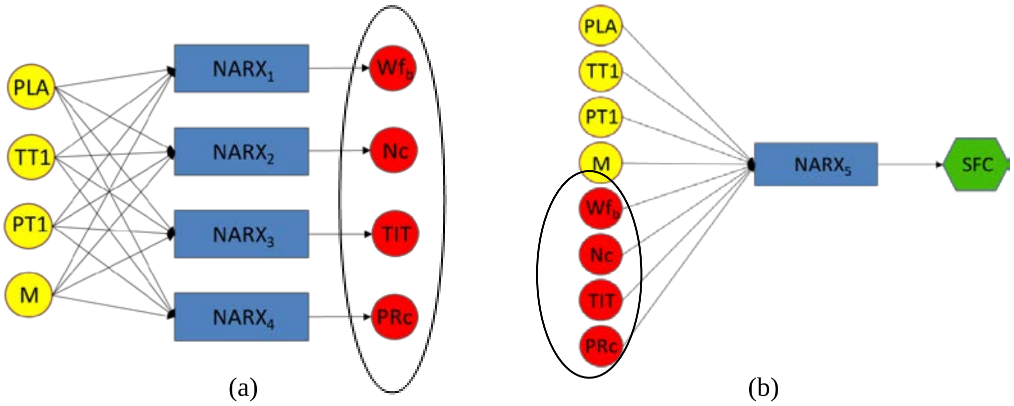
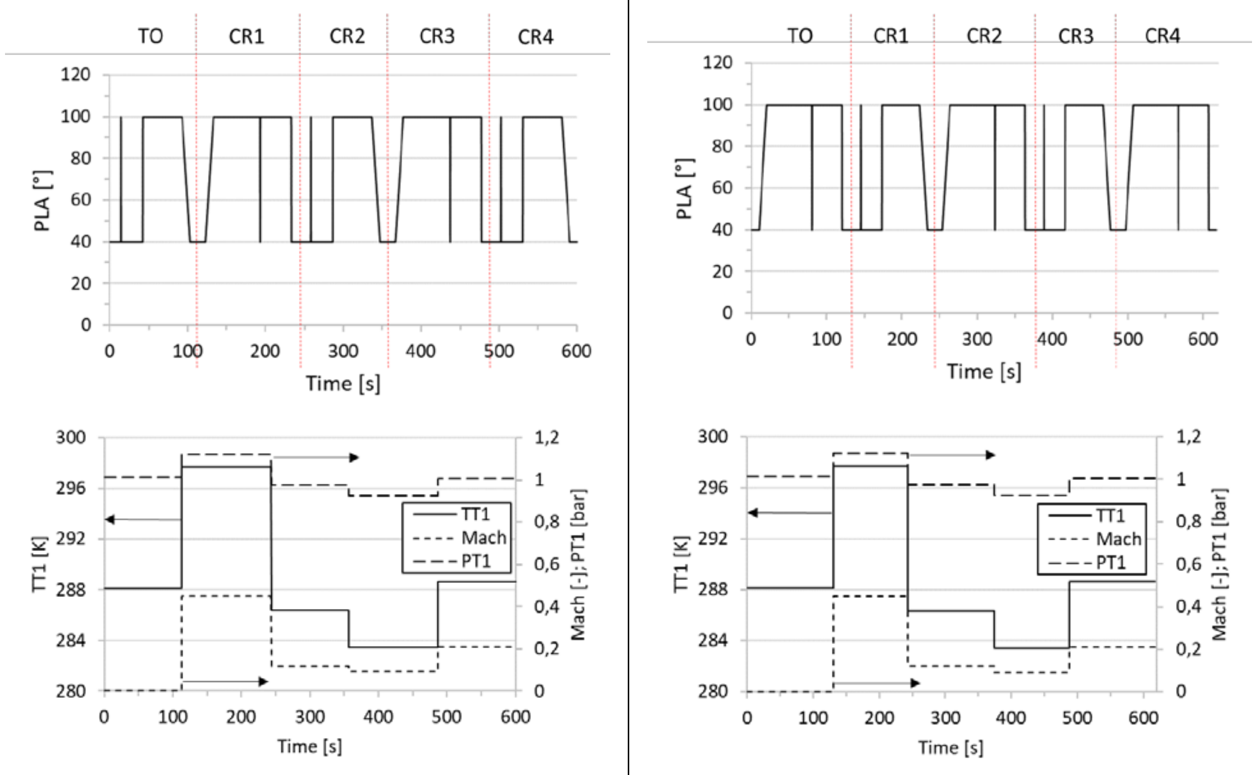


Figure 6: Diagram of the complete NARX model.

For each neural network the data need to be divided randomly into training (70%), validation (25%) and test (5%) sets. The validation set was used to ensure that there was no overfitting in the final results. The prediction has been performed for all the simulated cases but the data have been divided in training and testing data as follows:

Training datasets	Testing datasets



(a)	(b)

Figure 7: Training (a) and testing (b) datasets.

In this way, the data to be used for the prediction of the output variables are formed by concatenating the GSP results.

To run the NARX networks, it was decided to use, as training dataset, the PLA signal in Figure 7 (a) calculated in transient conditions with GSP the ambient conditions and Mach depicted in Figure 7 (a). Each model was trained by using the Bayesian regularization back-propagation functions as the training function, a delay parameter from 1 to 2 was assumed at the input in order to make good (improve) predictions performance and prevent overfitting. The number of neurons in the hidden layer was set equal 10. After the neural networks have been trained, they were tested, and validating using as input the PLA shown in Figure 7 (b), the ambient conditions and Mach depicted in Figure 7 (b). The prediction carried out is of the one-step-ahead type, which means that the network predicts the performance parameters value at the time t+1 by knowing the values of the inputs in the previous instants.

The parameters used for the comparison of the simulated data Y_{GSP} to the predictions of NARX models Y_{NN}, are:

- the *Root-Mean-Square-Error (RMSE)* defined as follows:

$$RMSE = \sqrt{\frac{\sum_i \left(\frac{Y_{GSP}(i) - Y_{NN}(i)}{Y_{GSP}(i)} \right)^2}{n}} \quad (2)$$

where n is the number of data of each data set;

- and the coefficient of determination R^2

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (3)$$

where SS_{res} is the residual sum of squares: $SS_{res} = \sum_i (Y_{GSP}(i) - Y_{NN}(i))^2$

and SS_{tot} is the total sum of squares (proportional to the variance of the data): $SS_{tot} = \sum_i (Y_{GSP}(i) - \bar{Y}_{GSP})^2$ with $\bar{Y}_{GSP} = \sum_i \frac{Y_{GSP}(i)}{n}$ the mean of the observed (simulated by GSP) data.

4.0 RESULTS AND DISCUSSIONS

In order to determine the correct operation of an aircraft engine and evaluate its health condition, it was decided to study the behaviour of its main performance parameters in different flight conditions.

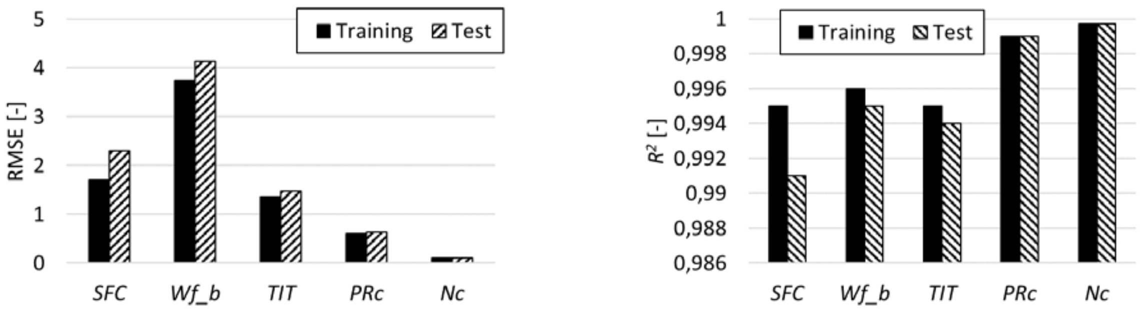
Therefore, to understand if the engine has malfunctions or anomalies during its flight conditions, it was decided to use the SFC, as the main parameters to be estimated one-step-ahead by ANNs technique.

The parameters selected as input in NARX models and were considered to have a correlation with the above performance parameters are:

- Engine parameters: shaft speed (*Nc*), turbine inlet total temperature (*TIT*), fuel mass flow rate (*Wf_b*) and compressor pressure ratio (*PRc*);
- Environment parameters: Mach number (*M*), atmospheric total temperature (T_{T1}) and total pressure (P_{T1}).

4.1 NARX neural networks prediction results

Figure 8 reports the results of the training and testing phase in terms of RMSE and R^2 for the datasets reported in Figure 7.

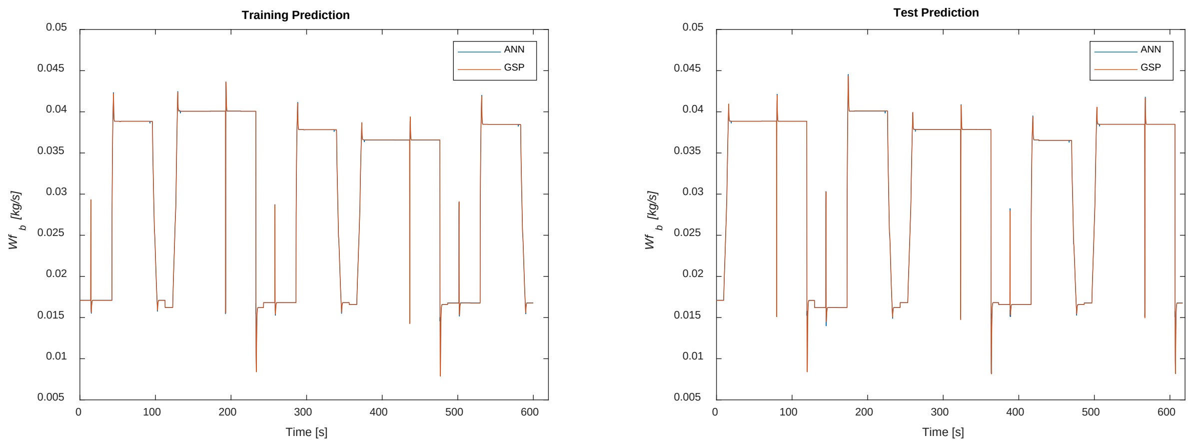


(a) (b)

Figure 8: RMSE and R^2 of the NARX models for the training and test manoeuvres for datasets in Figure7.

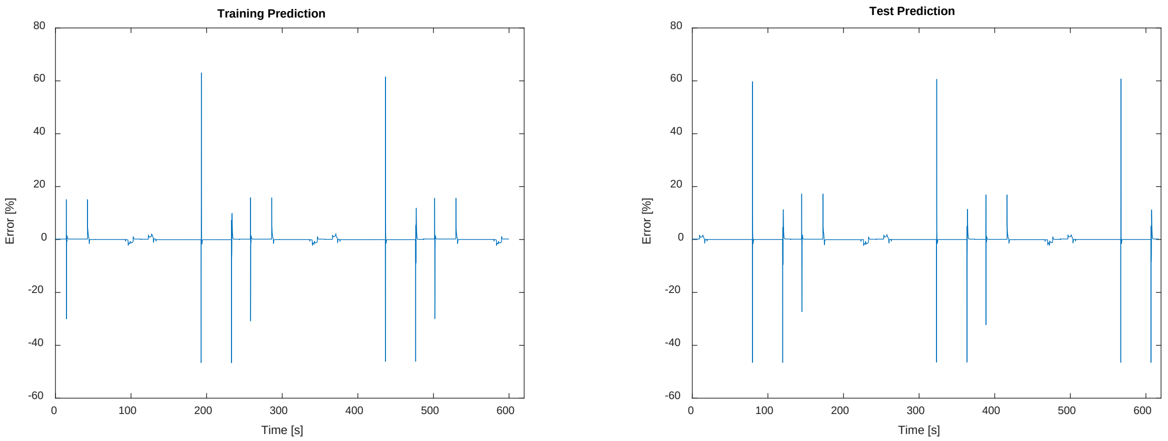
The low RMSE indicates that the neural network approximates well the observed data for both training and test phases. The confirmation of the correct prediction of the observed variable is given also from R^2. Its value is close to 1, it indicates a good predictive power of the network.

In the following figures, it is possible to note how the NARX predicts the behaviour of the observed variable, obtained from the simulation in GSP, in the training and test phases. At the different neural networks an index as been assigned depending on the variable to be predicted (i.e. NARX1 for prediction of *Wf_b*).



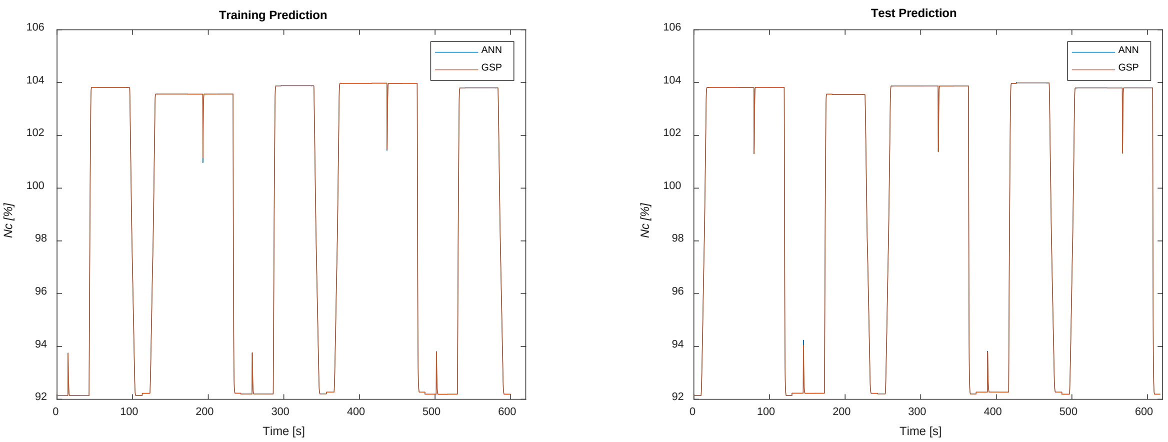
(a) (b)

Figure 9: Training (a) and testing (b) comparison between GSP and Net prediction of the NARX for the prediction of W_{f_b} under clean Conditions (NARX1 Clean).



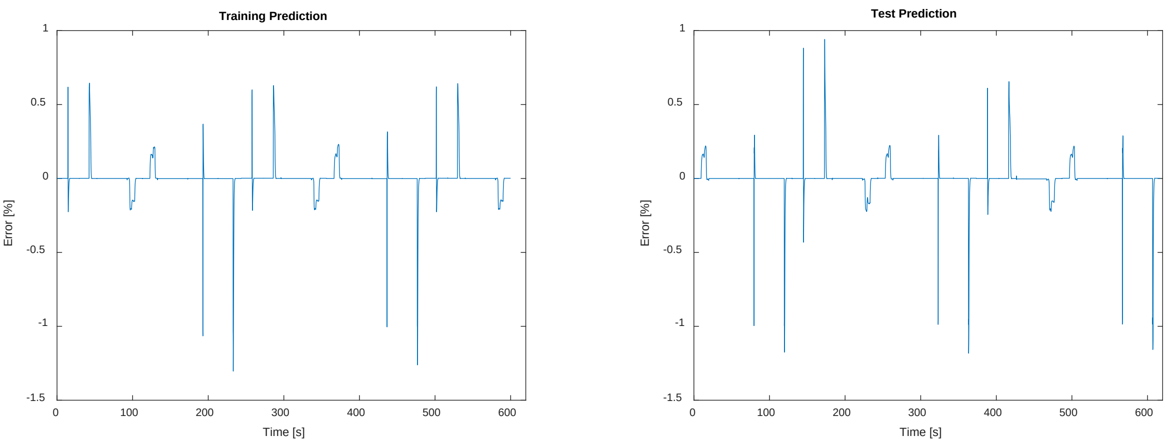
(a) (b)

Figure 10: Training (a) and testing (b) Error comparison between GSP and Net prediction of the NARX for the prediction of W_{f_b} under clean Conditions (NARX1 Clean).



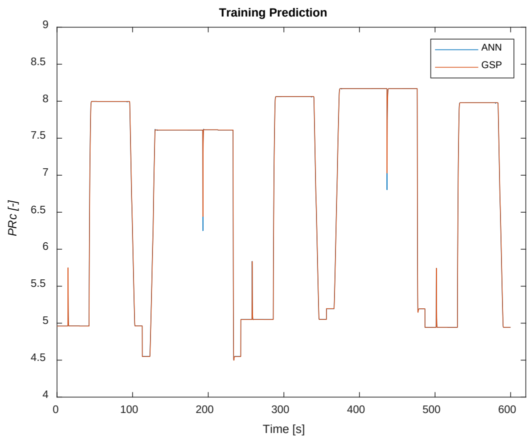
(a) (b)

Figure 11: Training (a) and testing (b) comparison between GSP and Net prediction of the NARX for the prediction of *Nc* under clean Conditions (NARX2 Clean).

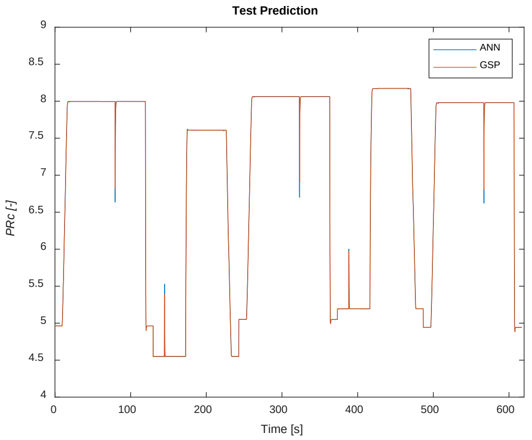


(a) (b)

Figure 12: Training (a) and testing (b) Error comparison between GSP and Net prediction of the NARX for the prediction of *Nc* under clean Conditions (NARX2 Clean).

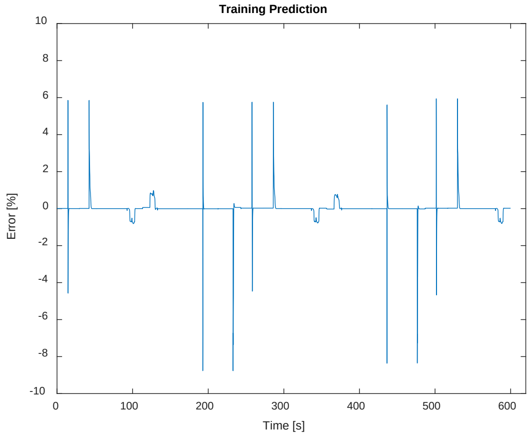


(a)

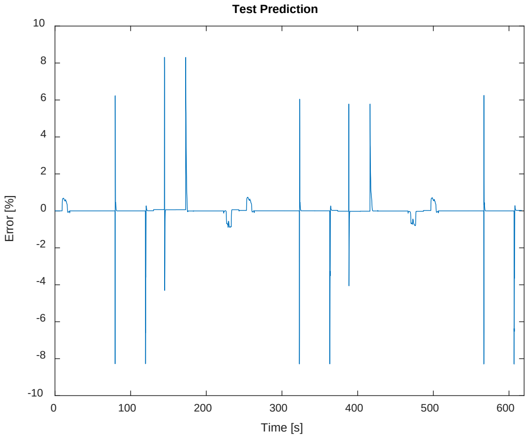


(b)

Figure 13: Training (a) and testing (b) comparison between GSP and Net prediction of the NARX for the prediction of *PRc* under clean conditions (NARX3 Clean).

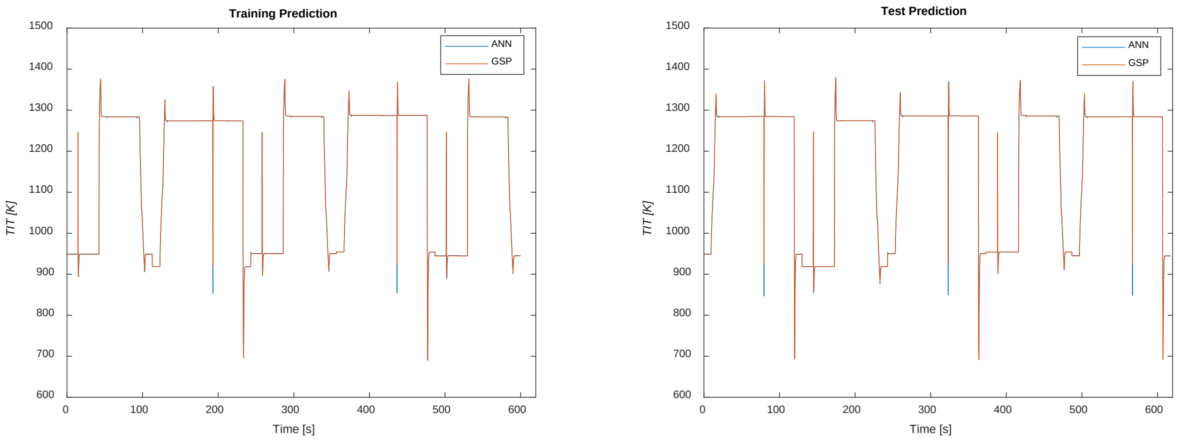


(a)



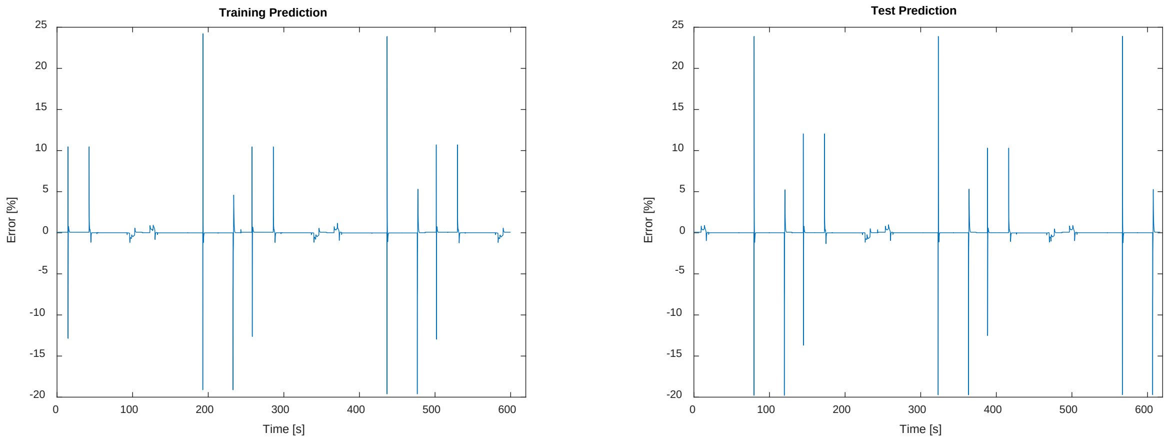
(b)

Figure 14: Training (a) and testing (b) Error comparison between GSP and Net prediction of the NARX for the prediction of *PRc* under clean conditions (NARX3 Clean).



(a) (b)

Figure 15: Training (a) and testing (b) comparison between GSP and Net prediction of the NARX for the prediction of *TIT* under clean Conditions (NARX4 Clean).



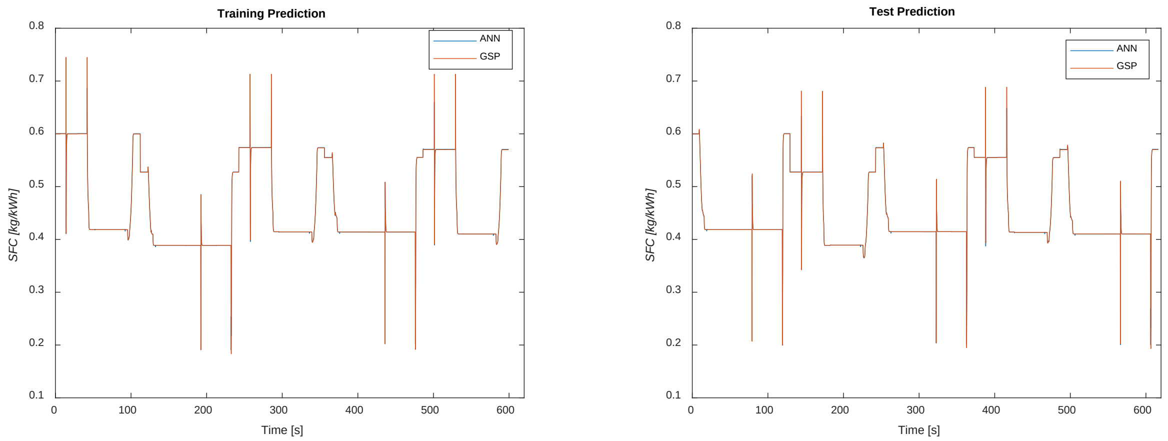
(a) (b)

Figure 16: Training (a) and testing (b) Error comparison between GSP and Net prediction of the NARX for the prediction of *TIT* under clean Conditions (NARX4 Clean).

As can be seen from Figure 9 to Figure 16, the neural networks (NARX1, NARX2, NARX3, NARX4) , useful for the prediction of the first set of the state measurable variables, successfully forecast the different variables.

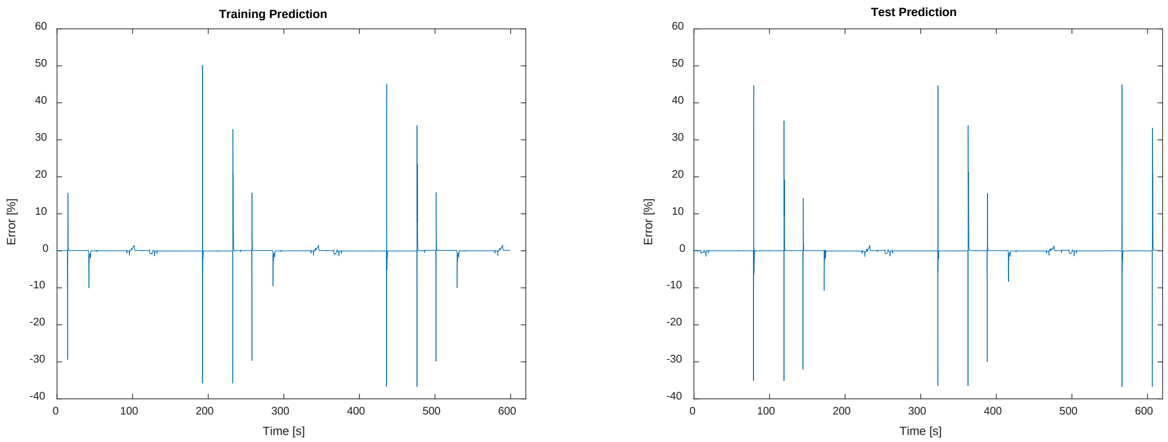
In fact, there is a good approximation for *Nc*, *PRc* with a low RMSE, 0,1 and respectively. While for the variables *Wf_b* and *TIT* the RMSE increase 3,7 and 1,4 respectively. For these two variables, it is possible to note a higher percentage of error.

In conclusion, it was observed that NARX can effectively learn complex sequences, passing from different conditions even if these conditions do not occur in real-conditions flight. Please note that the data has been concatenated without taking into account a real transit between the different configurations. It possible to note from the Figure 17 a slight difference between the GSP value and the value predicted by the NARX5. These errors, Figure 18, appear to have high but still very short peaks; it has been verified that these peaks coincide with the rapid adjustment performed by the PLA, which leads to a rapid change of the fuel flow, causing a rapid variation in the observed variables. In such situations, the neural network cannot accurately predict the instantaneous variation, producing high picks and high errors, due to a very short time delay in the prediction. But, when the PLA input "were not aggressive", the engine remained in steady-state conditions and the neural network is able to predict the output variables accurately.



(a) (b)

Figure 17: Training (a) and testing (b) comparison between GSP and Net prediction of the NARX for the prediction of *SFC* under Clean Conditions (NARX5 Clean).



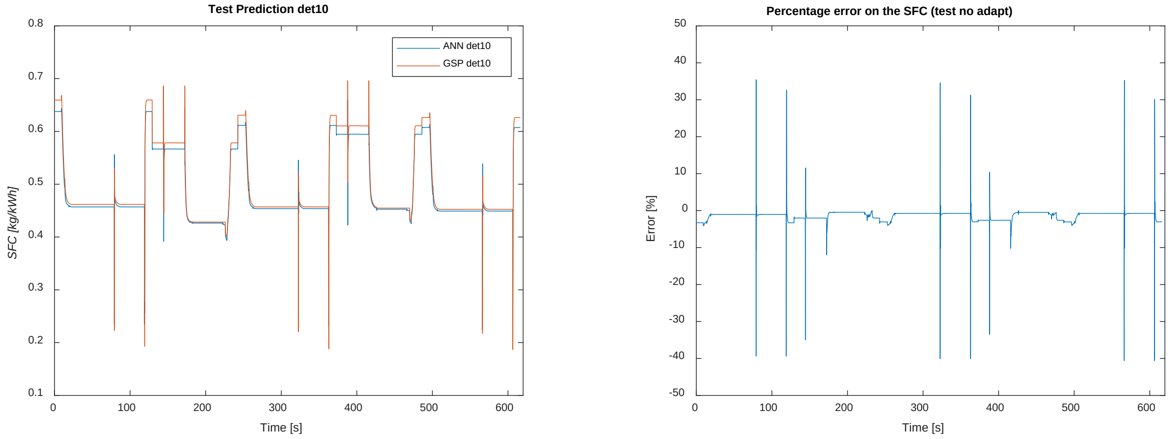
(a) (b)

Figure 18: Training (a) and testing (b) Error comparison between GSP and Net prediction of the NARX for the prediction of *SFC* under Clean Conditions (NARX5 Clean).

4.2 NARX neural networks prediction results degraded model

Data generated from engine model in the presence of compressor degradation, represented as a variation of 10% of its efficiency with respect to the clean case, were finally used to train and test the adaptive neural network implemented to predict *SFC* in degraded conditions. The adaptation procedure consists in updating the weights and bias of the network, previously obtained without deterioration. This network can be trained with the adaptive function to produce a particular output sequence. The new network returns the final weights, bias, and new output, in this section, degraded performance. It is possible to adapt the network by adding steps in its sequence to get the output even closer to the desired values. This function simulates the network on the input, while adjusting its weights and biases after each timestep in response to how closely its output matches the target.

First of all, the ANN previously implemented and validated without deterioration (clean case) were used to predict the performance with compressor deterioration. It is possible to note from Figure 19 that by using the network previously obtained in the clean case, without adapting to the new degraded conditions, it is not possible to accurately forecast the specific target *SFC* in degraded conditions.

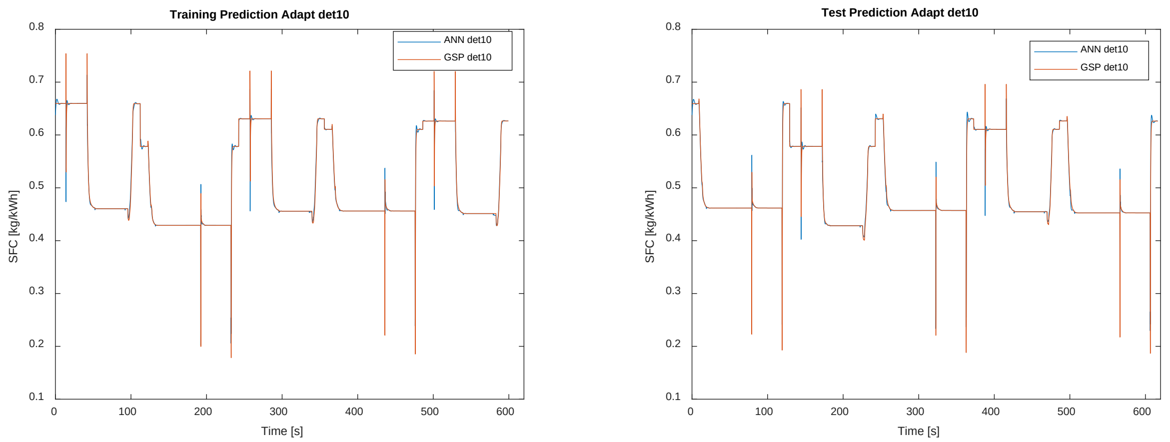


(a) (b)

Figure 19: *SFC* comparison between GSP and Net prediction under degraded conditions without adapting the ANN (NARX5 Clean), b) Error in the *SFC* predictions

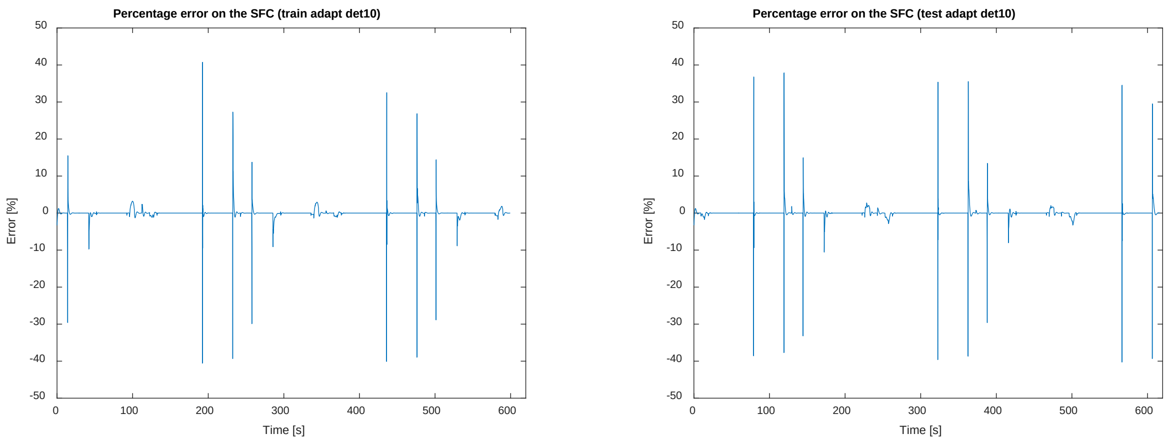
But, applying the adaptation function, it is possible to improve the prediction of *SFC* reported in Figure 20. Therefore, an improvement in the variable to be predicted by the adapted network has been achieved. In fact, the average relative error decreases from 1% to 0.4% with both training and test data using the adapted network.

The diagnostic methodology was implemented to predict engine performance degradation using the values of *SFC* assumed in each degraded engine condition and the ones in healthy engine. Hence, the training and test of the neural network were done using inputs that describe the flight conditions of the healthy engine connected to the degraded case.



(a) (b)

Figure 20: Training (a) and testing (b) adapted *SFC* comparison between GSP and Net prediction under degraded conditions with adapting (NARX 5 Adapted).



(a) (b)

Figure 21: Training (a) and testing (b) adapted *SFC* Error comparison between GSP and Net prediction under degraded conditions with adapting (NARX 5 Adapted).

5.0 CONCLUSIONS

The main aim of this research was to investigate the dynamic behaviour of a turboshaft engine in healthy and degraded conditions during transient phase. In order to create a data set, a 0-D model of the engine was developed using GSP software. The design parameters of each engine component were defined based on the datasheet; once the design point was fixed, the model was validated both in steady and transient conditions. The error of the 0-D model was very low, less than 1% in the case of the SFC. After the validation at the design point, a series of PLA adjustments were simulated by changing the power level angle PLA in different flight conditions, in terms of altitude and Mach. These PLA adjustments, were then concatenated to serve as input for Neural Network model. Artificial Neural Network has been used for the prediction of the performance parameter of the engine with one-step ahead prediction, called Nonlinear AutoRegressive with eXogenous inputs (NARX) neural network.

In this work two neural networks have been applied. The first one uses as inputs the ambient conditions, Mach number and PLA and gives as output a prediction of fuel flow rate, compressor rotational speed, turbine inlet temperature and compressor pressure ratio. Then these variables are used in the second network as an input, together again with ambient condition and Mach number, in order to predict engine performance parameters, in this case specific fuel consumption. These two neural networks have demonstrated an extraordinarily high capacity to learn and predict engine performance in healthy and degraded conditions. Neural networks have proven to be very effective models; thanks to the recurrent use of parameter values observed in the previous time instant, the training phase becomes so effective that the predictions are excellent even with a different time series. Results show a correlation, between true and predicted values, of about 98% for all parameters observed for different input signal sequences. In order to maintain the same correlation for a degraded system and in particular a reduction of compressor efficiency, the network needs an adaptation to the new conditions. In this way, it is possible to improve the prediction reducing the overall average error between an un-adapted network and an adapted network. The prediction and knowledge of a parameter in the immediate future is of great interest for the development of an engine control system that is therefore able to make corrections to the engine in advance. It is clear that it is possible to improve this forecast by switching from a one-step-ahead to a multi-step-ahead technique by trying to develop an SFC prediction for a longer time interval.

In the future, it will be possible to assign as target values, a degradation index or a health indicator and understand if the engine has malfunctions or anomalies during its flight conditions and subsequently estimate its Remaining Useful Life.

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