Proceedings of the International Gas Turbine Congress 2003 Tokyo
November 2-7, 2003

IGTC2003Tokyo TS-003

NEURAL NETWORKS FOR THE STUDY OF GAS TURBINE ENGINES AIR SYSTEM

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Abstract

This paper deals with the development of Artificial Intelligence (AI) tools for studying gas turbine air system. For this aim Back Propagation Neural Networks (BPNN) with different configurations are considered. The developed BPNNs allow the study of influence of air system of engine performance and behaviour. The paper describes also the main steps of a method for studying the behaviour of the air system. The derived computer code is the background for setting-up BPNNs for simulating the behaviour of airsystems working without and with faults. This way it is possible to carry out suitable diagnostics and trouble-shooting of air siystem.

The paper shows and discusses the problems, their most suitable solutions and the obtained results.

1.-INTRODUCTION

In the engine, besides the main stream generating the thrust or power, there are many other flows assuring either the correct working of whole engine and its integrity. All these flows form the engine air system.

There are bleeds from compressors for different tasks as: the aircraft conditioning, the cooling of engine hot parts (blades and disks), the pressurization of some parts of oil system, the pressurization of seals, etc.

All these flows must be exactly metered and delivered otherwise the working of engine may be endangered and its integrity runs serious risks. In fact, sometimes strange engine behaviour as well as performance decays are due to faults arising in the air system.

At the present the computer codes for the on-design and the off-design simulation of gas turbine engine furnish an accurate description of influence of air system on engine performance and behaviour. Moreover simulation may give useful information for detecting the faults arising in the engine air system.

An engine air system may be schematically considered just as a set of ducts linking each other some chambers, where the pressure is unknown, and external places where the pressure is known, fig. 1.

The study of an air system requires the evaluation of both the pressures in the various chambers and the mass flow rate in the ducts.

In the last years there has been a strong development of an amazing branch of Artificial Intelligence: Neural Networks. They are computer programs describing systems whose structure recalls the structure of human brain.

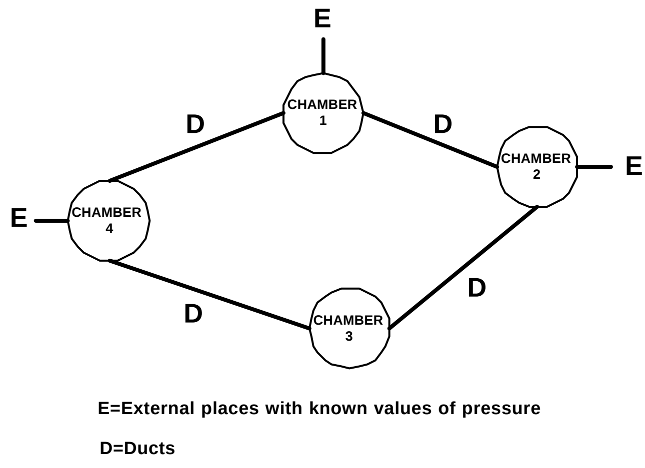

Fig. 1 Scheme of a part of a gas turbine air system

The aim of this paper was to develop Neural Networks for the simulation of the air system effects on gas turbine engine behaviour and performance.

For this study, the experience heaped up by the authors in the past suggested to use the Back Propagation Neural Networks [1],[2], [3],[4], [5].

First of all the paper deals with the bleed effects on the on-design performance and behavoiur of a large

Manuscript Received on April 14, 2003

separated flow turbofan with a low pressure compressor linked to the fan. Successively a method allowing the study of air system of a 600 SHP turboprop engine is presented. Owing to paper lenght only the main steps of the method are described. The set-up numerical code allows to consider the working of air system both without and with faults in its components.

Each step of study considers the problems linked to the construction of the BPNN best simulating the air system influence and working. The architecture, the transfer function, the training time involved parameters and both accurancy and robustness of BPNN are all topics considered and faced.

The following section show in full details all carried out activities.

2-THE DEVELOPMENT OF BPNN FOR ENGINE CYCLE AND PERFORMANCE ON DESIGN STUDY

The target of this phase of study is to show the problems encountered during the construction of BPNNs for simulating the influence of air system on performance of a gas turbine engine in on design conditions.

The engine is a two spool separated flow turbofan with a low pressure compressor linked to the fan. The considered engine resembles the CF6 configuration and the same level of thrust. The air system is formed by two bleeds from Low Pressure Compressor (LPC) three bleeds from High Pressure Compressor (HPC), four reentry bleeds one at High Pressure Turbine (HPT) inlet, one at HPT outlet, one at Low Pressure Turbine (LPT) inlet and finally one at LPT outlet.

As previously stated the Neural Networks used in this study are the Back Propagation Neural Networks. They are multilayered networks with supervised training; and the training is one of the most important step of the BPNN development. This means that input as well as corresponding output patterns are necessary. In this case each input pattern contains the values of bleed amounts, altitude and Mach number. All bleeds are defined as fractions of engine inlet mass flow rate.

The output patterns contain the values of total gross specific thrust, fan specific gross thrust, hot stream specific gross thrust, Engine Pressure Ratio (EPR), the ratio of fuel flow to inlet mass flow rate, the Specific Fuel Consumption (SFC), the ratio of hot stream exit area to inlet mass flow rate, the ratio of cold exit area to inlet mass flow rate, the Exhaust Gas Teperature (EGT).

A classical program for engine cycle simulation furnishes the patterns necessary for BPNN training.

The calculation have been carried out by randomly varying the values of bleed amounts, altitude and Mach number. The ranges of variation are depicted in table 1.

The engine cycle calculations furnish 10000 patters. 7000 pattersn were employed for the network training while the remained 3000 were used for the BPNN testing.

The number of both input and output parameters are important for defining the architecture of both input and output layers of BPNN.

The first attempt has dealt with a classical three layers BPNN. The input layer has 11 neurons + 1 bias connected to each element of hidden layer. The output layer has 9 neurons (one for each engine performance parameters).

Table 1 Range of input Parameters

INPUT PARAMETER	MIN	MAX
1st Bleed from LPC	0.0	0.06
2nd Bleed from LPC	0.0	0.06
1st Bleed from HPC	0.0	0.1
2nd Bleed from HPC	0.0	0.1
3rd Bleed from HPC	0.0	0.15
Reentry Bleed at HPT inlet	0.0	0.07
Reentry Bleed at HPT outlet	0.0	0.07
Reentry Bleed at LPT inlet	0.0	0.04
Reentry Bleed at LPT inlet	0.0	0.03
Mach Number	0.0	0.9
Altitude (meters)	0.0	11000

The study has considered different BPNNs with different neurons of hidden layer. Configuration with 22, 44, 88, 200 + 1 bias have been tested by a batch procedure. Moreover for both hidden layer and output layer a sigmoid transfer function has been used.

Unfortunately the BPNNs doesn't complete their trainig unless to consider a very low degree of accurancy.

The successive step has considered a BPNN with a completely different configuration.

Fig. 2 shows the partial scheme of used architecture. The BPNN has again 11 neurons of input layer. But each input has a different bias element.

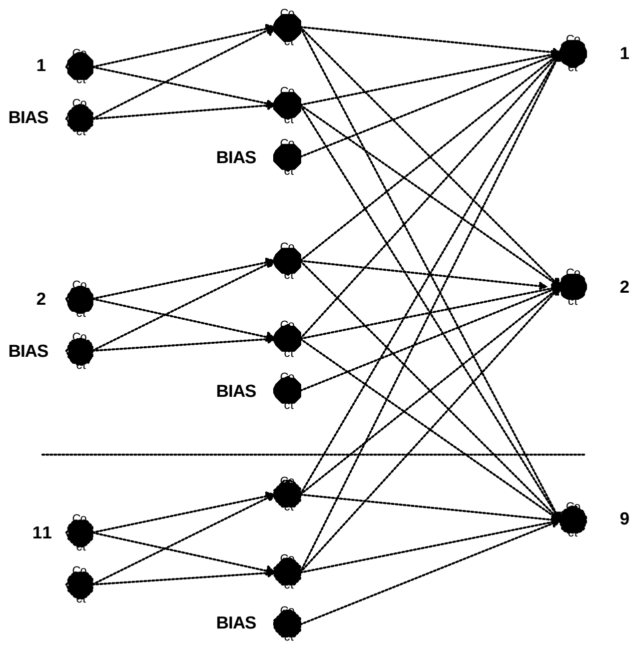

Fig. 2 Partial scheme of developed BPNN

The hidden layer is formed by 11 sets of hidden layer each formed by only two neurons plus 1 bias. Each neuron of an hidden layer is linked to all elements of output layer. While the bias of each hidden layer is linked to one of output elements.

The transfer function of hidden elements was the classical sigmoid while the transfer function of output element was the linear one.

The BPNN was costructed by the MatLab® release 6.1.

The study considered different algorithms for training the developed BPNN, the only one that has not been considered is the Levenberg-Marquarqt. Is is the most suitable for BPNN training but it is strongly limited by the number of patters used. It is actually impossible to use the method for the high number of patterns considered (7000).

The following sections deals with the results of used trainig algorithms and the reasons that lead to the selection of ‘Resilient Back-propagation’. The complete description of each algorithms is contained in [6]. Here the description has been not shown owing to paper lenght reasons.

2.1-Scaled Conjugate Gradient

This algorithms furnishes good results for both patters recognition and function approximation and is suggested for several patter usage. The results of training are depicted in fig.3. This figure, just as the other ones contained in the following sections, shows the amount of error versus the training epochs.

The results are good but the BPNN shows less quality performance than the Resilient Back-propagation’.

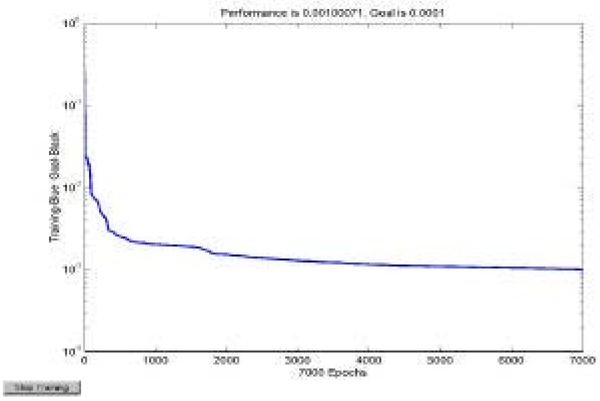

Fig. 3 Error decay versus training epochs

2.2-Gradient Descendent with momentum

This is a classical method for BPNN training but, even if the momentum technique is used, it is slow in convergence reaching. The results are depicted in fig.4

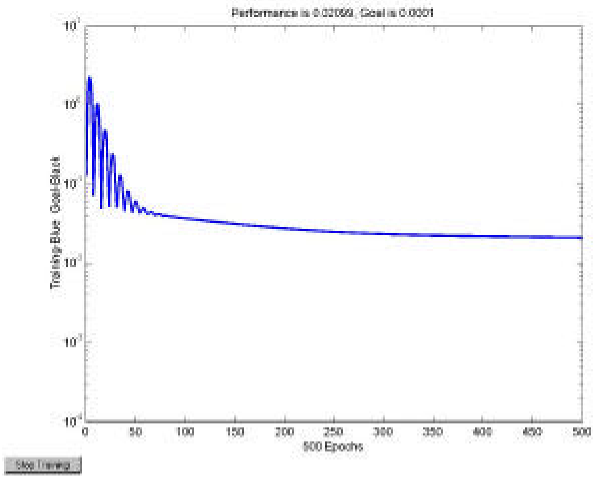

Fig. 4 Error decay versus training epochs

2.3-One Step Secant Algorithm.

This training method represents a good compromise between Gradient Descendent Method and Quasi Newton method. Again the training history is depicted in fig. 5.

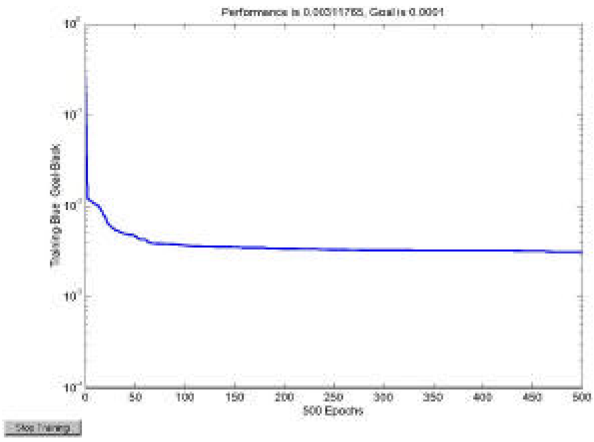

Fig. 5 Error decay versus training epochs

2.4-Quasi-Newton Algorithm

This method has been applied to the results of previous training in order to avoid the asymptotic behaviour and for improving the precision of training. The obtained results shows that the training precision is not yet substantially improved, fig.6.

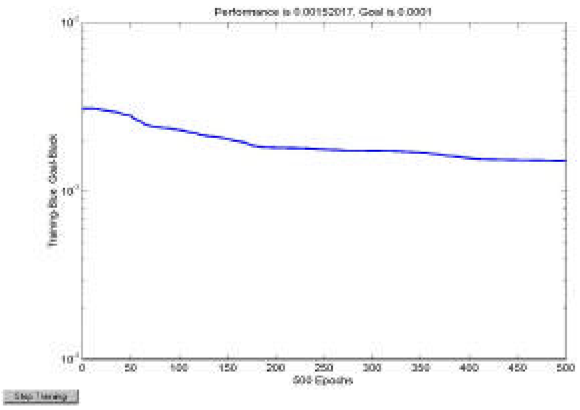

Figura 6 Error decay versus training epochs

2.5-Resilient Back-propagation

The results of this methods are shown in fig.7. The method has been proved to give the best results.

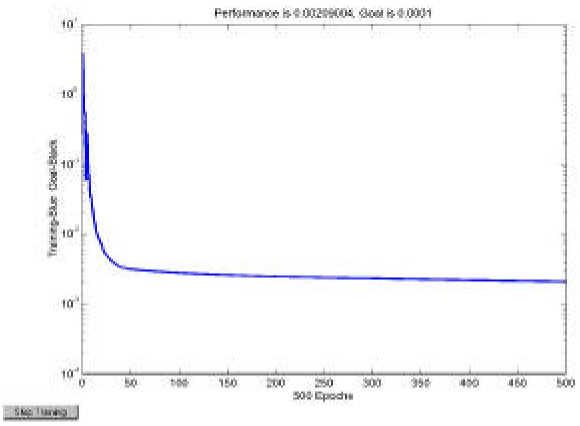

Figura 7 Error decay versus training epochs

At the present works are in full progress for developing Neural Network based simulator for studying on design cycle and performance of turbofan as well as of other engines. The activity shown in this section has been the necessary background and it has required a lot of work and long time. The simulators based on the developed BPNNs are the argument of a paper in progress.

3-<u>BPNN FOR THE SIMULATION OF WORKING OF A GENERIC AIR SYSTEM</u>

An air system may be considered as a set of ducts linking some chambers, where the values of pressure are unknown, and external places where the pressures are known [7].

The analysis of an air system means to evaluate the pressure in the different chambers and the mass flow rates in the ducts. These values depend upon the system geometry as well as upon the boundary conditions.

The study and the definition of an air system requires:

1. To establish the chambers where the pressure must be calculated;
2. To assign the external values of pressure and temperature;
3. To define the dimensions of the different ducts with the concentrated and/or distributed losses due to the sudden reduction or increase of area sections, labyrinth, etc.

Each component of air system cannot be considered as separated from the others because its behaviour depend upon the working and the behaviour of all other air system components even if they are not directly linked to the particular components [8], [9], [10].

The analysis of air system working, carried out in this study, is based on a relaxation iterative procedure. The developed method is composed by different steps:

1. Guessed values of pressure in the chambers and ducts are fixed;
2. The mass flow rate in the ducts is evaluated
3. The balance of mass flow rate in each chamber is carried out for identifying the chamber where the unbalance in the largest one;
4. The pressure in this chamber is varied so the continuity equation is satisfied. In other words the sum of inlet mass flow must be equal to the sum of oulet mass flow. If the unbalance in the chamber is positive the pressure must be reduced otherwise it must be increased.
5. The balance in the chamber causes an unbalance in another chamber so the procedure continues up to the balance is reached in all air system component.

Seals are the most important parts of any air system. The correct working of the whole engine as well as of the single components and system is strongly linked to the correct working of seals. Infact seals control the mass flow rate used for cooling and pressurization. This last aim is important both for avoiding the leakage of lubrication oil from bearing chambers and for preventing the input of main stream in the turbine disks cavities.

A gas turbine engine uses different seal types. The choice may be supported by several criteria, i.e.:

1. Working pressure and temperature,
2. The wear and tear
3. The heat generation
4. The weight
5. The size
6. The manutenibility

This study has focalized the attention on the simulation and behaviour of labyrinth seals [11], [12] .

Moreover the developed BPNN have been used for trouble-shooting and fault detection in this kind of seals. A typical labyrint seal is composed by a rotating set of little wings faced to a fixed ring constituted by abrasive material or honeycomb structure capable of supporting high temperature. During the engine starting the wings scrape against the coating; this way a miminum tip clearance is assured during any engine working condition.

The tip clerarance depends upon the thermal loading as well as upon the flexion of engine shafts. The most critical seals are the ones matching shafts rotating at different speeds.

It is clear that some of problems encountered during engine life is the wear and tear of seals. This leads to oil as well as air leakage and to engine performance decay.

This part of study deals with the air system a 600 single spool turboprop. The numerical computer code derived from the method, whose main steps have been previously described, was used for generating the patters for the traininig of BPNN.

A partial scheme of the air system used for setting up the method is depicted in fig. 8.

The main elements of the scheme are the chambers and the ducts.

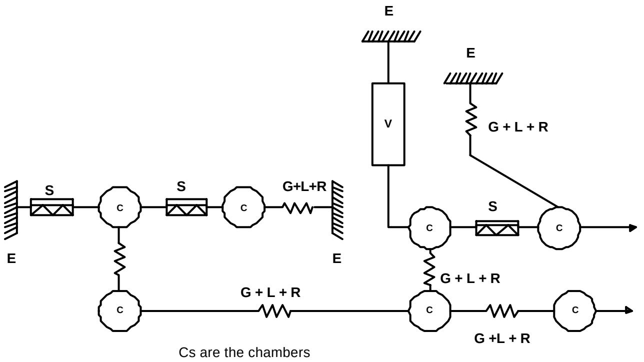

Fig. 8 General Scheme for the study of the Air System of a Gas Turbine Engine

The externals (the E elements in fig. 8), as the name indicates, are places outside the air system where both temperature and static pressure values are known. They represent the boundary condition of the problem.

Other important elements for air system calculation are the restictions where there are either slam reduction or increase of section areas. They are indicated as R in the scheme of fig. 8.

Other elements permit the evaluation of distributed losses due to friction. Their definition require the value of: idraulic diameter of duct section, the lenght and the actual section of duct. They are defined by letter L in the scheme of fig. 8.

Finally there are the elements representing the concentrated losses due to any other causes different from the one described by R elements. These elements are indicated by letter G in fig. 8.

The labyrint seals are another type of air system element. Only one of them may be present in a duct. They are defined by assigning the wings number, the clearance, the pitch, the tip width, the wing external diameters.

As previously stated this study deals with labyrinth seals. The considered engine has seven labyrinth seals placed in differet parts of the air system and having differet tasks.

Some of them guarantee the pressurization of engine bearings. Others are interstage seals and they avoid the leakage of hot gases in the cavities placed among the turbine disks..

The main parameter of seals is the geometry. Infact any variation of seal geometry affects both the behaviour of the whole air system as well as the behaviour and performance of the whole engine.

The first step of this study concerned with the determination of the geometric characteristic of the different seals assuring the correct working of both air system and engine.

The nominal values of seal geometry is reported in table 2

Table 2 The geometry (in meters x 10^3) of the seven seals

Seal 1	Seal 2	Seal 3	Seal 4	Seal 5	Seal 6	Seal 7
.105	.108	.128	.297	.412	.820	.120

The correct pressure values in the 12 chambers constituting the main elements of air system were computed by a computer program whose inputs were the geometrical characteristics of seals (table 2) and of ducts and whose output were the value of pressures in all parts of air system.

Table 3 contains the value of pressure in the different chambers by using the nominal values of seal geometry. These pressure values characterize the engine when there are no faults in progress. They are also the basdeline values for diagnostics calculations.

Table 4 The nominal values of chamber pressures

Chamber	Pressure(Pa)
C1	171.10
C2	93.607
C3	246.30
C4	257.95
C5	264.49
C6	649.71
C7	278.53
C8	227.08
C9	211.57
C10	175.78
C11	116.73
C12	83.535

In order to generate the patterns necessary for diagnostics calculation, the numerical code has been used for obtaining the chamber pressures while the geometries of seals were varied randomly of ? 90% of their nominal values. This phase of study lead to the generation of 6000 patterns.

The developed BPNN has one input layer with 13 elements (the values of pressure of each chambers + the bias); an hidden layer with 25 elements + 1 bias (this number has proved to be the best compromis e between the BPNN accurancy and the training time); one output layer with 7 elements (the geometry of seals responsible of the input values of pressure in the air system chambers).

For BPNN training were used 2000 of generated patterns.

The learning rate was selected to 0.7 and after 5000 training epochs the mean squared error reached the suitable value of 1.7E-07. Coniugate gradient method was used for traininig the BPNN.

Fig. 9 and 10 show the input used for the BPNN training. Figure 11 shows the trend of difference among actual and calculated output geometry of seal 1. The upper part of figure shows the difference between the actual values of output elements for the 1st seal and the calculated one. The second and third part of the same figure shows the percentage error as well as the absolute error. Fig. 12 is the zooming of the previous one and it was generated in order to undeerline the very small difference between the calculated pattern and the actual one.

Finally fig. 13 shows the trend of overall error during the BPNN training. After 5000 epochs the reached precision is very good and satis fying.

When the BPNN was trained, the simulation program was used in order to generate other 4000 new patters. These ones were used for testing the BPNN precision. Fig. 14 deals with the results about the seal numebr 1. As shown the precis ion reached is very satisfaying.

After the training and the testing, the developed BPNN was used as the core part of a code for the diagnostic of air system. An user-friendly interface was developd in MatLab®. By furnishing the values of pressure in the 12 chamber it is possible to detect if and where there is a fault and the kind of fault. Fig 15 and 16 show an example of Diagnostic program running.

Table 4 shows the values of the case under examination. It must be noted that the pressure values in chambers 1 and 9 are changed with respect to the ones shown in the table 3. The BPNN based diagnostics code elaborates the new values and detect the faults. It has been localized in the seals 4: tip clearance is increased.

The main andvantages of using BPNNs for diagnostics calculation are:

1. the codes are fast, reliable and require poor computer memory;
2. the codes work well and furnish good and reliable indications for fault detection even if input data are not complite and/or wrong. This is due to a characteristic of BPNN: the flexibility and robustness. Obviously there is a limit to this interesting capability and works are in progress for testing the limits of BPNN robustness and of reliability.

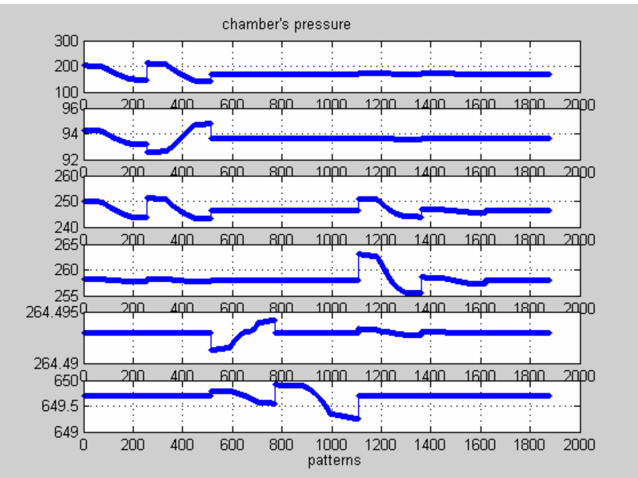

Fig. 9 Pressure values in the first 6 chambes

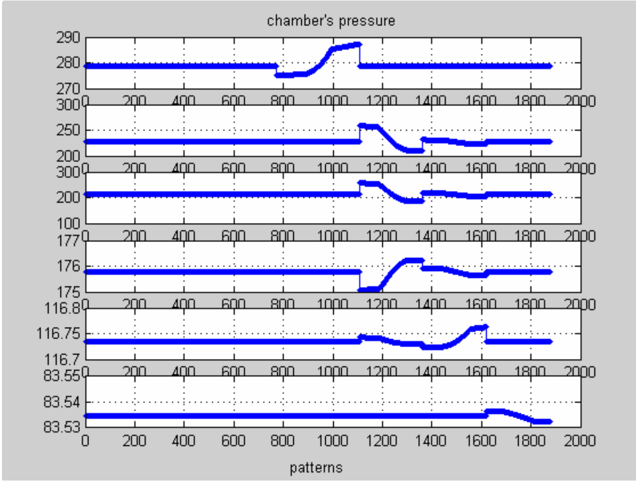

Fig. 10 Pressure values in the last 6 chambers

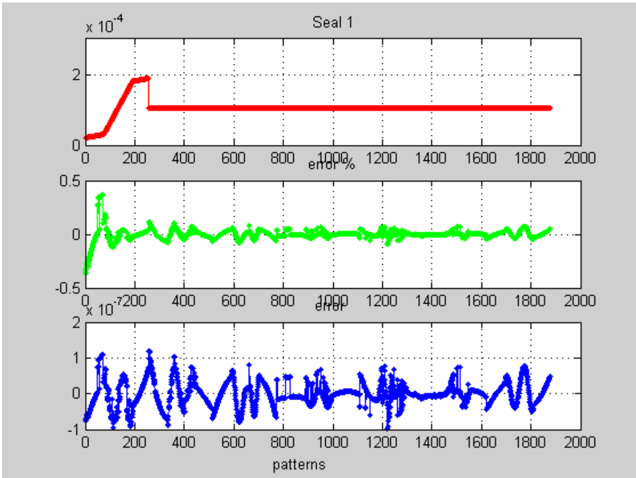

Fig. 11 Values in seal 1 during training

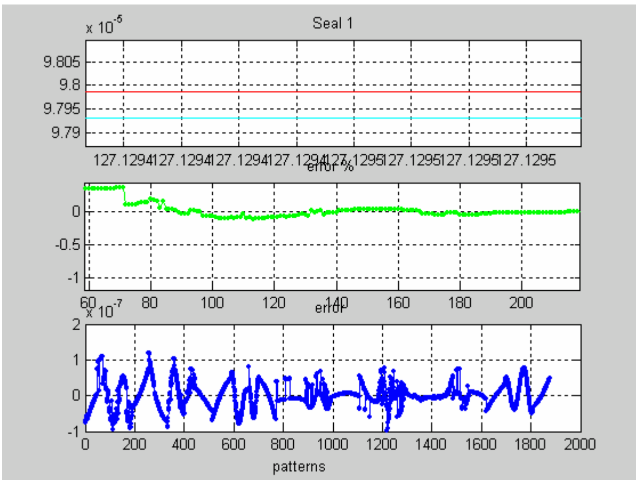

Fig. 12 The zoom of figure 11

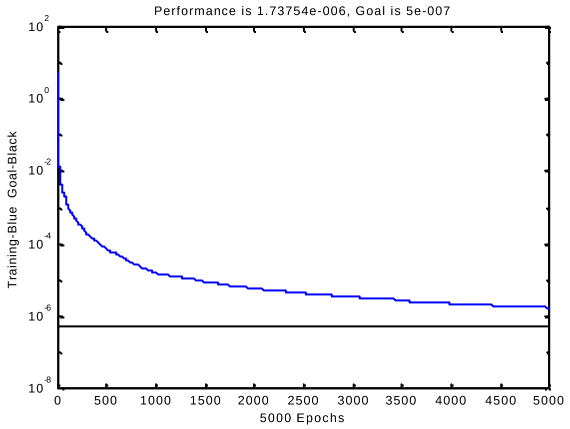

Fig. 13 History of BPNN training

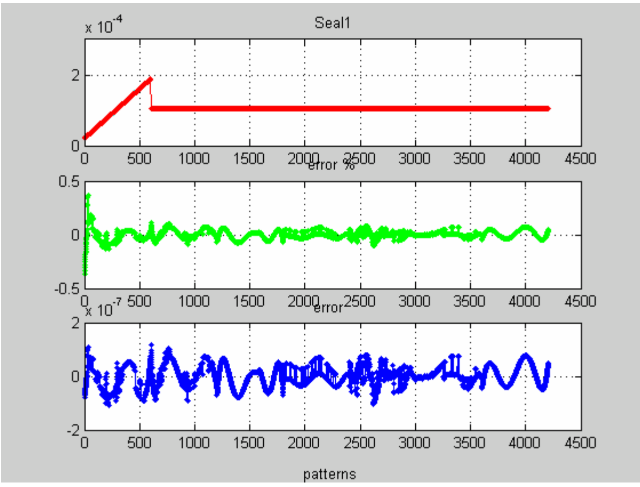

Fig. 14 Results during test calculations

Table 4 The values of chamber pressare when there is a fault in progress (the pressure in chamber 1 is increased of 3.26 %, pressure in chamber 9 is increased of 4.37%)

Chamber	Pressure(Pa)
C1	176.6931
C2	93.6821
C3	247.3424
C4	259.2722
C5	264.4927
C6	649.5798
C7	281.2295
C8	234.1625
C9	220.8071
C10	175.6592
C11	116.743
C12	83.5344

4-CONCLUSIONS

The study had the target to develop BPNN for the study of influence of gas turbine air system on both on design performance and working. Two different BPNN types have been developed. The first one delat with the on design simulation of a large turbofan engine. In order to improve the accurancy of networks different architecture configuration have been considered and tested. The possibility to use different hidden layer for each input neuron has proved the be effective in constructing the BPNN. Moreover different training method offered by MatLab have been tested and compared. The shown architecture as well as the Resilient Back-propagation training method have proved to be suitable for the aims of the research.

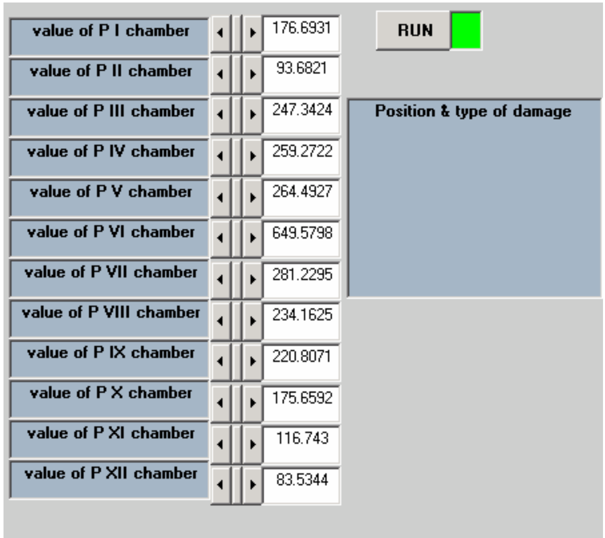

Fig. 15 An example of the utilization of BPNN based air system diagnostics code

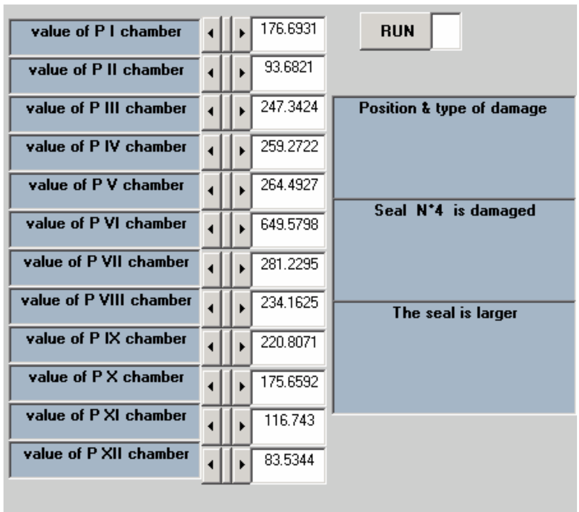

Fig. 16 An example of the utilization of BPNN based air system diagnostics code

The second one allow the study of air system working without and with faults in its components. The latter study allowed to develop a suitable Neural Network based code for the diagnostics and trouble-shooting.

It is necessary to underline tha the BPNN training has not considered multiple faults as well as the the influence of sensor noise and fault on the air system fault identification.

At the present works are in full progress for considering both sensor noise and multiple faiul effects. The study also are concerning with the test and the exploration of other BPNN configuration for both air system effects simulations and diagnostics.

5.-BIBLIOGRAPHY

[1]-G. TORELLA, G. LOMBARDO 'Neural Networks for the Maintenance of Aeroengines' AIAA paper 95-2351 1995

[2]-G. TORELLA, G. LOMBARDO 'Utilization of Neural Networks for Gas Turbine Engines' ISABE paper 95-7032, 12th International Symposium on Air Breathing Engines 10-15 September 1995, Melbourne, Australia

[3]-G.TORELLA 'Neural Networks for the Diagnostics and Fault Detection of Gas Turbine Engines' AIA '98 the 2nd Ankara International Aerospace Conference - Ankara 9-11 September 1998

[4]-G.TORELLA 'Neural Networks for the Diagnostics of Gas Turbine Engines ' 7th European Propulsion Forum Pau, FRANCE 10-12 March 1999

[5]-R.BETTOCCHI, P.R.SPINA,G.TORELLA 'Gas Turbine Health INDICES Determination by Using Neural Networks' ASME Paper to be published in Proceedings of ASME TURBO EXPO 2002 June 3–6, 2002, Amsterdam, The Netherlands

[6] HAGAN M., DEMUTH H., BEALE M. "Neural Network Design" PWS Publishing Company 1995

[7] DIXON "Fluid mechanics and thermodynamics of turbomachinery" ed. Pergamon Pres

[8] CHAPLYGIN S"Gas jets" Translation NACA TM 1063

[9] DAILY J.W. , NECE R.E."Chamber dimension effects on induced flow and nal of Basic Engineering, Vol.82, March 1960frictional resistence of enclosed rotating disks" Trans. ASME Jour

[10] "Fluid flow data book" General Electric

[11] EGLI A. "The leakage of steam through labyrinth seals",Trans. Asme, Vol. 57

[12] VERMES G"A fluid mechanics approach to the labyrinth seal leakage problem" Journal of Engineering for power, April 1961