Indirect evaluations of gas turbine parameters based on neural networks

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Abstract[1]

It is supposed, that gas turbine engine as the nonlinear plant of control on the ěstablished operating modes is described by means of the aspect equations (1). In practice the problem of indirect measurements is actual: on observations of an thermogas dynamic drive parametres output vector to define values of its operating actions (i.e. components of vector U).

1. Introduction

For example, on the measured values of parametres n_1, n_2, T_4^*, P_2^* etc. it is required to calculate value of the fuel consumption G_T in the combustion chamber.

Analytical statement of problem is reduced to definition of inverse nonlinear association f^{-1} in formula (1)

$$u = f^{-1}(A, Y) \quad (1)$$

Problem solving technique with use of a neural network we shall see below. Thus it is required to define structure and parametres of the NN ensuring a minimum error of training E on basis of procedure, presented on figure 1.

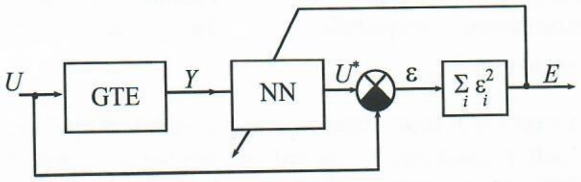

Fig. 1. Solution scheme of gas turbine inverse multimode model

Here $\varepsilon = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_k)^T$ - a vector of mismatches between the values of operating actions - actual and calculated by NN, i.e. $\varepsilon = U - U^*$; and $E = \sum_i \varepsilon_i^2$.

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After training neural network reproduces performances of gas turbine inverse model.

2. Input data preparation

As input data we will consider test result, received in the course of verification nature test at motor stand UMPO. These data are in table 1, with regard to usual atmospheric conditions. The fragment of a training selection for gas turbine multimode model is shown in table 1. Full training selection contains 109 lines.

Table 1. Fragment of training selection for multimode gas turbine model identification

Gt_r	n1_r	n2_r	Gv_r	P2_r	T4_r	R_r	T2_r	T3_r
0,193	0,538	0,736	0,418	0,328	0,518	0,153	0,445	0,573
0,131	0,348	0,549	0,252	0,205	0,476	0,056	0,254	0,612
0,203	0,548	0,742	0,427	0,336	0,524	0,161	0,451	0,578
0,480	0,798	0,879	0,757	0,643	0,758	0,500	0,809	0,763
0,150	0,408	0,617	0,304	0,243	0,468	0,085	0,299	0,575
0,353	0,712	0,837	0,619	0,505	0,671	0,336	0,668	0,694

Here in relative (dimensionless) units following parametres are equated:

$G_{t\text{-}pr}$ - the reduced fuel consumption;

$n_{1\text{-}r}$ - reduced rotor speed of low-pressure compressor;

$n_{2\text{-}r}$ - reduced rotor speed of high-pressure compressor;

$G_{v\text{-}r}$ - reduced air consumption;

$P_{2\text{-}r}$ - reduced air pressure behind the compressor;

$T_{4\text{-}r}$ - reduced outgassing temperature on an turbine output;

$R_{\text{-}r}$ - reduced engine thrust;

$T_{2\text{-}r}$ - reduced air temperature on an compressor output;

$T_{3\text{-}r}$ - reduced gas temperature on an turbine input.

One of the basic problems solved at stage of data analysis, the estimation of selection representativeness, i.e. completeness of its representation. The solution of the current problem is realized by one of the cluster or discriminant analysis methods.

Measurement of metric distance in the course of selection clustering, received in bench test process.

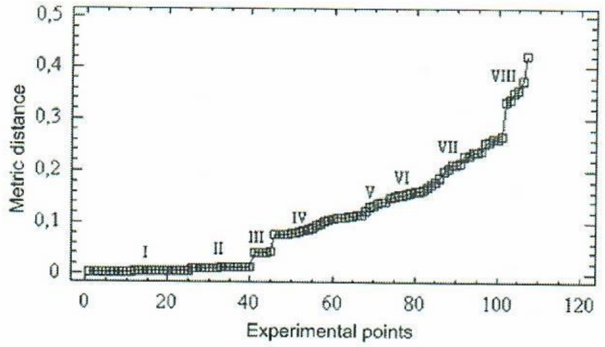

Fig. 2. Clusterization result of an original experimental selection (I … VIII - classes)

Change of metric distance in the learning sample clusterization process.

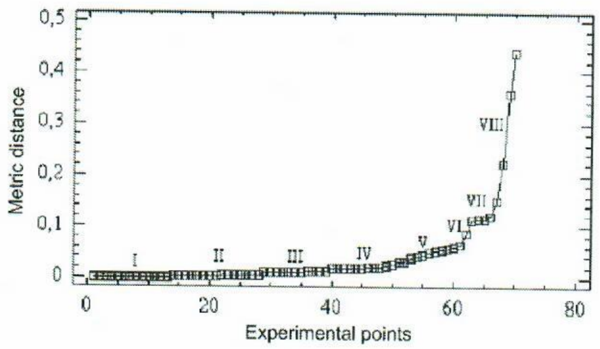

Fig. 3. Learning selection clusterization result

Change of metric distance in the test sample clusterization process.

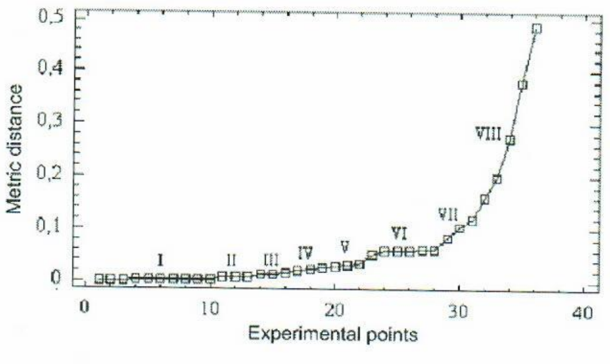

Fig. 4. Test selection clusterization result

The analysis of a figure 2 shows, that in clusterization process, using Statistica 8.0 software, eight classes have been selected. After randomization procedure learning and test selections (in the ratio 2:1, i.e. 67 % and 33 %) have been selected. Clusterization process of training (figure 3) and test (figure 4) selections shows, that they the same, and also like original selection (table 1), contain eight classes. Distance between clusters practically coincide in each of the considered selections. Therefore, learning and test selections are representative.

3. Preprocessing

The important question that is being considered during the prior elaboration of the measured data is the valuation of the homogeneity of the training and test samples. For this purpose we will take advantage of Fisher Snedekor's criterion [10, 11] for values of frequency rotations n_{1_r}, received thus outcomes are reduced in table 2. Table 2 analysis shows, that the ratio of σ^2_{max} to σ^2_{min} gives to variance count 1.28, which less than the critical value F taken from the standard table of Fisher – Snedekor. In our case, F = 3,44. Hence, samples are homogeneous.

Table 2. The estimation of a homogeneity training and test selections with use of Fisher - Snedekor's criterion (on an low pressure compressor rotation frequency data example - n_1)

Statistical estimate	n_{1_r} (training sample)	n_{1_r} (test sample)
Average	0,6214	0,6731
Dispersion	0,04819	0,06168
Greater to lesser dispersion ratio	1,28	
F – critical point	3,44	

The completion phase of statistical handling is rationing of data which can be perform by formula (1). Let's consider as an example the following problem. Values of the following gas turbine parametres normalized to standard atmospheric conditions (table 1) are known. It is required to construct multimode neural network mathematical model for calculation (indirect measurement) magnitudes of the reduced fuel consumption G_{t_r}.

The analysis of input datas (training sample) and process of their prehandling is carried out similarly to how it became in a previous problem.

4. Neural network construction

In the course of experimental researches as the basic architecture of NN, for a solution of the current problem were investigated perceptron and RBF. The architecture of RBF neural network for gas turbine inverse multimode model identification problem is shown in figure 5.

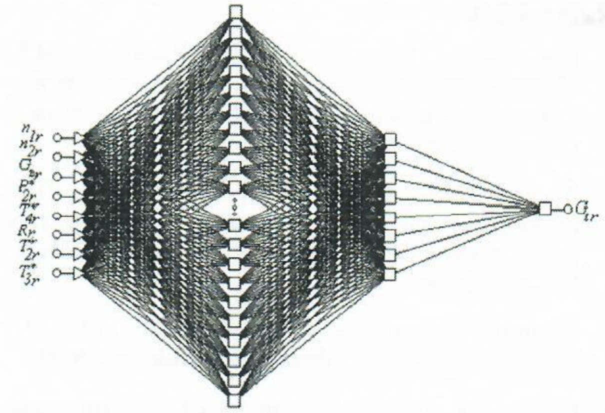

Fig. 5. Gas turbine inverse multimode model on the RBF neural network basis

Experimental researches for choice optimum structures of RBF and perceptron neural networks have shown, that optimum on NN complexity should have accordingly 12 and 16 neurons in the latent layer (Figure 6) and (Figure 7).

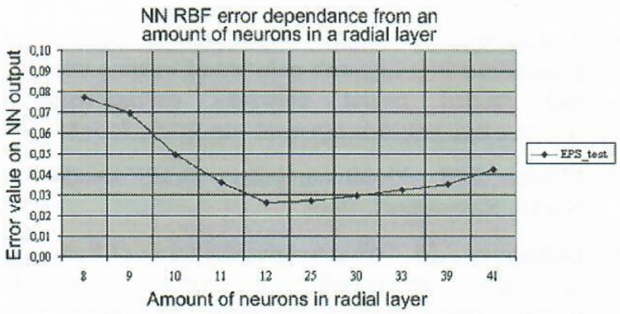

Fig. 6. Diagram of NN RBF error dependence from an amount of neurons in a radial layer

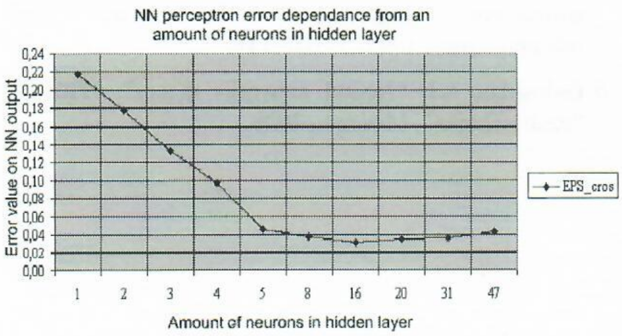

Fig. 7. Diagram of NN perceptron error dependence from an amount of neurons in a hidden layer

Therefore, on complexity structure of RBF NN for a gas turbine multimode model identification problem solve the structure 8 - 12 - 1 is optimum; and for perceptron - structure 8 - 16 - 1.

Activation functions are sigmoid.

Were used neural network training algorithms:

- For RBF NN - back propogation [8];
- For perceptron NN - levenberg-marquardt [8]:

$$w(t+1)=w(t)-\left([J(w(t))]^T\cdot J(w(t))+\mu\cdot I\right)^{-1}\cdot[J(w(t))]^T\cdot E(w(t)) \quad (2)$$

where w - a vector of adjusted NN weights;

J – Jacobian matrix;

N – Hessian matrix;

T – transposition sign;

μ – scalar parameter;

I – unit matrix.

5. Comparative analysis

The comparative analysis of NN accuracy (PTR, RBF) and classical least-squares procedure (LSP) methods of gas turbine multimodel inverse identification on test sample (figure 8) and on the same sample in the conditions of an additive making parasite (white noise with zero expectation *of* $M = 0$ and $\sigma = 0{,}01$), (figure 9) is carried out. Curves in figures (8, 9) correspond to errors of an evaluation of the reduced fuel consumption (D_G_t) for two classes of NN models (perceptron and RBF), and also for polynomial regressive model of 8th degree received by least-squares procedure.

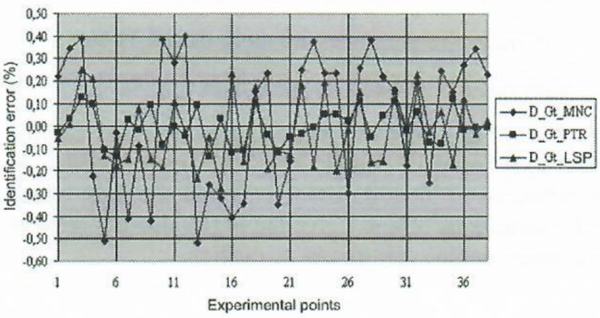

Fig. 8. Research results of neural and classical methods of gas turbine multimode model identification

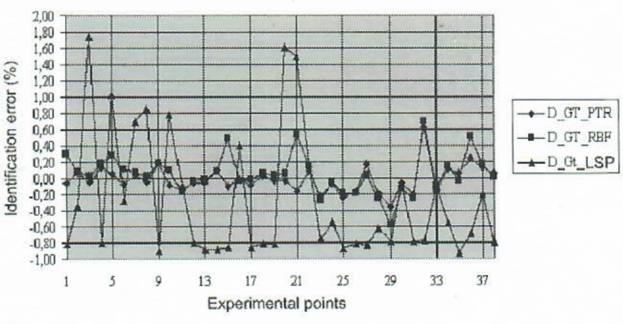

Fig. 9. Research results of neural and classical methods of gas turbine multimode model identification (with white noise)

Table 3. The comparative of neural and classical methods of gas turbine inverse moltimode model identification (indirect measurement of the fuel consumption)

Identi-fication method	Mean square error (without noise)	Absolute error (without noise) (%)	Mean square error (with noise)	Absolute error (with noise) (%)
LSP	0,06	0,51	1,40	1,75
Percep-tron	0,02	0,13	0,04	0,61
RBF	0,05	0,28	0,06	0,76

Analysis of results shows, that in the best performances possesses perceptron NN which allows to spend indirect measurements of the fuel consumption in a wide range of gas turbine running (from a "Small gas" mode to "Forcing" mode):

- without noise presence - with an error no more than 0,13 %;
- with noise presence (= 0,01) - with an error no more than 0,61 %.

Application of least-squares procedure in these conditions allows to receive an error value:

- without noise presence - no more than 0,51 %;
- with noise presence - no more than 1,75 %.

Therefore, at indirect evaluations of gas turbine multimode model, neural networks more robust to perturbations of input data than classical methods, which in the conditions of noise give the big evaluation error of an aviation engine parameters evaluation.

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