COMPUTER-AIDED METHOD OF DIAGNOSTICS OF GAS TURBINE BLADES

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Abstract: The article presents a computer-aided method of diagnostics of gas turbine blades with use of artificial neural networks. The subject of presentation is the developed neural network, with help of which – on the basis of features of blade surface images – realised is determination of their condition (operable element – inoperable element). Basing on conclusions formulated on the basis of microstructure examinations and concerning evaluation of state of overheating (blades suitable and not suitable for further operation), as patterns assumed were surface images representing blades in various states (neural pattern classification). Additionally, combining and segregating (according to their applicability for the network teaching process) image parameters, acquired from histograms as well as from matrix of events, automated and increased was the credibility (computer aiding) of decision process. The application of artificial neural network enables better representation of complex relations between blade image and its condition, than in the case of subjective methods used currently by diagnosticians.

1. INTRODUCTION

Selection of material for gas turbine blade of required resistance must consider the spectrum of coercion in the zone of influence of maximum exhaust gas temperature. Frequent cause of damage to gas turbine is overheating of material as well as thermal fatigue of blades of nozzle unit and rotor caused by both excessive temperature and time of its action as well as chemical activity of exhaust gas. During the entire period of operation observed is change in colour of surface of blade feathers. Colour changes resulted from various degree of material overheating. Defects resulting from overheating of blade material lead to faulty operation of gas turbine. This type of defect is repaired always in the course of engine general overhaul. As for today, the decision about necessity of engine repair is taken by a diagnostician, who, using the visual method with help of a videoscope, can diagnose the condition of hardly-accessible elements of turbine. The evaluation of condition is realised on the basis of recorded image of surface of diagnosed element and comparison of this image with pattern images of suitable and unsuitable surfaces of similar elements of turbine blades. Such criteria of evaluation are very imprecise, because the vision of a diagnostician (organoleptic method of evaluation) causes deformation of blade diagnostics results due to subjectivism of examination. Additionally, the colour is a physicopsychological phenomenon, what causes that the evaluation of blade condition made by a diagnostician can be crippled with great error. Until now there is no objective and fully credible method of non-destructive detection of overheating of gas turbine blades. Application of digital technology of image recording combined with computer analysis and computer-aided decision making (neural networks) will contribute to increase of objectivism and credibility of diagnostics of these turbine elements. As for possibilities of diagnostics of blade condition on the basis of image of its surface, i.e. on the basis of parameters determined from histogram (information about lightness) and matrix of events (information about texture – repeatability of pattern on surface of blades), various technical conditions of blades can be correlated with information contained in recorded digital images. For defined technical condition blade surfaces have similar colour and roughness (texture). On the basis of parameters determined from histogram and matrix of events, and with help of neural network (pattern classification) will be possible to assign the blade image (recorded surface) to certain class representing given state (operable, inoperable).

2. ACQUISITION OF IMAGES OF GAS TURBINE BLADES

The subject of examinations are new blades (annealed in five values of temperature close to working temperatures – alloy EI-867 WD – blades of gas turbine rotor of an aircraft turbojet engine) as well as used ones (alloy ŻS-6K – blades of gas turbine stator ring of an aircraft turbojet engine). Acquisition of images was realised at special laboratory stand with help of digital camera and industrial videoscope; guaranteed was also proper repeatability and quality of surface images (Bogdan, 2008). Next, carried out were metallographic examinations aimed at determination of technical condition of examined turbine element. Considered were parameters of microstructure, i.e. change in thickness of aluminium protective coating and change in average size of precipitations of γ' (phase reinforcing the alloy, which mainly determines creep-resistance properties) (Błachnio, 2009). This allowed systematisation of blades according to their technical condition. Fig. 1 shows an example of assumed classification of blades in various technical condition (material criterion).

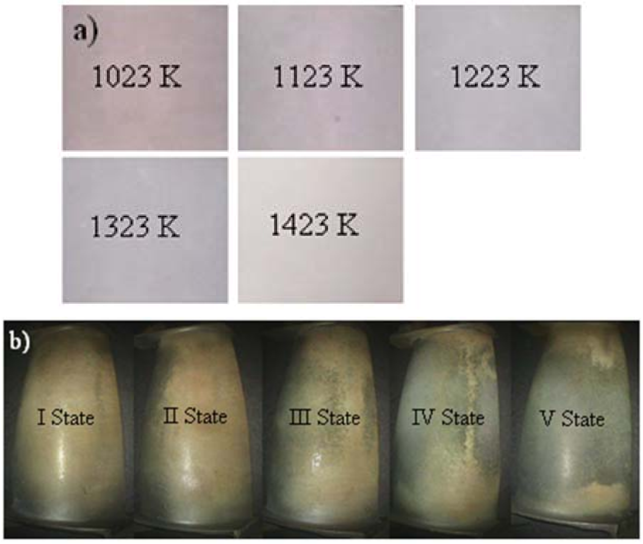

Fig. 1. Acquisition of image of blade surface: a) annealed – with help of digital camera), b) used – with help of videoscope

As a result of influence of high temperatures occurs change of structure of superalloys. Modification of microstructure is simultaneously accompanied by change of coating roughness. The state of coating has influence on reflection and absorption of light stream. Utilised are relations between wave properties of light and physicochemical properties of examined surfaces, which determine angle relations between falling and reflected light as well as absorption of individual wavelengths of electromagnetic radiation spectrum. Additionally, on the basis of examination of chemical composition we have discovered that as a result of influence of high temperatures modified was the weight concentration of elements forming the coating.

3. NEURAL NETWORKS

The assessment of the value of classification error (or classification adequacy) is realised on the basis of simulation of test data set in a previously trained network. Additionally, for the test data set the real classification is already known. This allows to compare decision made by modelled network with real classification and to find out, whether, and to which extent the neural network appropriately anticipates adherence to certain class (group). Overall error rate is defined as the relation (Osowski, 1996):

$$\varepsilon_{ov} = \frac{n_{bl}}{n_{test}}, \tag{1}$$

where: n_{bl} – number of incorrectly classified test data, n_{test} – total number of test data. The measure of classification adequacy (accuracy, efficiency) is defined as the supplement to one of overall classification error:

$$\eta_{ov} = 1 - \varepsilon_{ov} = 1 - \frac{n_{bl}}{n_{test}} = \frac{n_{popr}}{n_{test}}, \tag{2}$$

These measures are alternatively presented in percent on a 100-percent scale. The bigger η_{ov} (the smaller ε_{ov}) the more effective is classification made by „trained" network. At present available are many models of supervised networks, although they are actually variants or modifications of limited number of models. Considered were only those, which gave best results (verification of classification adequacy on a test data set) i.e. the multilayer perceptron (MLP) and the network with radial basis functions (RBF). Exemplary structures of these networks are shown in Fig. 2.

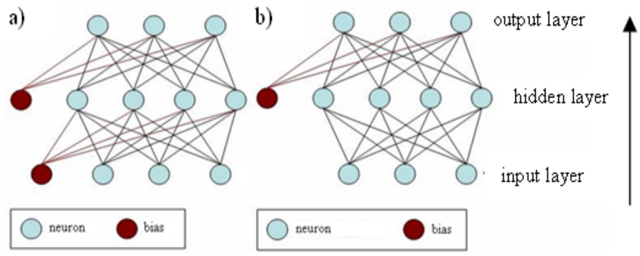

Fig. 2. Scheme of network structure (Zieliński and Strzelecki, 2002): a) multilayer perceptron; b) network with radial basis functions

Number of hidden layers can be virtually arbitrary, however it was proved that two layers are quite sufficient for any mapping of input data into output data. Learning of this type of networks is realised usually with help of a teacher, with first- or second-order gradient method, through minimization of error function. In the case of a multilayer perceptron the level of neuron excitation is the weighted sum of inputs (plus the threshold value added as so-called bias). Introduction of an additional bias input to the neuron causes that the network has increased ability (capability) of learning, what is connected with possibility of shifting of activation threshold depending on weight of bias. In a network with radial basis functions bias is connected only with neurons in output layer. Moreover, this type of network makes use of radial basis functions and has usually one hidden layer containing neurons with radial function of activation. Output neurons are usually the weighted sum of signals send by radial neurons of hidden layer. Learning of this type of network consists in selection of weights of output layer and parameters of Gauss radial functions (Zieliński and Strzelecki, 2002).

4. DIAGNOSTICS OF BLADE CONDITION ON THE BASIC OF PATTERN CLASSIFICATION WITH HELP OF NEURAL NETWORKS

Having tested at least a few computer programs for building and modelling of neural networks we have chosen the program STATISTICA 8 – Data Miner (Bogdan, 2008). This choice allowed us to obtain better, more accurate and more repeatable results. The task of developed neural classifier was elaboration of the method (computer-aided), which enables determination of blade condition on the basis of image (its properties) of its surface. Considered was the following case i.e. two-state classification (new annealed blades and used blades): class 1 – operable state (non-overheated blade), class 2 – inoperable state (overheated blade). The first stage was acquisition of data, which were later used for modelling of the network (input data) and its testing (examination of ability of correct classification). To reduce information size, coloured images were transformed to monochromatic images (8-bit grey-scale 0-255). Next, selected were 10 input parameters (image properties). First six parameters (P1-P6) describe the histogram, or distribution of brightness of pixels for examined image fragments. Next four parameters (P7-P10) were determined from the matrix of events (for the distance equal to 1 and angle 0º) – table 1 (Zieliński and Strzelecki, 2002).

Tab. 1. Input data – vector of properties

Designation	Description	Designation	Description
P1	value of maximum saturation	P6	histogram excess
P2	value of average brightness	P7	contrast
P3	variation of bright-ness distribution	P8	correlation
P4	histogram skewness	P9	energy
P5	histogram kurtosis	P10	homogeneity

Thanks to metallographic examination (material criterion) we hale discovered that new blades annealed at 1023K and 1123K have correct structure, and annealed at 1323K and 1423 – overheated structure. However, in the case of used blades, blades in state I and II have correct structure; and blades in state IV i V – overheated structure. This classification allowed modelling of the network with STATISTICA program. The stages of modelling were as follows:

– Standardisation of data and encoding of inputs (classes);
– Division of data into learning sample and test sample (ratio 50% : 50%);
– Adjustment of parameters of neural network creator, e.g.: minimum and maximum number of hidden layers (for MLP and RBF), types of activation functions for hidden neurons as well as for output neurons (for MLP), minimum and maximum weight reduction for hidden neurons and output neurons (for MLP).

The network was learned with the set of input data due to small number of surface images, without current verification of learning progress with help of the validation set. As a result of simulation in learning as well as in testing mode we obtained optimum models of neural networks (see table 2) for the case No. 1 (two-state classification of annealed blades).

Tab. 2. Models of networks for the problem of two-state classification (diagnostics) of annealed blades

Network No.	Network name	Quality (learning)	Quality (testing)	Learning algorithm	Error function	Activation (hidden)	Activation (output)
1	RBF 10-6-2	88,9	94,4	RBFT	SOS	Gauss	Linear
2	MLP 10-9-2	94,4	88,9	BFGS 24	SOS	Exponential	Exponential
3	MLP 10-7-2	100	88,9	BFGS 25	SOS	Exponential	Logistic
4	MLP 10-15-2	94,4	88,9	BFGS 24	SOS	Exponential	Exponential

Tab. 3. Models of networks after reduction of input data for the problem of classification (diagnostics) of annealed blades

Network No.	Network name	Quality (learning)	Quality (testing)	Learning algorithm	Error function	Activation (hidden)	Activation (output)
1	MLP 8-10-2	100,0000	94,44444	RBFT	Entropy	Exponential	Softmax
2	MLP 10-9-2	94,4	88,9	BFGS 24	SOS	Exponential	Exponential

Tab. 4. Models of networks for the problem of two-state classification (diagnostics) of operating blades

Network No.	Network name	Quality (learning)	Quality (testing)	Learning algorithm	Error function	Activation (hidden)	Activation (output)
1	MLP 10-7-2	100,0000	100,0000	BFGS 23	Entropy	Tanh	Softmax
2	MLP 10-5-2	100,0000	100,0000	BFGS 21	Entropy	Line	Line
3	MLP 10-10-2	100,0000	100,0000	BFGS 19	SOS	Exponential	Sinus
1	MLP 10-7-2	100,0000	100,0000	BFGS 23	Entropy	Tanh	Softmax

Thick models of neural networks (No. = 2, 3, 4) have relatively high quality (ability) of learning and simultaneously high level of testing quality 89%. However, in two cases a blade in inoperable state was considered as an operable one. Such situation is disadvantageous from the point of view of diagnostics of turbine blade. To eliminate these classification errors we have examined applicability of individual parameters (P1-P10) for differentiation of classes (states). For two classes (groups) of data we have carried out the test, which purpose was the comparison of basic statistics for 10 variables with 18 trials for each class. The data set was arranged in such way, so that each case represents one unit identified with grouping variable (state). On the basis of obtained results we have stated that parameters P3 and P4 are unnecessary, because they do not provide valuable information for the „classification problem". In the table 3 presented are results of modelling of neural networks after reduction of input data.

The ability of restoration of learning set – the measure of retention ability of learning data amounts in this case to 100%, however, the ability of generation of correct solutions for data contained in testing set, on which the network was not trained (measure of generalization ability) amounts to 94% .The same method of creation of models of neural networks was applied for used blades. In the table 4 presented are some neural networks – for input data obtained from blade surface images recorded with an American videoscope.

In the case of assessment of condition of used blades with help of neural classification we hale obtained network models (No. = 1-3), which learn and map classes correctly – three types of network have made no mistakes during testing.

5. SUMMARY

On the basis of obtained results it was stated that neural networks are valuable tool for assessment of blade condition both new (annealed) and used ones (tab. 3, 4). Developed neural classification model (network of certain architecture) enables assessment of blade condition on the basis of properties (parameters) of its image with satisfactory credibility. Additional advantage of this type of approach is the possibility of full automation of diagnostic process in operational conditions (without disassembly of the turbine), i.e. the image of surface of examined turbine element acquired with videoscope is transferred to the computer, where, with help of suitable software, recognized are its properties, and on this basis the „modelled network" (correctly trained) correctly determines technical condition of the blade.

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