International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:1, No:2, 2007

Identification of Aircraft Gas Turbine Engine's Temperature Condition

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***Abstract*—**Groundlessness of application probability-statistic methods are especially shown at an early stage of the aviation GTE technical condition diagnosing, when the volume of the information has property of the fuzzy, limitations, uncertainty and efficiency of application of new technology Soft computing at these diagnosing stages by using the fuzzy logic and neural networks methods. It is made training with high accuracy of multiple linear and nonlinear models (the regression equations) received on the statistical fuzzy data basis.

At the information sufficiency it is offered to use recurrent algorithm of aviation GTE technical condition identification on measurements of input and output parameters of the multiple linear and nonlinear generalized models at presence of noise measured (the new recursive least squares method (LSM)). As application of the given technique the estimation of the new operating aviation engine D30KU-154 technical condition at height H=10600 m was made.

***Keywords*—**Identification of a technical condition, aviation gas turbine engine, fuzzy logic and neural networks.

NOMENCLATURE

Symbols

H	flight altitude	[m]
M	Mach number	-
T_H^*	atmosphere temperature	[°C]
p_H^*	atmosphere pressure	[Pa]
n_{LP}	low pressure compressor speed (RPM)	[%]
T_4^*	exhaust gas temperature (EGT)	[°C]
G_T	fuel flow	[kg/h]
p_T	fuel pressure	[kg/cm^2]
p_M	oil pressure	[kg/cm^2]
T_M	oil temperature	[°C]
V_{BS}	back support vibration	[mm/s]
V_{FS}	forward support vibration	[mm/s]
$a_1, a_2, a_3, \ldots$	regression coefficients in initial linear multiple regression equation of GTE condition model	
$a'_1, a'_2, a'_3, \ldots$	regression coefficients in actual linear multiple regression equation of GTE condition model	
$\tilde{a}_1, \tilde{a}_2, \tilde{a}_3, \ldots$	fuzzy regression coefficients in linear multiple regression equation of GTE condition model	
$\tilde{X}, \tilde{Y}$	measured fuzzy input and output parameters of GTE condition model	
$\otimes$	fuzzy multiply operation	

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Subscripts

ini	initial
act	actual

I. Introduction

One of the important maintenance conditions of the modern gas turbine engines (GTE) on condition is the presence of efficient parametric system of technical diagnostic. As it is known the GTE diagnostic problem of the following aircraft's Yak-40, Yak-42, Tu-134, Tu-154(B, M) etc. basically consists that onboard systems of the objective control written down not all engine work parameters. This circumstance causes additional registration of other parameters of work GTE manually. Consequently there is the necessity to create the diagnostic system providing the possibility of GTE condition monitoring and elaboration of exact recommendation on the further maintenance of GTE by registered data either on manual record and onboard recorders.

Currently in the subdivisions of CIS airlines are operated various automatic diagnostic systems (ASD) of GTE technical conditions (Diagnostic D-30, Diagnostic D-36, Control-8-2U). The essence of ASD method is mainly to form the flexible ranges for the recorded parameters as the result of engine operating time and comparison of recorded meaning of parameters with their point or interval estimations (values).

However, it should be noted that statistic data processing on the above mentioned methods are conducted by the preliminary allowance of the law normality of the recorded parameters meaning distribution. This allowance affects on the GTE technical condition monitoring reliability and cause the error decision in the diagnostic and GTE operating process [1-3]. More over some combination of the various parameters changes of engine work can be caused by the different reasons. Finally it complicates the definition of the defect address.

insufficiently and fuzzy, GTE conditions is estimated by the Soft Computing methods-fuzzy logic (FL) method and neural networks. In spite of the rough parameters estimations of GTE conditions the privilege of this stage is the possible creation of initial image (initial condition) of the engine on the indefinite information. One of estimation methods of aviation GTE technical condition used in our and foreign practice is the temperature level control and analysis of this level change tendency in operation. Application of the various mathematical models described by the regression equations for aviation GTE condition estimation is present in [4, 5].

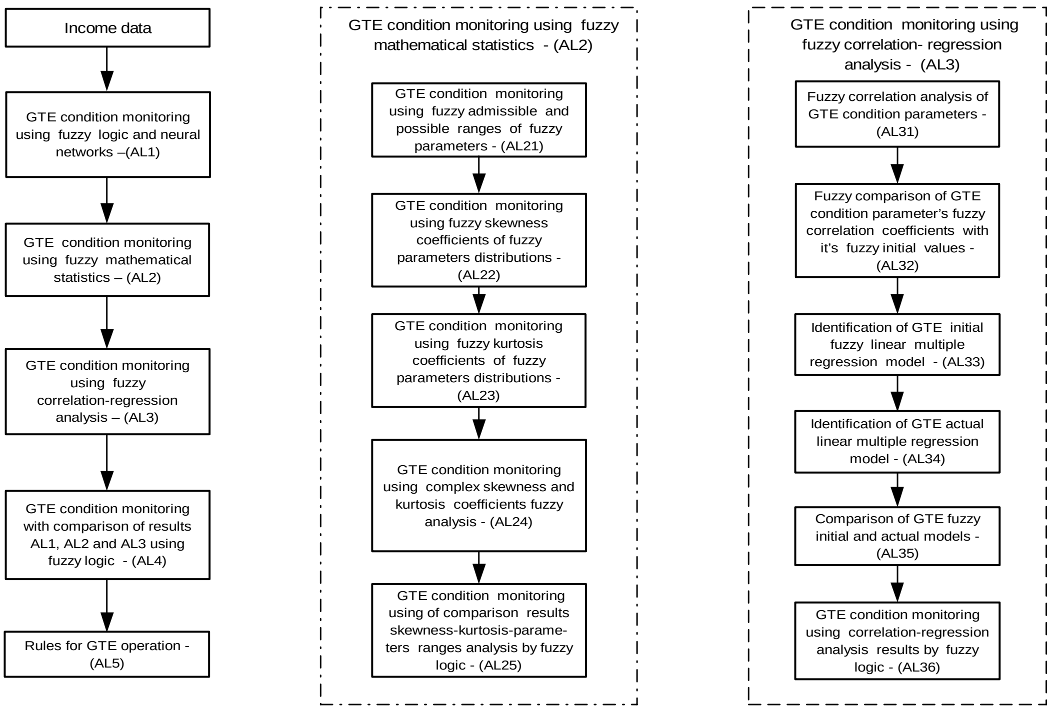


Fig. 1 Flow chart of aircraft gas turbine engine fuzzy-parametric diagnostic algorithm

II. Basics of Recommended Condition Monitoring System

It is suggested that the combined diagnostic method of GTE condition monitoring based on the evaluation of engine parameters by soft computing methods, mathematical statistic (high order statistics) and regression analysis.

The method provides for stage-by-stage evaluation of GTE technical conditions (Fig. 1).

To creation of this method was preceded detail analysis of 15 engines conditions during 2 years (total engine operating time was over 5000 flights).

Experimental investigation conducted by manual records shows that at the beginning of operation during 40÷60 measurements accumulated meaning of recorded parameters correctly operating GTE aren't subordinated to the normal law of distribution.

Consequently, on the first stage of diagnostic process (at the preliminary stage of GTE operation) when initial data

Let's consider mathematical model of aviation GTE temperature state, described by fuzzy regression equations:

$$\tilde{Y}_i = \sum_{j=1}^{n} \tilde{a}_{ij} \otimes \tilde{x}_j ; i = \overline{1,m} \qquad (1)$$

$$\tilde{Y}_i = \sum_{r,s} \tilde{a}_{rs} \otimes \tilde{x}_1^r \otimes \tilde{x}_2^s ; r = \overline{0,l}; s = \overline{0,l}; r + s \le l \qquad (2)$$

where $\tilde{Y}_i = \tilde{T}_4^*$ - fuzzy output parameter, $\tilde{a}_{ij}, \tilde{a}_{rs}$ - required fuzzy parameters (fuzzy regression coefficients).

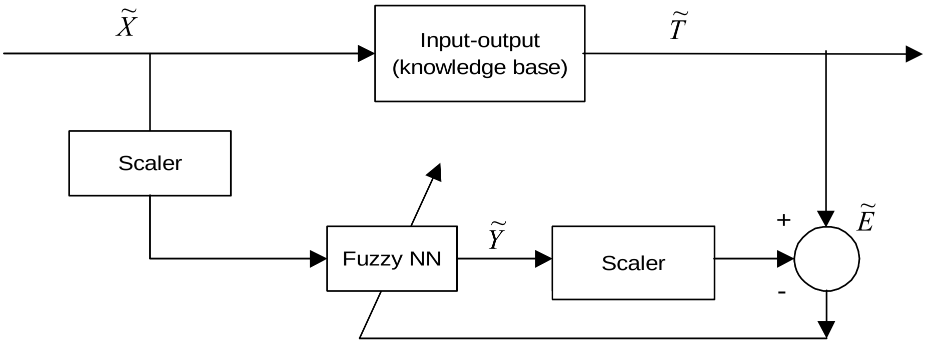


Fig. 2 Neural identification system

The definition task of fuzzy values $\widetilde{a}_{ij}$ and $\widetilde{a}_{rs}$ parameters of the equation (1) and equations (2) is put on the basis of the statistical experimental fuzzy data of process, that is input $\widetilde{x}_j$ and $\widetilde{x}_1, \widetilde{x}_2$, output coordinates $\widetilde{Y}$ of model.

Let's consider the decision of the given tasks by using fuzzy logic and neural networks [6-8].

Neural network (NN) consists from connected between their sets fuzzy neurons. At use NN for the decision (1) and (2) input signals of the network are accordingly fuzzy values of variable $\widetilde{X} = (\widetilde{x}_1, \widetilde{x}_2, ..., \widetilde{x}_n)$, $\widetilde{X} = (\widetilde{x}_1, \widetilde{x}_2)$ and output $\widetilde{Y}$.

As parameters of the network are fuzzy values of parameters $\widetilde{a}_{ij}$ and $\widetilde{a}_{rs}$. We shall present fuzzy variables in the triangular form which membership functions are calculated under the formula:

$$\mu(x) = \begin{cases} 1 - (\bar{x} - x)/\alpha, & if\ \bar{x} - \alpha < x < \bar{x}; \\ 1 - (\bar{x} - x)/\beta, & if\ \bar{x} < x < \bar{x} + \beta; \\ 0, & otherwise. \end{cases}$$

At the decision of the identification task of parameters $\widetilde{a}_{ij}$ and $\widetilde{a}_{rs}$ for the equations (1) and (2) with using NN, the basic problem is training the last. For training values of parameters we shall take advantage of a α-cut [8].

We allow, there are statistical fuzzy data received on the basis of experiments. On the basis of these input and output data is made training pairs $(\widetilde{X}, \widetilde{T})$ for training a network. For construction of process model on input $\widetilde{X}$ NN input signals (Fig. 2) move and outputs are compared with reference output signals $\widetilde{T}$.

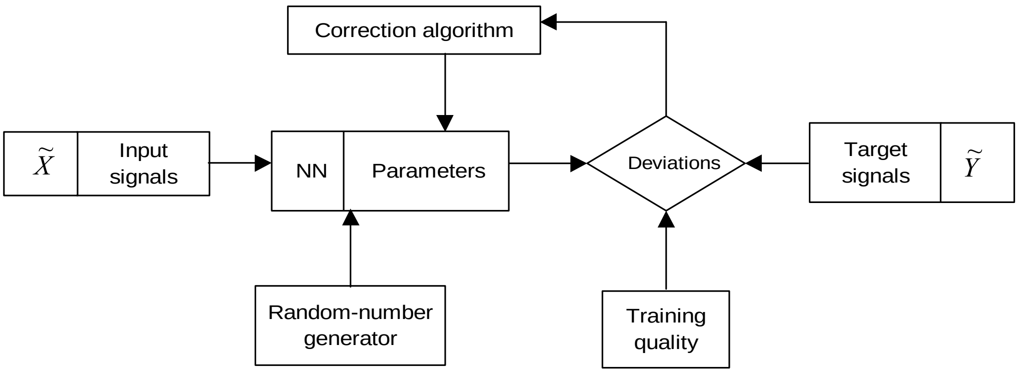


Fig. 3 System for network-parameter (weights, threshold) training (with feedback)

After comparison the deviation value is calculated: $\widetilde{E} = \frac{1}{2}\sum_{j=1}^{k}(\widetilde{Y}_j - \widetilde{T}_j)^2$

With application a α-cut for the left and right part of deviation value are calculated under formulas

$$E_1 = \frac{1}{2}\sum_{j=1}^{k}\left[y_{j1}(\alpha) - t_{j1}(\alpha)\right]^2, \quad E_1 = \frac{1}{2}\sum_{j=1}^{k}\left[y_{j1}(\alpha) - t_{j1}(\alpha)\right]^2,$$

$$E = E_1 + E_2,$$

where

$$\widetilde{Y}_j(\alpha) = \left[y_{j1}(\alpha), y_{j2}(\alpha)\right]; \quad \widetilde{T}_j(\alpha) = \left[t_{j1}(\alpha), t_{j2}(\alpha)\right].$$

If for all training pairs, deviation value E less given then training (correction) parameters of a network comes to end (Fig. 3). In opposite case it continues until value E will not reach minimum.

Correction of network parameters for left and right part is carried out as follows:

$$a^{н}_{rs1} = a^{c}_{rs1} + \gamma \frac{\partial E}{\partial a_{rs}}, \qquad a^{н}_{rs2} = a^{c}_{rs2} + \gamma \frac{\partial E}{\partial a_{rs}},$$

where $a^{c}_{rs1}, a^{н}_{rs1}, a^{c}_{rs2}, a^{н}_{rs2}$ - old and new values of left and right parts NN parameters, $\widetilde{a}_{rs} = [a_{rs1}, a_{rs2}]$; γ -training speed.

The structure of NN for identification the equation (1) parameters are given on Fig. 4.

For the equation (2) we shall consider a concrete special case as the regression equation of the second order

$$\widetilde{Y} = \widetilde{a}_{00} + \widetilde{a}_{10}\widetilde{x}_1 + \widetilde{a}_{01}\widetilde{x}_2 + \widetilde{a}_{11}\widetilde{x}_1\widetilde{x}_2 + \widetilde{a}_{20}\widetilde{x}_1^2 + \widetilde{a}_{02}\widetilde{x}_2^2 \qquad (3)$$

following kind: $y_{41} = a_{111}x_{12}x_{22}$; $y_{42} = a_{112}x_{12}x_{21}$,

and the correction formulas

$$\frac{\partial E_1}{\partial a_{111}} = \sum_{j=1}^{k}(y_{j1} - t_{j1})x_{12}x_{22}; \quad \frac{\partial E_2}{\partial a_{112}} = \sum_{j=1}^{k}(y_{j2} - t_{j2})x_{11}x_{21};$$

For value $\alpha = 1$ we shall receive

$$\frac{\partial E_3}{\partial a_{003}} = \sum_{j=1}^{k}(y_{j3} - t_{j3}); \quad \frac{\partial E_3}{\partial a_{113}} = \sum_{j=1}^{k}(y_{j3} - t_{j3})x_{13}x_{23};$$

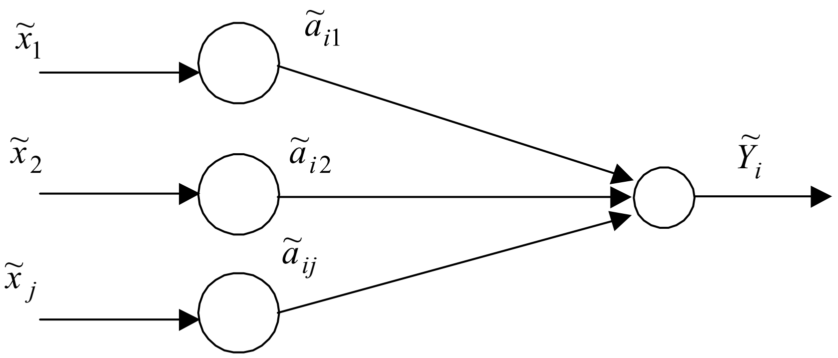


Fig. 4 Neural network structure for multiple linear regression equation

Let's construct neural structure for decision of the equation (2) where as parameters of the network are coefficients $\widetilde{a}_{00}$, $\widetilde{a}_{10}$, $\widetilde{a}_{01}$, $\widetilde{a}_{11}$, $\widetilde{a}_{20}$, $\widetilde{a}_{02}$. Thus the structure of NN will have four inputs and one output (Fig. 5).

Using NN structure we are training network parameters. For value $\alpha = 0$ we shall receive the following expressions:

$$\frac{\partial E_1}{\partial a_{001}} = \sum_{j=1}^{k}(y_{j1} - t_{j1}); \frac{\partial E_2}{\partial a_{002}} = \sum_{j=1}^{k}(y_{j2} - t_{j2});$$

$$\frac{\partial E_1}{\partial a_{101}} = \sum_{j=1}^{k}(y_{j1} - t_{j1})x_{11}; \frac{\partial E_2}{\partial a_{102}} = \sum_{j=1}^{k}(y_{j2} - t_{j2})x_{12};$$

$$\frac{\partial E_1}{\partial a_{011}} = \sum_{j=1}^{k}(y_{j1} - t_{j1})x_{21}; \frac{\partial E_2}{\partial a_{012}} = \sum_{j=1}^{k}(y_{j2} - t_{j2})x_{22};$$

$$\frac{\partial E_1}{\partial a_{111}} = \sum_{j=1}^{k}(y_{j1} - t_{j1})x_{11}x_{21}; \frac{\partial E_2}{\partial a_{112}} = \sum_{j=1}^{k}(y_{j2} - t_{j2})x_{12}x_{22};$$

$$\frac{\partial E_1}{\partial a_{201}} = \sum_{j=1}^{k}(y_{j1} - t_{j1})x_{11}^2; \frac{\partial E_2}{\partial a_{202}} = \sum_{j=1}^{k}(y_{j2} - t_{j2})x_{12}^2;$$

$$\frac{\partial E_1}{\partial a_{021}} = \sum_{j=1}^{k}(y_{j1} - t_{j1})x_{21}^2; \frac{\partial E_2}{\partial a_{022}} = \sum_{j=1}^{k}(y_{j2} - t_{j2})^2 x_{22}^2; \qquad (4)$$

It is necessary to note, that at negative values of the coefficients $\widetilde{a}_{rs}$ ($\widetilde{a}_{rs} < 0$), calculation formulas of expressions which include parameters $\widetilde{a}_{rs}$ in (3) and correction of the given parameter in (4) will change the form. For example, we allow $\widetilde{a}_{rs} < 0$, then formula calculations of the fourth expression, which includes in (3) will be had with the

$$\frac{\partial E_3}{\partial a_{103}} = \sum_{j=1}^{k}(y_{j3} - t_{j3})x_{13}; \quad \frac{\partial E_3}{\partial a_{203}} = \sum_{j=1}^{k}(y_{j3} - t_{j3})x_{13}^2;$$

$$\frac{\partial E_3}{\partial a_{013}} = \sum_{j=1}^{k}(y_{j3} - t_{j3})x_{23}; \quad \frac{\partial E_3}{\partial a_{023}} = \sum_{j=1}^{k}(y_{j3} - t_{j3})x_{23}^2; \qquad (5)$$

As a result of training (4), (5) we find parameters of a network satisfying the knowledge base with required training quality.

The analysis show that during following 60-120 measurements happens the approach of individual parameters of GTE work to normal distribution. So, on the second stage as result of accumulation definite information by the means of the mathematical statistic is estimated of GTE conditions. Here the given and enumerated to the one GTE work mode parameters are controlled is accordance with calculated admissible and possible ranges.

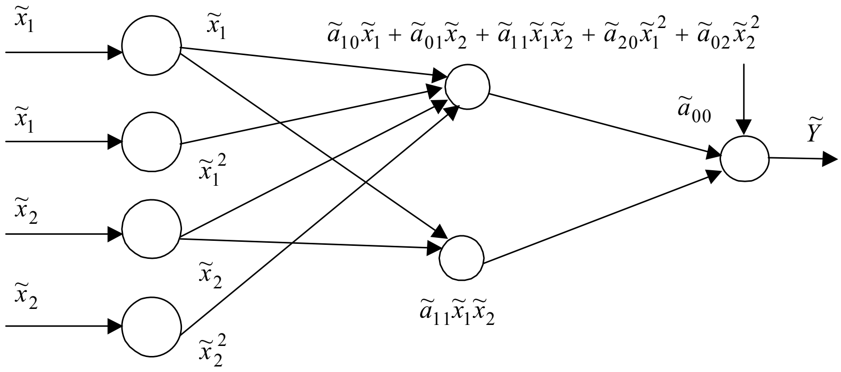


Fig. 5 Structure of neural network for second-order regression equation

Further by the means of the Least Squares Method (LSM) there are identified the multiple linear regression models of GTE conditions changes. These models are made for each correct subcontrol engine of the park at the initial operation period. In such case on the basis analysis of regression coefficients meaning (coefficients of influence) of engine's multiple regression models in park by the means of the mathematical statistic are formed base and admissible range of coefficients [3,9].

Let's consider mathematical model of aviation GTE temperature state- described with help the multiple linear regression model (application of various regression models for the estimation of GTE condition is present in [4-7]).

$$y_i(k) = \sum_{j=1}^{n} a_{ij} x_j(k), \quad (i = \overline{1,m}) \qquad (6)$$

where y_i-output parameter of system; x_j-input influence; a_{ij}-unknown (estimated) influence factors (regression coefficients); n- number of input influences, k - number of iteration.

Let the equations of measurements of input and output coordinates of the model look like

$$z_{y_i}(k) = y_i(k) + \xi_{y_i}(k)$$

$$z_{x_j}(k) = x_j(k) + \xi_{x_j}(k) \qquad (7)$$

where $\xi_{y_i}(k)$, $\xi_{x_j}(k)$-casual errors of measurements with Gauss distribution and statistical characteristics

$$E[\xi_{y_i}(k)] = E[\xi_{x_j}(k)] = 0$$
$$E[\xi_{y_i}(k)\xi_{y_i}(j)] = D_{y_i}\delta(k,j)$$
$$E[\xi_{x_j}(k)\xi_{x_j}(l)] = D_{x_j}\delta(k,l) \qquad (8)$$

where E the operator of statistical averaging; $\delta(k,l)$- Kronecker delta-function:

$$\delta(k,l) = \begin{cases} 1, k = l \\ 0, k \neq l \end{cases}$$

For the decision of similar problems the LSM well approaches. However classical LSM may be used then when values of arguments are known precisely x_j. As arguments x_j are measured with a margin error use LSM in this case may result in the displaced results and in main will give wrong estimations of their errors. For data processing in a similar case is expedient to use confluent methods analysis [10,11].

The choice confluent a method depends on the kind of mathematical model and the priory information concerning arguments values and parameters. In many cases recurrent application LSM yields good results [3,9]. However, thus is necessary the additional information about measuring parameters (input and output coordinates of system). Practical examples show that the dependences found thus essentially may differ from constructed usual LSM.

Before to use the recurrent form LSM, taking into account errors of input influences, for model parameters estimation (6), we shall present it in the vector form

$$y_i(k) = X^T(k) \cdot \theta_i, (k = \overline{1,l}) \qquad (9)$$

where $\theta_i^T = \|a_{i1}, a_{i2}, ..., a_{im}\|$-vector of estimated factors; $X^T(k) = \|x_1(k), x_2(k), ..., x_m(k)\|$-vector of input coordinates.

The algorithm of model (4) parameters estimation in view of an error of input coordinates has the following kind

$$\theta_i(k) = \theta_i(k-1) + \qquad (10)$$
$$+ K_i(k)\left[Z_{y_i}(k) - X^T(k)\theta_i(k-1)\right];$$

$$K_i(k) = \frac{D_i(k-1)X(k)}{\begin{pmatrix} D_{y_i}(k) + \theta_i^T(k-1)D_x(k)\theta(k- \\ -1) + X^T(k)D_i(k-1)X(k) \end{pmatrix}};$$

$$D_i(k) = D_i(k-1) - \frac{\left(D_i(k-1)X(k)X^T(k)D_i(k-1)\right)}{\begin{pmatrix} D_{y_i}(k) + \theta_i^T(k-1)D_x(k)\theta(k-1) + \\ + X^T(k)D_i(k-1)X(k) \end{pmatrix}}$$

ISSN: 2517-9950
Vol:1, No:2, 2007

where $K_i(x)$-amplification coefficient of the filter; $D_i(k)$-dispersion matrix of estimations errors; $D_x(k)$-dispersion matrix of input coordinates errors; $D_{y_i}(k)$-dispersion matrix of output coordinates errors.

Let's consider the distinct regression equation of second order with two variables

$$y = a_{00} + a_{10}x_1 + a_{01}x_2 + a_{11}x_1x_2 + a_{20}x_1^2 + a_{02}x_2^2 \qquad (11)$$

Output and input coordinates of the model (11) are registered by the measuring equipment. Casual errors of measurements have Gauss distribution and their statistical characteristics (random variables means equally to zero) are known. It is required to estimate (unknown) coefficients a_{00}, a_{10}, a_{01}, a_{11}, a_{20}, a_{02} of the regression equations (11).

Let x_1 and x_2 are defined with the errors which dispersions are accordingly equal D_{x_1} and D_{x_2}. Then input influence errors (with the purpose of this error definition we shall take advantage of the linearation method [12] in view of that variables is not enough correlated) can be defined with help of expressions preliminary, having designated $x_4 = x_1x_2$; $x_5 = x_1^2$; $x_6 = x_2^2$):

$$D_{x_4} = \left(\frac{\partial x_1 x_2}{\partial x_1}\right)^2 D_{x_1} + \left(\frac{\partial x_1 x_2}{\partial x_2}\right)^2 D_{x_2} =$$

$$x_2^2 D_{x_1} + x_1^2 D_{x_2},\ D_{x_5} = \left(\frac{\partial x_1^2}{\partial x_1}\right)^2 D_{x_1} = 4x_1^2 D_{x_1}$$

$$D_{x_6} = \left(\frac{\partial x_2^2}{\partial x_2}\right)^2 D_{x_2} = 4x_2^2 D_{x_2}.$$

Then find average quadratic deviations of errors and errors dispersion matrix of input coordinates, it is possible to estimate coefficients of the equations (6) and (9), using of the recurcive LSM (10).

On the third stage (for more than 120 measurements) by the LSM estimation results are conducted the detail analyse of GTE conditions. Essence of these procedures is in making actual model (multiple linear regression equation) of GTE conditions and in comparison actual coefficients of influence (regression coefficients) with their base are admissible range. The reliability of diagnostic results on this stage is high and equalled to 0.95÷0.99. The influence coefficients meaning going out the mention ranges make it's possible to draw into conclusion about the meaning changes of phases process influence on the concrete parameters of GTE. The stable going out one or several coefficient influence beyond of the above-mentioned range witness about additional feature of incorrectness and permit to accurate address and possible reason of faults. In this case to receive the stable estimations by LSM are used ridge-regression analysis.

For the purpose of prediction of GTE conditions the regression coefficients are approximated by the polynomials of second and third degree.

For example to apply the above mentioned method there was investigated the changes of GTE conditions, repeatedly putting into operation engine D-30KU-154 (Tu-154M) (engine 03059229212434, ATB “AZAL”, airport “Bina”, Baku, Azerbaijan), which during 2600 hours (690 flights) are operated correctly. At the preliminary stage, when number of measurements $N \le 60$, GTE technical condition is described by the fuzzy linear regression equation (1). Identification of fuzzy linear model of GTE is made with help NN which structure is given on Fig. 4. Thus as the output parameter of GTE model is accepted the temperature

$$(\widetilde{T}_4^*)_{ini} = \widetilde{a}_1\widetilde{H} + \widetilde{a}_2\widetilde{M} + \widetilde{a}_3\widetilde{T}_H^* + \widetilde{a}_4\widetilde{n}_{LP} + \widetilde{a}_5\widetilde{p}_T + \widetilde{a}_6\widetilde{p}_M + $$
$$+ \widetilde{a}_7\widetilde{T}_M + \widetilde{a}_8\widetilde{G}_T + \widetilde{a}_9\widetilde{V}_{FS} + \widetilde{a}_{10}\widetilde{V}_{BS} + \widetilde{a}_{11}\widetilde{p}_H^* \qquad (12)$$

And at the subsequent stage for each current measurement's $N > 60$, when observes the normal distribution of the engine work parameters, GTE temperature condition describes by linear regression equation (6) which parameters is estimated by recurrent algorithm (10)

$$D = (T_4^*)_{act} = a_1'H + a_2'M + a_3'T_H^* + a_4'n_{LP} + a_5'p_T + a_6'p_M + $$
$$+ a_7'T_M + a_8'G_T + a_9'V_{FS} + a_{10}'V_{BS} + a_{11}'p_H^* \qquad (13)$$

As the result of the carried out researches for the varied technical condition of the considered engine was revealed certain dynamics of the regression coefficients values changes which is given in Table I (see the Appendix).

For the third stage there were made the following admission of regression coefficients (coefficients of influence of various parameters) of various parameters on exhaust gas temperature in linear multiple regression equation (2): frequency of engine rotation (RPM of (low pressure) LP compressor)-0.00456÷0.00496; fuel pressure-1.16÷1.25; fuel flow-0.0240÷0.0252; oil pressure-11.75÷12.45; oil temperature-1.1÷1.; vibration of the forward support-3.0÷5.4; vibration of the back support-1.2÷1.9; atmosphere pressure-112÷128; atmosphere temperature-(-0.84) ÷(-0.64); flight speed (Mach number)-57.8÷60.6; flight altitude-0.00456÷0.00496. Within the limits of the specified admissions of regression coefficients was carried out approximation of the their (regression coefficients) current values by the polynoms of the second and third degree with help LSM and with use cubic splines (Fig. 6).

III. Conclusion

1. The GTE technical condition combined diagnosing approach is offered, which is based on engine work parameters estimation with the help of methods Soft Computing (fuzzy logic and neural networks) and the confluent analysis.

2. It is shown, that application of Soft Computing (fuzzy logic and neural networks) methods in recognition GTE technical condition has the certain advantages in comparison with traditional probability-statistical approaches. First of all, it is connected by that the offered methods may be used irrespective of the kind of GTE work parameters distributions. As at early stage of the engine work, because of the limited volume of the information, the kind of distribution of

parameters is difficult for establishing.

3. By complex analysis is established, that:

- between aerogastermodynamic and mechanical parameters of GTE work are certain relations, which degree in operating process and in dependence of concrete diagnostic situation changes dynamics is increases or decreases, that describes the GTE design and work and it's systems, as whole.
- for various situations of malfunctions development's is observed different dynamics (changes) of connections (correlation coefficients) between parameters of the engine work in operating, caused by occurrence or disappearance of factors influencing to GTE technical condition. Hence, in any considered time of operation the concrete GTE technical condition is characterized by this or that group of parameters in which values is reflected presence of influencing factors.

The suggested methods make it's possible not only to diagnose and to predict the safe engine runtime. This methods give the tangible results and can be recommended to practical application as for automatic engine diagnostic system where the handle record are used as initial information as well for onboard system of engine work control.

References

[1] Sadiqov R.A. Identification of the quality surveillance equation parameters //Reliability and quality surveillance.-M., 1999, № 6, p. 36-39.

[2] Sadiqov R.A., Makarov N.V., Abdullayev P.S. V International Symposium an Aeronautical Sciences «New Aviation Technologies of the XXI century»//A collection of technical papers., section №4-№24, Zhukovsky, Russia, august, 1999.

[3] Pashayev A.M., Sadiqov R.A., Makarov N.V., Abdullayev P. S. Efficiency of GTE diagnostics with provision for laws of the distribution parameter in maintenance. Full-grown. VI International STC "Machine building and technosphere on border 21 century" //Collection of the scientific works// Org. Donechki Gov.Tech.Univ., Sevastopol, Ukraine, september, 1999, p.234-237.

[4] Ivanov L.A. and etc. The technique of civil aircraft GTE technical condition diagnosing and forecasting on registered rotor vibrations parameters changes in service.- M: GOS NII GA, 1984.- 88p.

[5] Doroshko S.M. The control and diagnosing of GTE technical condition on vibration parameters. - M.: Transport, 1984.-128 p.

[6] Abasov M.T., Sadiqov A.H., Aliyarov R.Y. Fuzzy neural networks in the system of oil and gas geology and geophysics // Third International Conference on Application of Fuzzy Systems and Soft computing/ Wiesbaden, Germany, 1998,- p.108-117.

[7] Yager R.R., Zadeh L.A. (Eds). Fuzzy sets, neural networks and soft computing. VAN Nostrand Reinhold. N.-Y. - № 4,1994.

[8] Mohamad H. Hassoun. Fundamentals of artificial neutral networks / A Bradford Book. The MIT press Cambridge, Massachusetts, London, England, 1995.

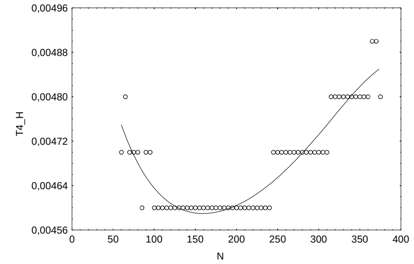
[9] Pashayev A.M., Sadiqov R.A., Makarov N.V., Abdullayev P.S. Estimation of GTE technical condition on flight information//Abstracts of XI All-Russian interinstit.science-techn.conf. "Gaz turbine and combined installations and engines" dedicated to 170 year MGTU nam. N.E.BAUMAN, sec. 1. N.E.BAUMAN MGTU., 15-17 november., Moscow.-2000.- p.22-24.

[10] Granovskiy V.A. and Siraya T.N. Methods of experimental-data processing in measurements [in Russian], Energoatomizdat, Moscow, 1990.

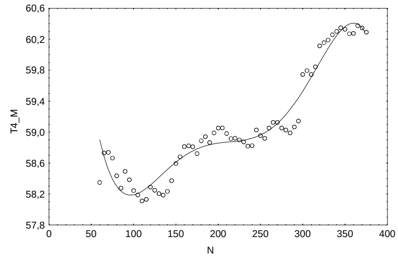
[11] Greshilov A.A., Analysis and Synthesis of Stochastic Systems. Parametric Models and Confluence Analysis (in russian), Radio i Svyaz, Moscow, 1990.

[12] Pugachev V.S., Probability theory and mathematical statistics [in russian], Nauka, Moscow, 1979.

APPENDIX



a)



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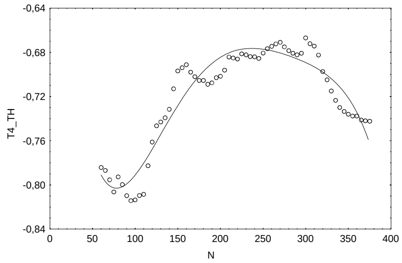

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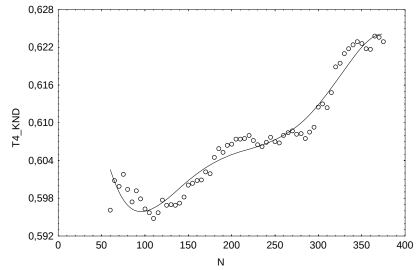

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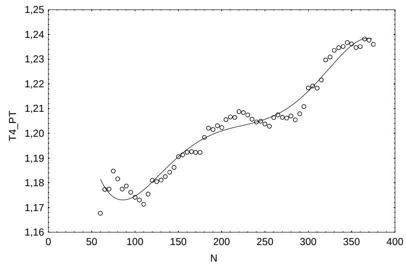

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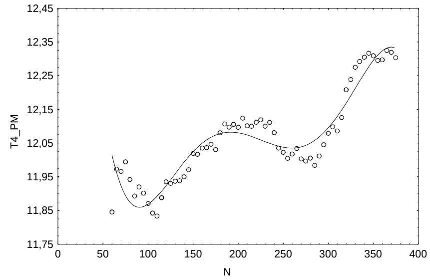

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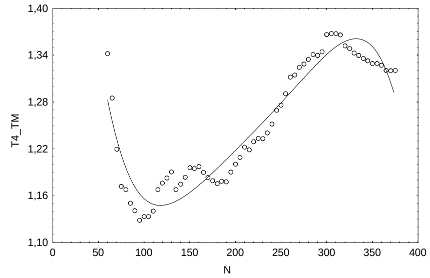

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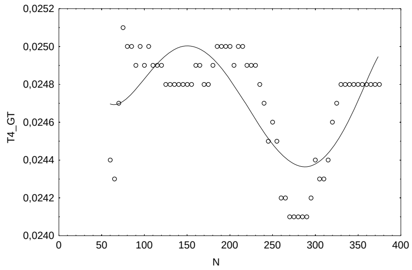

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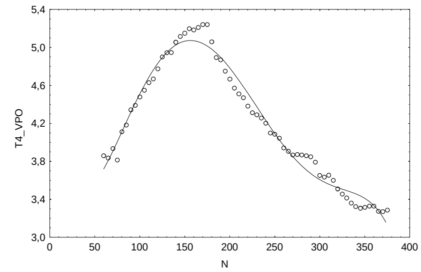

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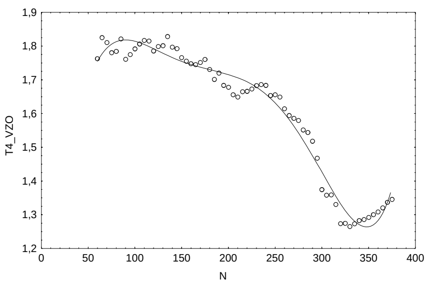

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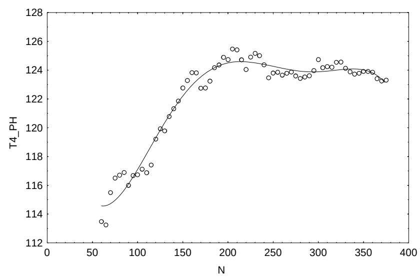

l)

Fig. 6 Change of regression coefficient's values (influence) of parameters included in linear multiple regression equation $D=(T_4^*)_{act}$ to T_4^* in GTE operation: a) T4_H – influence H on T_4^* (coefficient a_1'); b) T4_M - influence M on T_4^* (coefficient a_2'); c) T4_TH - influence T_H^* on T_4^* (coefficient a_3'); d) T4_KND – influence n_{LP} on T_4^* (coefficient a_4'); e) T4_PT - influence p_T on T_4^* (coefficient a_5'); f) T4_PM – influence p_M on T_4^* (coefficient a_6'); g) T4_TM - influence T_M on T_4^* (coefficient a_7'); h) T4_GT – influence G_T on T_4^* (coefficient a_8'); i) T4_VPO - influence V_{FS} on T_4^* (coefficient a_9'); j) T4_VZO - influence V_{BS} on T_4^* (coefficient a_{10}'); k) T4_PH - influence p_H^* on T_4^* (coefficient a_{11}'); N-number of measurements

International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:1, No:2, 2007

TABLE I
CHANGE OF REGRESSION COEFFICIENT'S VALUES (INFLUENCES OF GTE WORK PARAMETERS) INCLUDED IN ACTUAL (DISTINCT) LINEAR MULTIPLE REGRESSION EQUATION OF GTE CONDITION MODEL (FOR EACH MEASUREMENTS $N > 60$)

$$D = (T_4^*)_{act} = a_1 H + a_2 M + a_3 T_H^* + a_4 n_{LP} + a_5 p_T + a_6 p_M + a_7 T_M + a_8 G_T + a_9 V_{FS} + a_{10} V_{BS} + a_{11} p_H^*$$

Number of measurements,	a'_1	a'_2	a'_3	a'_4	a'_5	a'_6	a'_7	a'_8	a'_9	a'_{10}	a'_{11}
61	0.004700	58.34970	-0.784300	0.596100	1.167700	11.846000	1.341800	0.024400	3.86020	1.76250	113.48780
65	0.004800	58.73030	-0.786900	0.600800	1.177300	11.972600	1.285200	0.024300	3.83480	1.82490	113.24980
70	0.004700	58.73590	-0.795400	0.599900	1.177500	11.966200	1.219400	0.024700	3.93370	1.81080	115.49090
75	0.004700	58.66450	-0.806400	0.601800	1.184800	11.994000	1.171700	0.025100	3.81470	1.78040	116.50720
80	0.004700	58.43500	-0.792700	0.599400	1.181600	11.941900	1.167800	0.025000	4.11150	1.78450	116.70140
85	0.004600	58.27580	-0.799700	0.597400	1.177500	11.892900	1.150600	0.025000	4.18240	1.82120	116.88750
90	0.004700	58.49320	-0.809700	0.599200	1.178700	11.920200	1.140800	0.024900	4.34230	1.76070	116.00490
95	0.004700	58.38340	-0.814300	0.597900	1.176200	11.901800	1.128500	0.025000	4.38980	1.77470	116.68020
100	0.004600	58.24260	-0.813500	0.596300	1.174200	11.870900	1.133100	0.024900	4.47960	1.79180	116.73330
105	0.004600	58.18840	-0.809600	0.595700	1.173000	11.842300	1.133300	0.025000	4.54920	1.80630	117.12730
110	0.004600	58.11110	-0.808500	0.594800	1.171300	11.834000	1.140100	0.024900	4.62970	1.81710	116.87370
115	0.004600	58.13040	-0.782600	0.595700	1.175500	11.888100	1.167800	0.024900	4.66770	1.81490	117.41360
120	0.004600	58.28980	-0.761200	0.597700	1.181000	11.935300	1.176100	0.024900	4.77430	1.78560	119.21610
125	0.004600	58.24940	-0.746400	0.596900	1.180500	11.930500	1.182600	0.024800	4.89850	1.79850	119.92660
130	0.004600	58.20610	-0.743000	0.597000	1.181100	11.936800	1.190400	0.024800	4.94380	1.80120	119.78990
135	0.004600	58.18430	-0.739300	0.596900	1.182500	11.938200	1.167800	0.024800	4.94700	1.82840	120.77820
140	0.004600	58.23210	-0.731500	0.597200	1.184300	11.950000	1.174800	0.024800	5.05560	1.79670	121.32370
145	0.004600	58.37240	-0.713000	0.598200	1.186200	11.970800	1.183700	0.024800	5.11620	1.79210	121.85460
150	0.004600	58.59360	-0.696900	0.600100	1.190600	12.018800	1.195900	0.024800	5.15060	1.76580	122.76810
155	0.004600	58.68150	-0.693900	0.600400	1.191300	12.017200	1.194700	0.024800	5.19790	1.75550	123.28450
160	0.004600	58.81220	-0.691200	0.600800	1.192400	12.035100	1.197200	0.024900	5.18340	1.74790	123.83280
165	0.004600	58.82190	-0.697900	0.600900	1.192600	12.036300	1.189800	0.024900	5.21040	1.74500	123.81770
170	0.004600	58.81090	-0.702100	0.602200	1.192300	12.046500	1.183200	0.024800	5.24140	1.75160	122.75520
175	0.004600	58.72210	-0.705500	0.601900	1.192300	12.031100	1.179100	0.024800	5.23970	1.76060	122.76490
180	0.004600	58.88700	-0.705500	0.604500	1.198400	12.080300	1.175300	0.024900	5.05970	1.73100	123.24240
185	0.004600	58.94110	-0.708900	0.605900	1.202100	12.106900	1.178600	0.025000	4.89210	1.70090	124.17580
190	0.004600	58.86480	-0.707600	0.605300	1.201500	12.097700	1.177600	0.025000	4.86890	1.71980	124.35910
195	0.004600	58.98770	-0.703000	0.606400	1.203100	12.105700	1.190100	0.025000	4.75000	1.68340	124.88690
200	0.004600	59.05180	-0.701700	0.606600	1.202300	12.097200	1.200500	0.025000	4.66720	1.67770	124.73990
205	0.004600	59.05380	-0.696100	0.607400	1.205600	12.123800	1.209000	0.024900	4.57100	1.65570	125.46330
210	0.004600	58.98050	-0.684200	0.607400	1.206600	12.101200	1.222300	0.025000	4.51140	1.64870	125.41730
215	0.004600	58.91570	-0.685200	0.607500	1.206500	12.099900	1.218600	0.025000	4.47090	1.66490	124.71620
220	0.004600	58.92000	-0.686000	0.608000	1.208800	12.112300	1.229100	0.024900	4.38040	1.66560	124.04490
225	0.004600	58.89710	-0.681400	0.607200	1.208400	12.118900	1.233400	0.024900	4.31280	1.67250	124.90670
230	0.004600	58.87320	-0.682200	0.606500	1.207400	12.100100	1.233100	0.024900	4.29100	1.68300	125.16360
235	0.004600	58.81690	-0.683800	0.606200	1.205700	12.111200	1.240400	0.024800	4.25650	1.68610	125.00640
240	0.004600	58.82610	-0.684000	0.606900	1.204600	12.081300	1.251700	0.024700	4.20230	1.68370	124.38160
245	0.004700	59.02520	-0.685500	0.607700	1.204900	12.034900	1.269500	0.024500	4.09930	1.65310	123.47200
250	0.004700	58.95300	-0.680600	0.607000	1.203800	12.022700	1.276000	0.024600	4.08680	1.65560	123.80630
255	0.004700	58.91810	-0.676700	0.606800	1.202900	12.004700	1.290600	0.024500	4.04380	1.64910	123.85880
260	0.004700	59.05160	-0.674600	0.608000	1.206400	12.017300	1.311700	0.024200	3.94110	1.61450	123.66010
265	0.004700	59.12350	-0.672400	0.608400	1.207500	12.034000	1.314400	0.024200	3.90580	1.59440	123.78940
270	0.004700	59.12540	-0.671000	0.608700	1.206500	12.003100	1.324100	0.024100	3.86750	1.58610	123.87320
275	0.004700	59.05120	-0.675000	0.608200	1.206200	11.996500	1.328600	0.024100	3.87280	1.57960	123.59290
280	0.004700	59.02760	-0.678500	0.608300	1.207000	12.005900	1.334400	0.024100	3.86680	1.55130	123.42980
285	0.004700	58.98820	-0.680900	0.607500	1.205500	11.984300	1.340700	0.024100	3.85950	1.54390	123.52580
290	0.004700	59.06620	-0.682300	0.608500	1.207900	12.011800	1.339600	0.024100	3.84790	1.51770	123.61700
295	0.004700	59.14230	-0.680800	0.609300	1.210800	12.045400	1.344100	0.024200	3.79270	1.46750	123.97740
300	0.004700	59.74390	-0.666900	0.612500	1.218400	12.079400	1.366300	0.024400	3.65240	1.37450	124.73320
305	0.004700	59.79560	-0.672100	0.613000	1.219200	12.098000	1.367600	0.024300	3.63530	1.35780	124.17450
310	0.004700	59.74420	-0.674400	0.612400	1.218300	12.086000	1.367500	0.024300	3.65370	1.35880	124.24200
315	0.004800	59.84190	-0.682400	0.614800	1.221600	12.125700	1.365800	0.024400	3.60090	1.33030	124.20200
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365	0.004900	60.37590	-0.741200	0.623800	1.238200	12.324500	1.320300	0.024800	3.27490	1.32050	123.40440
370	0.004900	60.34680	-0.741900	0.623600	1.237700	12.319300	1.319900	0.024800	3.27020	1.33640	123.25590
375	0.004800	60.29140	-0.742400	0.622900	1.236000	12.303100	1.320300	0.024800	3.28660	1.34520	123.30510