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Complex Condition Monitoring System of Aircraft Gas Turbine Engine

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***Abstract*—**Researches show that probability-statistical methods application, especially at the early stage of the aviation Gas Turbine Engine (GTE) technical condition diagnosing, when the flight information has property of the fuzzy, limitation and uncertainty is unfounded. Hence the efficiency of application of new technology Soft Computing at these diagnosing stages with the using of the Fuzzy Logic and Neural Networks methods is considered. According to the purpose of this problem training with high accuracy of fuzzy multiple linear and non-linear models (fuzzy regression equations) which received on the statistical fuzzy data basis is made.

For GTE technical condition more adequate model making dynamics of skewness and kurtosis coefficients' changes are analysed. Researches of skewness and kurtosis coefficients values' changes show that, distributions of GTE work parameters have fuzzy character. Hence consideration of fuzzy skewness and kurtosis coefficients is expedient.

Investigation of the basic characteristics changes' dynamics of GTE work parameters allows to draw conclusion on necessity of the Fuzzy Statistical Analysis at preliminary identification of the engines' technical condition.

Researches of correlation coefficients values' changes shows also on their fuzzy character. Therefore for models choice the application of the Fuzzy Correlation Analysis results is offered.

At the information sufficiency is offered to use recurrent algorithm of aviation GTE technical condition identification (Hard Computing technology is used) on measurements of input and output parameters of the multiple linear and non-linear generalised models at presence of noise measured (the new recursive Least Squares Method (LSM)).

The developed GTE condition monitoring system provides stage-by-stage estimation of engine technical conditions.

As application of the given technique the estimation of the new operating aviation engine technical condition was made.

***Keywords*—**aviation gas turbine engine, technical condition, fuzzy logic, neural networks, fuzzy statistics

I. Introduction

One of the important maintenance requirements of the modern aviation GTE on condition is the presence of efficient parametric technical diagnostic system. As it is known the GTE diagnostic problem of the aircraft's is mainly in the fact that onboard systems of the objective control do not register all engine work parameters. This circumstance causes additional manual registration of other parameters of GTE work. 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. 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, is should be noted that statistic data processing on the above-mentioned method are conducted by the preliminary allowance of the recorded parameters meaning normal distribution. This allowance affects the GTE technical condition monitoring reliability and causes of the error decision in the GTE diagnostic and operating process [1-3]. More over some same combination of the various parameters changes of engine work can be caused by different malfunctions. Finally it complicates the definition of the defect address.

II. Basics of Recommended Condition Monitoring System

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 is suggested.

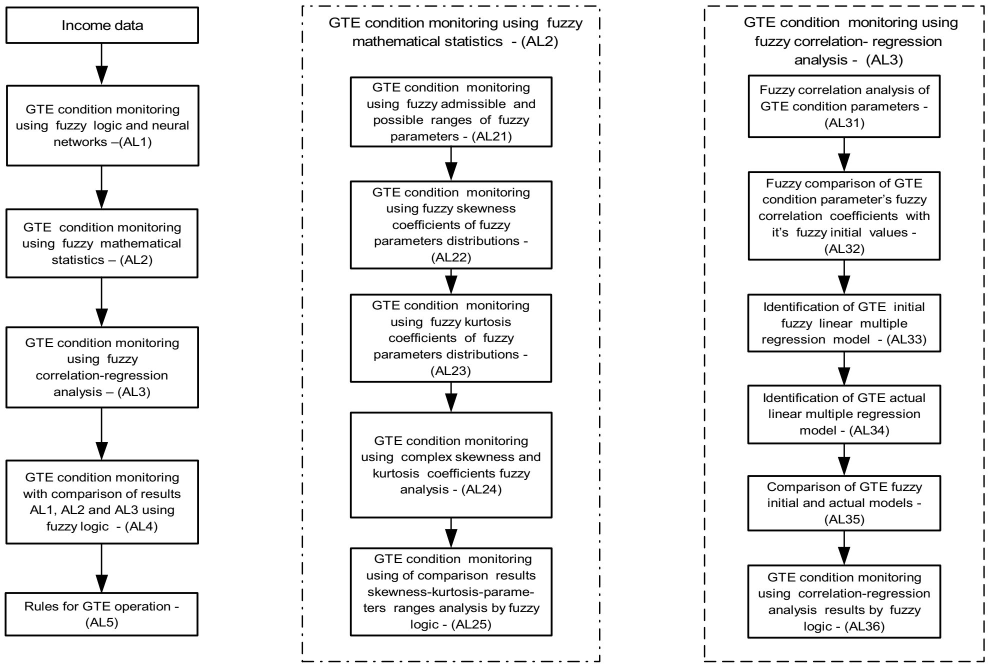

Fig. 1. Flow chart of aircraft gas turbine engine fuzzy-parametric diagnostic algorithm

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

Experimental investigation conducted by manual records shows that at the beginning of operation during 40÷60 measurements accumulated values of recorded parameters of good working order GTE aren't distribute normality.

Consequently, on the first stage of diagnostic process (at the preliminary stage of GTE operation) when initial data is insufficient and fuzzy, GTE condition is estimated by the Soft Computing methods-fuzzy logic (FL) method and neural networks (NN). 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.

As is known one of aviation GTE technical condition estimation methods, used in our and foreign practice is the vibrations level control and analysis of this level change tendency in operation. Application of various mathematical models described by the regression equations for aviation GTE condition estimation is presented in [4,5].

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

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

$$\tilde{Y}_i = \sum_{r,s} \tilde{a}_{rs} \otimes \tilde{x}_1^r \otimes \tilde{x}_2^s ; \; r = \overline{1,l}; \; s = \overline{1,l} \; ; r + s \le l \tag{2}$$

where $\tilde{Y}_i$ fuzzy output parameter (e.g. GTE vibration), $\tilde{x}_j$ or $\tilde{x}_1, \tilde{x}_2$ input parameters (engine parameters - H, M, T_H^*, p_H^*, n_{LP}, T_4^*, G_T, p_T, p_M, T_M), $\tilde{a}_{ij}$ and $\tilde{a}_{rs}$-required fuzzy parameters (fuzzy regression coefficients).

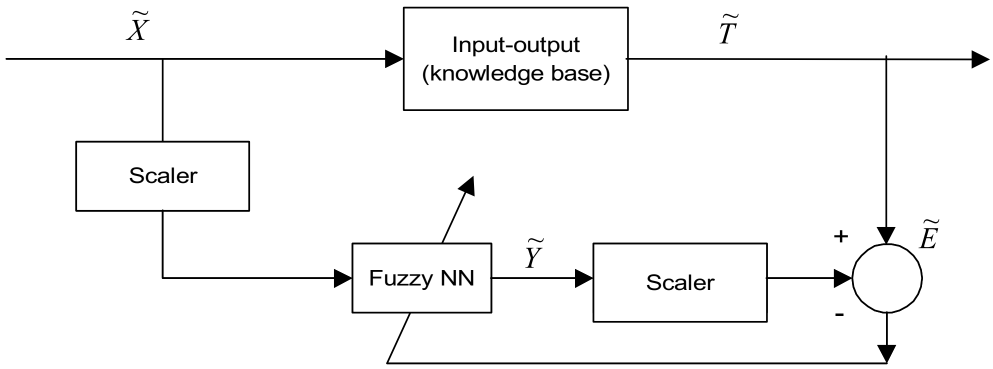

Fig.2. Neural identification system

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

Let's consider the decision of the given tasks by using FL and NN [6-8]. NN consists of interconnected fuzzy neurons sets. At NN use for the decision (1) and (2) input signals of the network are accordingly fuzzy values of variable $\tilde{X} = (\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_n)$, $\tilde{X} = (\tilde{x}_1, \tilde{x}_2)$ and output $\tilde{Y}$.

If for all training pairs, deviation value E is less than given then training (correction) parameters of a network comes to end (fig. 3). In opposite case it continues until value E reach minimum.

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

$$a^n_{rs1} = a^o_{rs1} + \gamma \frac{\partial E}{\partial a_{rs}}, \qquad a^n_{rs2} = a^o_{rs2} + \gamma \frac{\partial E}{\partial a_{rs}},$$

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

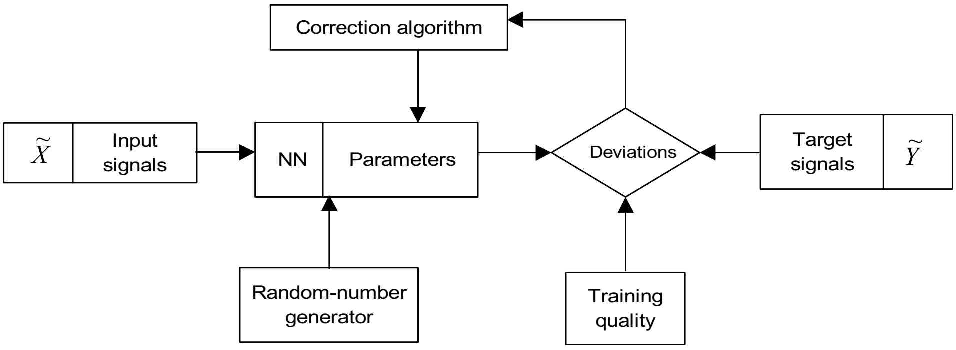

Fig.3. System for network-parameter (weights, threshold) training (with feedback)

As parameters of the network are fuzzy values of parameters $\tilde{a}_{ij}$ and $\tilde{a}_{rs}$. 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 $\tilde{a}_{ij}$ and $\tilde{a}_{rs}$ for 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 suppose, there are statistical fuzzy data received on the basis of experiments. On the basis of these input and output data are made training pairs $(\tilde{X}, \tilde{T})$ for training a network. For construction of process model on the input of NN gives input signals $\tilde{X}$ and further outputs are compared with reference output signals $\tilde{T}$ (fig.2).

After comparison the deviation value is calculated

$$\tilde{E} = \frac{1}{2} \sum_{j=1}^{k} (\tilde{Y}_j - \tilde{T}_j)^2$$

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

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

$$E_2 = \frac{1}{2} \sum_{j=1}^{k} \left[y_{j2}(\alpha) - t_{j2}(\alpha) \right]^2, \ E = E_1 + E_2,$$

where

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

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

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

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

Let's construct neural structure for decision of the equation (2) where as parameters of the network are coefficients $\tilde{a}_{00}$, $\tilde{a}_{10}$, $\tilde{a}_{01}$, $\tilde{a}_{11}$, $\tilde{a}_{20}$, $\tilde{a}_{02}$. 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:

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

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

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

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

$$\frac{\partial E_1}{\partial a_{201}} = \sum_{j=1}^{k} (y_{j1} - t_{j1}) x_{11}^2; \quad \frac{\partial E_2}{\partial a_{202}} = \sum_{j=1}^{k} (y_{j2} - t_{j2}) x_{12}^2; \quad (4)$$

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

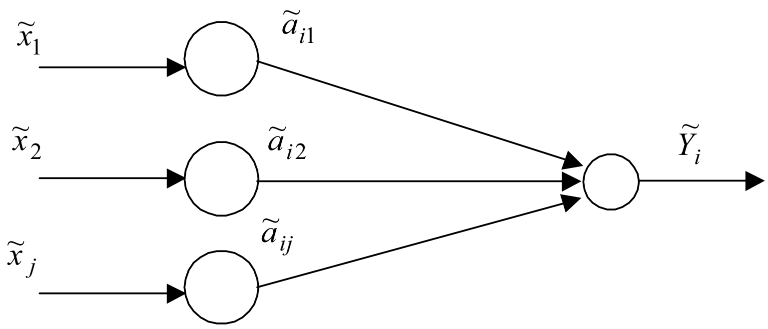

Fig.4. Neural network structure for multiple linear regression equation

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 have the following kind: $y_{41} = a_{111}x_{12}x_{22}$; $y_{42} = a_{112}x_{12}x_{21}$, and the correction formulas

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

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

For value $\alpha = 1$ we shall receive

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

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

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

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

Choice of GTE technical condition model (linear or nonlinear) may be made with the help of the complex comparison analysis of fuzzy correlation coefficients $\widetilde{r}_{xy}$ and fuzzy correlation ratios $\widetilde{\rho}_{y/x}$ values. Thus the following cases are possible:

a) if $\widetilde{y}$ is not dependent from $\widetilde{x}$, $\widetilde{\rho}_{y/x} \cong 0$;

b) if there is the fuzzy functional linear dependence $\widetilde{y}$ from $\widetilde{x}$, $\widetilde{r}_{xy} \cong \widetilde{\rho}_{y/x} \cong 1$;

c) if there is the fuzzy functional nonlinear dependence $\widetilde{y}$ from $\widetilde{x}$, $\widetilde{r}_{xy} \lesssim \widetilde{\rho}_{y/x} \cong 1$;

d) if there is the fuzzy linear regression $\widetilde{y}$ from $\widetilde{x}$, but there is not functional dependence, $\widetilde{r}_{xy} \cong \widetilde{\rho}_{y/x} \lesssim 1$;

e) if there is some fuzzy nonlinear regression $\widetilde{y}$ from $\widetilde{x}$, but there is not functional dependence, $\widetilde{r}_{xy} \lesssim \widetilde{\rho}_{y/x} \lesssim 1$,

where $\lesssim$, $\cong$ - fuzzy relations which are determined by the appropriate membership functions $\mu(r_{xy})$ and $\mu(\rho_{y/x})$.

Values of $\widetilde{r}_{xy}$ and $\widetilde{\rho}_{y/x}$ may be estimated as follows

$$\widetilde{r}_{xy} = \frac{\widetilde{R}}{\widetilde{R}_x \otimes \widetilde{R}_y}; \quad \widetilde{\rho}_{y/x} = \sqrt{1 - \frac{\widetilde{\sigma}^2_{y/x}}{\widetilde{\sigma}^2_y}}$$

where

$$\widetilde{R} = \sum \widetilde{x} \otimes \widetilde{y} - \frac{1}{n}\sum \widetilde{x} \otimes \sum \widetilde{y};$$

$$\widetilde{R}_x = \sqrt{\sum \widetilde{x}^2 - \frac{1}{n}\left(\sum \widetilde{x}\right)^2};$$

$$\widetilde{R}_y = \sqrt{\sum \widetilde{y}^2 - \frac{1}{n}\left(\sum \widetilde{y}\right)^2}; \qquad \widetilde{\sigma}^2_{y/x} = \frac{\sum(\widetilde{y} - \widetilde{\bar{y}}_x)^2}{n}$$

- residual dispersion $\widetilde{y}$, which is formed by $\widetilde{x}$ influence; $\widetilde{\sigma}^2_y = \frac{\sum(\widetilde{y} - \widetilde{\bar{y}})^2}{n}$ - general variation, which is taking into account all fuzzy factors influences; $\widetilde{\bar{y}}_x$ - partial fuzzy average value of $\widetilde{y}$, which is formed by $\widetilde{x}$ influence; $\widetilde{\bar{y}}$ - general fuzzy average value of $\widetilde{y}$.

The analysis show, that during following 60÷120 measurements occurs the approach of individual parameters values of GTE work to normal distribution. Therefore at the second stage, on accumulation of the certain information, with the help of mathematical statistics are estimated GTE conditions. Here the given and enumerated to the one GTE work mode parameters are controlled on conformity to their calculated admissible and possible ranges.

Further by the means of the Least Squares Method (LSM) (confluent methods analysis, recursive LSM) there are identified the multiple linear regression models of GTE conditions changes [3,10,11]. These models are made for each correct subcontrol engine of the fleet at the initial operation period. In such case on the basis analysis of regression coefficient's values (coefficients of influence) of all fleet engine's multiple regression models with the help of mathematical statistics are formed base and admissible range of coefficients [3,9].

On the third stage (for more than 120 measurements) by the LSM estimation conducts the detail analysis of GTE conditions. Essence of this 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 admissible ranges. The reliability of diagnostic results on this stage is high and equal to 0.95÷0.99. The influence coefficient's values going out the mentioned ranges allows make conclusion about the meaning changes of physical process influence on the concrete GTE work parameters. The stable going out one or several coefficient's influences beyond the above-mentioned range affirms about additional feature of incorrectness and permits to determine address and possible reason of faults. Thus, for receiving stable (robust) estimations by LSM is used ridge-regression analysis.

With the view of forecasting of GTE conditions the regression coefficients are approximated by the polynomials of second and third degree.

As an example on application of the above-mentioned method changes of GTE conditions has been investigated (repeatedly putting into operation engine D-30KU-154 during 2600 hours or 690 flights operated correctly). At the preliminary stage, when number of measurements is $N \le 60$, GTE technical condition is described by the fuzzy linear regression equation (1). Identification of fuzzy linear model of GTE is made with help of NN which structure is given on fig.2. Thus as the output parameter of GTE model is accepted the vibration of the engine back support

$$(\tilde{V}_{BS})_{ini} = \tilde{a}_1\tilde{H} + \tilde{a}_2\tilde{M} + \tilde{a}_3\tilde{T}_H^* + \tilde{a}_4\tilde{p}_H^* + \tilde{a}_5\tilde{n}_{LP} + \tilde{a}_6\tilde{T}_4^* + \tilde{a}_7\tilde{G}_T + \tilde{a}_8\tilde{p}_T + \tilde{a}_9\tilde{p}_M + \tilde{a}_{10}\tilde{T}_M + \tilde{a}_{11}\tilde{V}_{FS} \quad (6)$$

On the subsequent stage for each current measurement's $N > 60$, when observes the normal distribution of the engine work parameters, GTE vibration condition describes by linear regression equation which parameters is estimated by recurrent algorithm [3,10-12]

$$D = (V_{BS})_{act} = a'_1 H + a'_2 M + a'_3 T_H^* + a'_4 p_H^* + a'_5 n_{LP} + a'_6 T_4^* + a'_7 G_T + a'_8 p_T + a'_9 p_M + a'_{10} T_M + a'_{11} V_{FS} \quad (7)$$

As the result of the carried out researches for the varied technical condition of the considered engine was revealed certain dynamics of the correlation and regression coefficients values changes (see Appendix: Fig.6 and Table 1).

The statistical characteristics of correlation coefficients show the necessity of fuzzy NN application at the flight information processing. In that case correct application of this approach on describing up of the GTE technical condition changes is possible by fuzzy linear or nonlinear model [3,10,11].

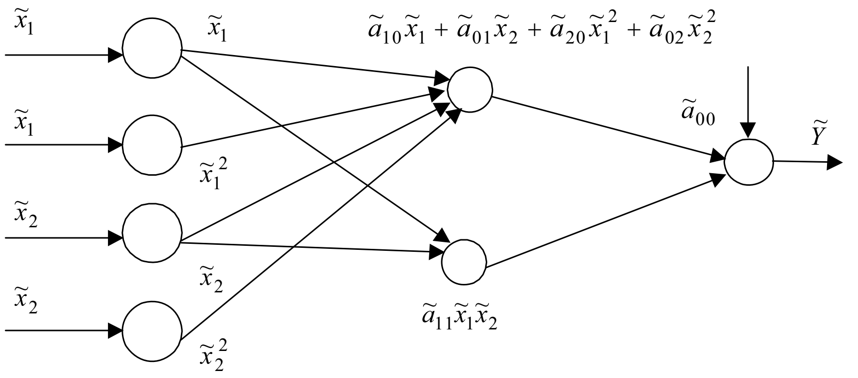

Fig. 5. Structure of neural network for second-order regression equation

For the third stage was made the following admission of regression coefficients (coefficients of influence of various parameters) of various parameters on back support vibration in linear multiple regression equation (1): frequency of engine rotation (RPM of (low pressure) LP compressor (n_{LP})-0.0133÷0.0196; fuel pressure (p_T)- 0.028÷0.037; fuel flow (G_T)-0.0005÷0.0011; exhaust gas temperature (T_4^*)-0.0021÷0.0032; oil pressure (p_M)-0.289÷0.374; oil temperature (T_M)-0.026÷0.084; vibration of the forward support (V_{FS}) - 0.22÷0.53; atmosphere pressure (p_H^*)-1.44÷3.62; atmosphere temperature (T_H^*)-(-0.041)÷(-0.029); flight speed (Mach number-M) -1.17÷1.77; flight altitude (H)-0.0001÷0.0002. Within the limits of the specified admissions of regression coefficients was carried out approximation of the their (regression coefficients) current values by the polynomials of the second and third degree with help LSM and with use cubic splines [1,3,10,11].

III. Conclusions

1. The GTE technical condition combined diagnosing approach is offered, which is based on engine work fuzzy and non-fuzzy parameters estimation with the help of Soft Computing methods (Fuzzy Logic and Neural Networks) and the confluent analysis.
2. It is shown, that application of Soft Computing methods in recognition GTE technical condition has 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 the 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 fuzzy thermodynamic and mechanical parameters of GTE work there are certain fuzzy relations, which degree in operating process and in dependence of fuzzy diagnostic situation changes' dynamics increases or decreases.
- for various situations of malfunctions development is observed different fuzzy dynamics (changes) of connections (correlation coefficients) between engine work fuzzy parameters in operating, caused by occurrence or disappearance of factors influencing GTE technical condition.

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.

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APPENDIX

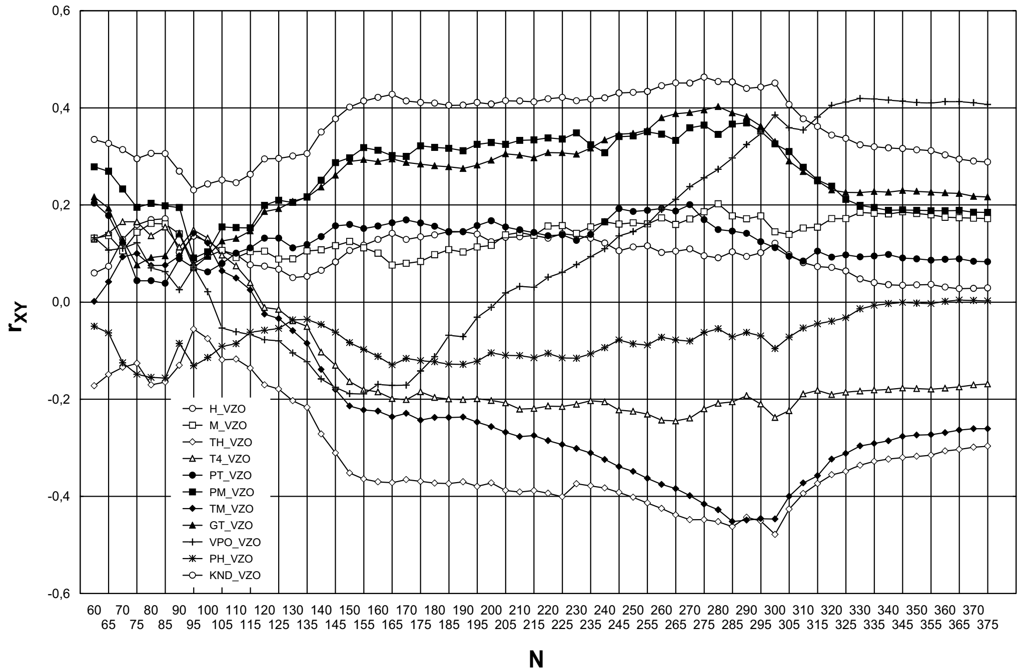

Fig. 6 Change of correlation coefficient's values (relation values) between parameters included in linear multiple regression equation $D = (V_{BS})_{act}$ in GTE operation:

A) H_VZO- relation between H and V_{BS} (correlation coefficient $r_{H,V_{BS}}$); b) M_VZO- relation between M and V_{BS} (correlation coefficient $r_{M,V_{BS}}$); c) TH_VZO-relation between T_H^* and V_{BS} (correlation coefficient $r_{T_H^*,V_{BS}}$); d) T4_VZO– relation between T_4^* and V_{BS} (correlation coefficient $r_{T_4^*,V_{BS}}$); e) PT_VZO- relation between p_T on V_{BS} (correlation coefficient $r_{p_T,V_{BS}}$); f) PM_VZO – relation between p_M and V_{BS} (correlation coefficient $r_{p_M,V_{BS}}$); g) TM_VZO– relation between T_M and V_{BS} (correlation coefficient $r_{T_M,V_{BS}}$); h) GT_VZO- relation between G_T and V_{BS} (correlation coefficient $r_{G_T,V_{BS}}$); i) VPO_VZO– relation between V_{FS} and V_{BS} (correlation coefficient $r_{V_{FS},V_{BS}}$); j) PH_VZO - relation between p_H and V_{BS} (correlation coefficient $r_{p_H,V_{BS}}$); k) KND_VZO – relation between n_{LP} and V_{BS} (correlation coefficient $r_{n_{LP},V_{BS}}$); N-number of measurements.

TABLE I
BASIC CHARACTERISTICS OF FUZZY CORRELATION COEFFICIENTS

Correlation coefficients $r_{X,Y}$	Mean of $r_{X,Y}$	Minimum of $r_{X,Y}$	Maximum of $r_{X,Y}$	Standard deviation of $r_{X,Y}$	$\widetilde{r}_{X,Y} = (r_{X,Y}, \alpha, \beta)$
$r_{H,V_{BS}}$	0.098569	0.027764	0.171722	0.039039	(0.126, 0.098, 0.046)
$r_{M,V_{BS}}$	0.140608	0.070871	0.202407	0.034495	(0.157, 0.086, 0.045)
$r_{T_H^*,V_{BS}}$	-0.318031	-0.478252	-0.055527	0.111266	(-0.423, 0.056, 0.367)
$r_{T_4^*,V_{BS}}$	-0.126122	-0.244704	0.165399	0.131245	(-0.179, 0.066, 0.344)
$r_{p_T,V_{BS}}$	0.127778	0.038779	0.203882	0.040909	(0.142, 0.103, 0.062)
$r_{p_M,V_{BS}}$	0.266707	0.090810	0.368872	0.073460	(0.348, 0.257, 0.021)
$r_{T_M,V_{BS}}$	-0.217393	-0.451692	0.141657	0.167810	(-0.368, 0.084, 0.510)
$r_{G_T,V_{BS}}$	0.256634	0.076418	0.402499	0.084452	(0.288, 0.211, 0.115)
$r_{V_{FS},V_{BS}}$	0.124647	-0.189260	0.419226	0.205637	(0.222, 0.411, 0.641)
$r_{p_H,V_{BS}}$	-0.075837	-0.156228	0.004146	0.043771	(-0.091, 0.066, 0.095)
$r_{n_{LP},V_{BS}}$	0.366038	0.230781	0.463275	0.066236	(0.396, 0.165, 0.067)