TECHNICAL STATE ASSESSMENT OF CHARGE EXCHANGE SYSTEM OF SELF-IGNITION ENGINE, BASED ON THE EXHAUST GAS COMPOSITION TESTING

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ABSTRACT

This paper presents possible use of results of exhaust gas composition testing of self - ignition engine for technical state assessment of its charge exchange system under assumption that there is strong correlation between considered structure parameters and output signals in the form of concentration of toxic compounds (ZT) as well as unambiguous character of their changes. Concentration of the analyzed ZT may be hence considered to be symptoms of engine technical state. At given values of the signals and their estimates it is also possible to determine values of residues which may indicate a type of failure. Available tool programs aimed at analysis of experimental data commonly make use of multiple regression model which allows to investigate effects and interaction between model input quantities and one output variable. Application of multi-equation models provides great freedom during analysis of measurement data as it makes it possible to simultaneously analyze effects and interaction of many output variables. It may be also implemented as a tool for preparation of experimental material for other advanced diagnostic tools such as neural networks which, in contrast to multi-equation models, make it possible to recognize a state at multistate classification and - in consequence – to do diagnostic inference. Here, these authors present merits of application of the above mentioned analytical tools on the example of tests conducted on an experimental engine test stand.

Keywords: diagnostic model , self-ignition engine, exhaust gas components, artificial neural networks

INTRODUCTION

During execution of engine running process, parameters of its structure undergo changes. It is not without any impact on its performance described by a set of output parameters. Mutual relation between engine structure parameters and output parameters makes it possible, in determined conditions , to take output parameters as engine technical state symptoms measured without its disassembling , because physical- chemical processes taking place during running process and quantities describing them can be generally observed and measured from outside. Amount of emission of exhaust gas components belongs a. o. to the quantities in question [2, 5, 6, 8].

Correct run of working cycle (especially run of combustion in engine cylinder) depends to a large extent on correctly working charge exchange system which has to ensure first of all effective discharging the combustion products and filling the working space with an required amount of air of appropriate quality.

Technical state identification of elements of charge exchange system is practically impossible in view of existing standard measurement equipment of engine. Known diagnostic methods are first of all based on the assessing of data concerning flow of working medium volume or mass and its losses in engine cylinders [11].

The following elements were taken to represent charge exchange system of typical ship engine (Fig. 1):

- air filter;
- air compressor;
- air cooler;
- engine cylinders together with elements of air inlets and exhaust gas outlets;
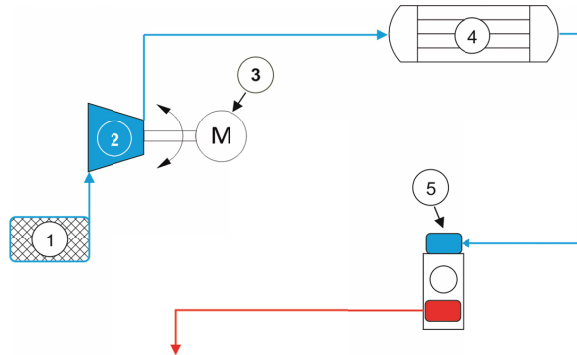- gas turbine.

Fig. 1 Schematic functional diagram of engine charge exchange system. 1 – air filter, 2 – compressor, 3 – electric drive motor of air compressor, 4 – air cooler, 5 – engine cylinders together with air inlet and exhaust gas outlet elements

INITIAL ASSUMPTIONS

On the basis of analysis of the set of quantities characterizing the charge exchange system an initial version of diagnostic table (Tab. 1) and the system's topological model (Fig. 2) was prepared [13].

In view of occurrence of many cases of intuitive determination of changes as well as due to rather not strong relations of the exhaust gas toxicity indices shown in Tab.1 with the engine running parameters and these with structure parameters (failures), it is necessary to verify data of Tab. 1 empirically and determine the existing relations by simulation investigations.

Tab. 1 Initial diagnostic table for charge exchange system of self-ignition engine

Diagnostic parameter			Failure location and type				
			air filter	air compressor	air cooler	engine cylinder	
			contamination of filter	wear, contamination of flow part	contamination of cooler	untightness of TPC	untightness of valves
Pressure drop on air filter		Δp_F	+	0	0	0	0
Compressor compression ratio		π_s	0	-	0	0	0
Compressor adiabatic efficiency		η_{ad}	0	-	0	0	0
Supercharging air pressure drop		Δp_{ba}	0	0	+	0	0
Air temperature drop in cooler		ΔT_{ba}	0	0	-	0	0
Cooler efficiency (cooling effectiveness)		η_{ch}	0	0	-	0	0
Air excess coefficient		λ	-	-	-	-	-
Specific fuel consumption		b	+	+	+	+	+
Supercharging air pressure		p_{ba}	-	-	-	-	-
Compression pressure in engine cylinder		p_c	-	-	-	-	-
Maximum combustion pressure		p_{max}	-	-	-	-	-
Exhaust gas temperature		T_{g1}	-	-	-	-	-
Turbo-compressor rotational speed		n_t	-	-	-	-	-
Concentration of nitrogen oxides	in collector	$C_{NOx(k)}$	-	-	-	-	-
	in casing	$C_{NOx(s)}$	-	-	-	-	0
Concentration of carbon oxide	in collector	$C_{CO(k)}$	+	+	+	+	+
	in casing	$C_{CO(s)}$	0	0	0	+	0
Concentration of hydrocarbons	in collector	$C_{HC(k)}$	+	+	+	+	+
	in casing	$C_{HC(s)}$	0	0	0	+	0
Exhaust gas smokiness.	in collector	D	+	+	+	+	+

Notation:
„-" – decrease in value of a parameter; „+" - increase in value of a parameter; „0" – without any change.
Comment: The diagnostic parameters Δp_F, π_s, η_{ad}, Δp_{ba}, ΔT_{ba}, η_{ch}, b are complex quantities determined on the basis of results of direct measurements.
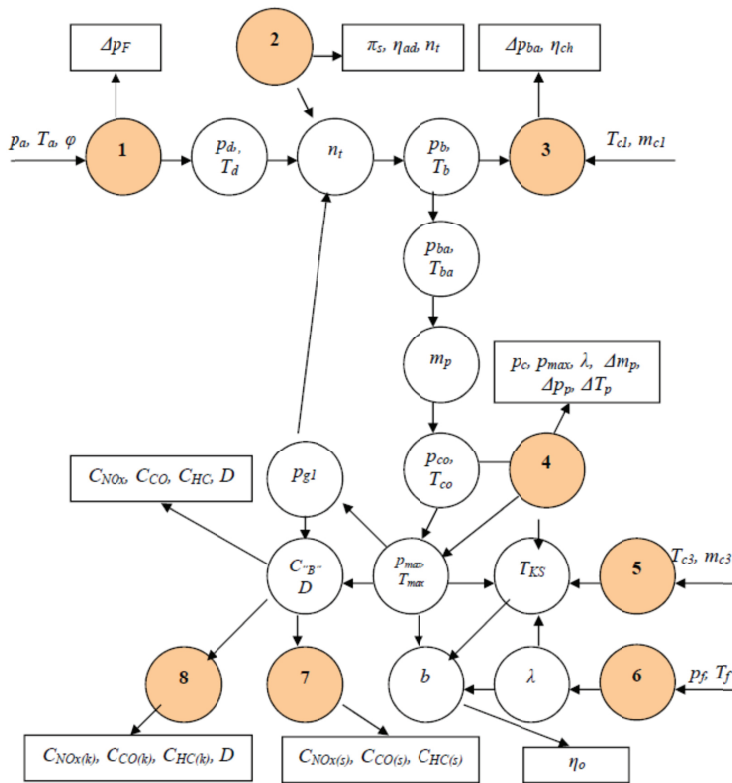
Fig. 2 Topological model of engine charge exchange system
1 – air filter 2 – compressor, 3 – air cooler, 4 – engine combustion chamber, 5 – fresh water cooler, 6 – injection apparatus, 7 – engine crankshaft casing, 8 – exhaust gas collector

SET OF EMPIRICAL METHODS FOR SIMULATION INVESTIGATIONS ON CHARGE EXCHANGE SYSTEM

Simulation investigations are mainly aimed at determining whether it is possible to identify state of charge exchange system on the basis of assessment of changes in exhaust gas toxicity indices, including the following [12]:

- verification of the parameters given in Tab. 1;
- verification of changes in values of diagnostic parameters, depending on location and type of unserviceability of elements of charge exchange system;
- determination (detection) of connections (relations) of structure parameters of elements of charge exchange system with engine working parameters, and these with diagnostic parameters – exhaust gas toxicity indices;
- possible selection , out of exhaust gas toxicity indices , crucial diagnostic parameters , and , out of engine running indices, auxiliary (verifying) diagnostic parameters of state of elements of engine charge exchange system.

The unserviceability types selected as a result of the performed analysis of elements of charge exchange system were simulated in the following way:

- contamination of air filter – by throttling partly (shadowing) its active surface p_f;

- wear or contamination of compressor flow part - by throttling partly air at inlet p_s;
- untightness of piston – rings – cylinder unit – by grinding partly sealing surface of rings as well as enlarging the piston-ring joints to get assumed values of the cross-section area of untightness S_u;
- untightness of inlet and outlet valves – by grinding partly fying face to get assumed values of the cross-section area of untightness S_z.

The approximate wear values given in Tab. 2 served as a basis for preparation of the specified unserviceability events to be used in basic simulation investigations. The way of their preparation consisted in the following :

- removal (e.g. by grinding or machining) given volumes of material out of surfaces of cooperating elements of combustion chamber space , which correspond to preliminarily calculated wear values or result from experimental data (verifying data from repair workshop),
- execution of preliminary tests in respect to unserviceability events which decide on quality of filling. The percentage changes in the air flow drag ps (0;33,3 %) result from the air volume fluxes at clean (V = 0,12 m³/s) and contaminated (V = 0,08 m³/s) flow part of air compressor. And, the changes in the air flow drag pf (0;50 %) result from the difference between the air filter active surface of clean flow (4071,5 mm²) and that contaminated (2035,75 mm²).

In view of a vast range of necessary experimental measurements , resulting from the aim of simulation investigations , it was assumed , like in case of fuelling system testing, to carry out laboratory tests aided by experiment planning theory [4, 7] as well as the computer software STATISTICA PL.

1. The set of input data X:

x_1 - engine rotational speed n [rpm];
x_2 – engine torque T_{tq} [N×m];
x_3 – air filter contamination p_F [%];
x_4 – contamination of compressor flow part p_s [%];
x_5 – untightness of TPC unit S_u [mm2];
x_6 – untightness of valves S_z [mm2].

2. The set of output data Z :

z_1 - engine power P_i [kW];
z_2 – air excess ratio λ;
z_3 – hourly fuel consumption B [g/h]
z_4 - maximum pressure in injection pipe $p_{wtr(max)}$;
z_5 – maximum compression pressure $p_{c(max)}$ [MPa];
z_6 - cylinder exhaust gas temperature T_{g1} [K];
z_7 – mean indicated pressure p_{mi} [MPa];
z_8 – compression pressure in the instant of fuel injection p_c [MPa];
z_9 – maximum combustion pressure p_{max} [MPa];
z_{10} – carbon oxide concentration within exhaust gas outlet collector $C_{CO(k)}$ [ppm];

Tab. 2. Input data in the plan of experimental test on charge exchange system

No.	Input quantity	Notation	Dimension	Values of input quantities		Remarks
				min (-1)	max (+1)	
1	Rotational speed	n	rpm	850	1100	
2	Torque	T_{tq}	N·m	0	77	
3	Untightness of rings of TPC unit	S_u	mm²	0,57	1,178	grinding sealing surface and joint
4	Untightness of inlet and outlet valves.	S_z	mm²	0	0,75	Groove in fying face of inlet and outlet valve
5	Flow drag increase within filter	p_F	%	0	50	Flow throttling
6	Flow drag increase within flow part of compressor	p_s	%	0	33	Flow throttling

z_{11} – carbon oxide concentration within crankshaft casing $C_{CO(s)}$ [ppm];

z_{12} – concentration of hydrocarbons within exhaust gas outlet collector $C_{HC(k)}$ [ppm];

z_{13} – concentration of hydrocarbons within crankshaft casing $C_{HC(s)}$ *[ppm]*;

z_{14} – nitrogen oxides concentration within exhaust gas outlet collector $C_{NOx(k)}$ *[ppm]*;

z_{15} – nitrogen oxides concentration within crankshaft casing $C_{NOx(s)}$ *[ppm]*;

z_{16} – oxygen concentration in exhaust gas C_{O2} *[%]*;

z_{17} – pressure increase rate in cylinder *(Δp/Δα)s*;

z_{18} – indicated specific fuel consumption *bi*;

z_{19} – engine indicated efficiency η_i.

3. The set of the constants, *C*, which may occur during measurements and have influence on changes in output quantities *Z* (e.g. resulting from a used kind of fuel oil , lubricating oil) . As assumed , the experimental investigations will be short-lasting and carried out in similar conditions , i.e. they will be not taken into account in the experiment plan and it should deal only with one measurement block.

4. The set of the disturbing quantities, *H*, which may undergo changes during execution of the experiment:

h_1 – ambient temperature t_a *[oC]*;

h_2 - atmospheric pressure p_a *[hPa]*;

h_3 – relative humidity of air in the laboratory φ *[%]*.

STATISTICAL ANALYSIS OF RESULTS OF THE EXPERIMENT

In view of the assumed linear model of influence of charge exchange system structure parameters on engine working indices , especially concerning exhaust gas components, a simplified statistical analysis of results of the experiment was performed. As a result of the analysis the following was obtained:

- approximating polynomials (functions of the experiment's object) describing functional model of charge exchange system;
- assessment of main effects and interactions of the determined (assumed) model;
- correlation of input and output quantities describing the experiment's object;
- assessment of adequacy of function of the experiment's object.

Based on an analysis of the models possible to be used and the data given in Tab. 3, was assumed a model which takes into account two-factor interactions, despite more favourable values of the basic coefficients (R^2, MS) for estimation of representation (approximation) of relations between input and output quantities of the experiment's object , with taking into account interactions of a higher order, e.g. three-factor ones [3, 14].

As results from the data of Tab. 3 , the model with three-factor interactions covers entirely all the relations (variations) between input and output quantities (the coefficient of determination $R^2 = 1$), which simultaneously means that no residues are rejected and they are not taken into account in the model (MS = 0). However ,as results from mathematical description of any empirical relation , its accuracy increases along with number of interactions which contribute simultaneously to increasing confounding of approximated relations. Hence, confounding degree influences clarity of subject-matter analysis of describing problem (phenomenon) and , consequently, may lead to incorrect conclusions and decisions. In such cases , as a result of the confounding (especially multi-factor one), obtained calculation results are often incorrect and inconsistent with both theoretical physical principles and empirical reality of a phenomenon under investigation. Therefore , taking into account minor differences between values of the analyzed statistical measures , one assumed the model of two-factor interactions for subject-matter analysis. For the models , were determined approximating polynomials for output quantities

Tab. 3 Set of values of selected statistical measures for empirical functional models of charge exchange system

Output quantities	Model without interactions		Model with two-factor interactions		Model with three-factor interactions	
	R^2	MS	R^2	MS	R^2	MS
B	0,009662	0,009663	0,99766	0,00114	1	0
A/F	0,93843	18,2333	0,97808	29,2124	1	0
λ	0,93752	0,08526	0,97774	0,13666	1	0
$C_{CO(k)}$	0,87006	97291	0,99916	2816,31	1	0
$C_{CO(s)}$	0,56833	16,583	0,87708	21,2500	1	0
$C_{HC(k)}$	0,81543	1501,49	0,99677	210,125	1	0
$C_{HC(s)}$	0,70837	1126,9	0,99998	0,5000	1	0
$C_{NOx(k)}$	0,88088	1102,3	0,95341	19,400	1	0
$C_{CO2(k)}$	0,97955	0,13079	0,99512	0,14051	1	0
C_{O2}	0,97314	0,38387	0,99593	0,26153	1	0
t_{g1}	0,95357	757,25	0,99786	157,250	1	0
p_c	0,7297	0,0244139	0,99775	0,0009125	1	0
$p_{c(max)}$	0,84452	0,0292583	0,99272	0,0061625	1	0
p_{mi}	0,88763	4562,319	0,98978	3321,125	1	0
p_{max}	0,85422	0,0258563	0,99811	0,0015062	1	0
b_i	0,50217	690,7553	0,98854	127,2012	1	0

describing state of investigated engine with unserviceable charge exchange system as well as statistical correlations between input and output variables of the experiment's object. The determined approximating polynomials make it possible to determine any relation between particular variables and also to calculate and estimate influence of introduced (simulated) failures (wear) of elements of charge exchange system on engine running and toxicity indices. It may be also assumed that it would be possible to determine mutual relations between structure parameters and exhaust gas toxicity indices – directly or indirectly through engine running indices. As assumed, it will be this way possible to reveal, out of exhaust gas components, diagnostic parameters for given engine fuelling elements or units . Correctness of the assumption is confirmed by the existing relationships (correlations) between wear of elements of charge exchange system and concentration of toxic components in engine exhaust gas.

CONCEPT OF A NEURAL DIAGNOSTIC SYSTEM

Since the form of approximating polynomials for output quantities describing state of investigated engine with unserviceable charge exchange system is complex , an applicable alternative may be a neural approximating model which, based on experimental results as well as determined coefficients of approximating polynomials , may be applied to the modelling of arbitrary nonlinearity and which is highly resistant against disturbances [1, 9, 10].

A condition for reaching correct responses from used neural networks is appropriately numerous set of learning data. To work out such a set can be made possible by using the above described approximating polynomials.

For the purposes of the simulation investigations whose results are presented in the further part of this paper, a general schematic diagram of neural failure detection system was worked out under the following assumptions :

- the system identifies the following classes of engine technical states:
  - the class of states S_0 – technically serviceable engine,
  - the class of states S_1 – untightness of sealing rings,
  - the class of states S_2 – untightness of inlet and/or outlet valves,
  - the class of states S_3 – increase of flow drag within air filter,
  - the class of states S_4 – increase of drag within flow part of air compressor,
- for each of the class of states of technically unserviceable engine will be worked out a separate neural sub-network (4 sub-networks in total) which generates , at its outlet , the value „True" (1) – in case of identification of a dedicated class of states or the value „False" (0) – in the opposite case. The schematic diagram of separate sub-network is shown in Fig. 3
- the engine torque T_{tq} and engine rotational speed n were assumed to be independent variables (input parameters),
- parameters under diagnostic surveillance:
  - exhaust gas temperature $tg1$,
  - concentration of nitrogen oxides within exhaust gas collector , $C_{NOx(k)}$,
  - concentration of carbon oxide within exhaust gas collector , $C_{CO(k)}$,
  - concentration of hydrocarbons within exhaust gas collector , $C_{HC(k)}$,
  - concentration of oxygen in exhaust gas , C_{O2},
- for each of the parameters a neural model will be worked out and all the models prepared this way
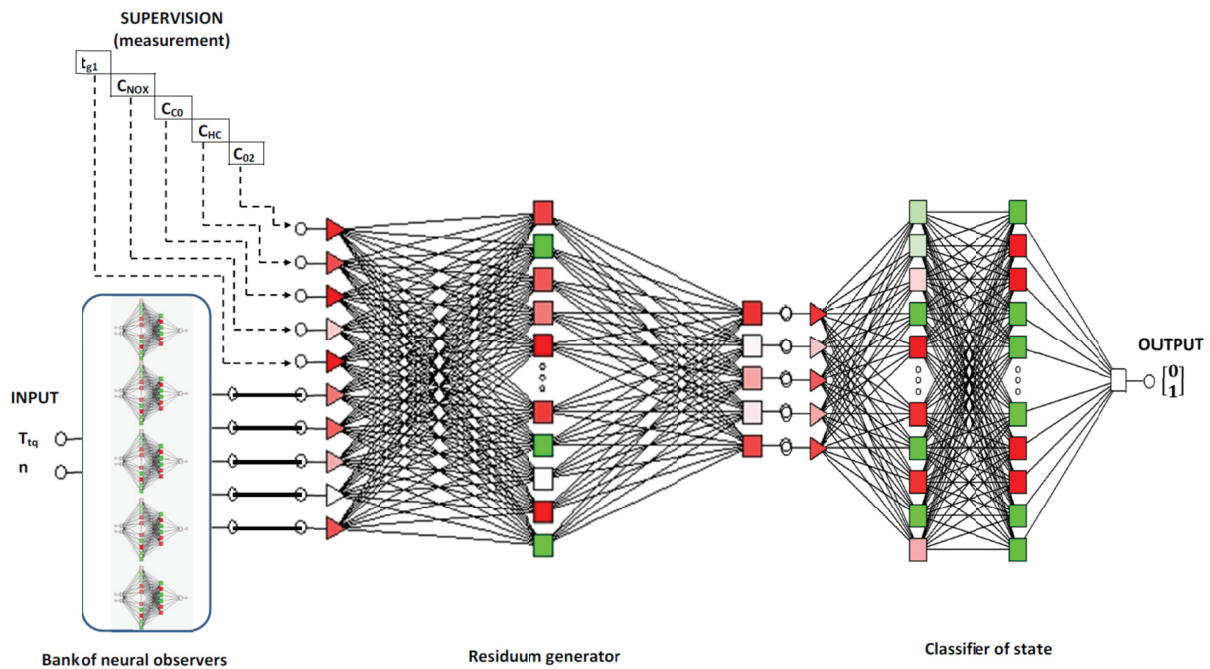
Fig. 3 Schematic diagram of the neural subsystem for detection of the state Si, (i = 0, 1, …4)

will form the so-called bank of neural observers [1, 8], intended for the modelling of values of the considered parameters in normal (free of failures) engine running state,

- by comparing output signals from the model and diagnosed engine, residues, i.e. signals representing discrepancies between model and engine, will be determined,
- the obtained vector of residues $r = [r_1 \dots r_5]$ will be analyzed by a neural classifier of residues whose task will be to determine if a failure occurred – in such case the value "*True*" (1) will be generated at its output, otherwise the system will generate the value "*False*" (0),
- the vector $a = [w_1 \dots w_4]$ (wi $= 0 \cup 1$) achieved as a result of action of the entire system (4 sub-networks), will constitute a diagnostic information source (e.g. in case of obtaining the vector [0 0 0 0] there exist premises to consider the current state of engine as that belonging to the class of states S_0 etc)

The results presented in the further part of the paper was limited to only one sub-network – in this case - to the network which identifies occurrence of the class of states S_1

RUN AND RESULTS OF SIMULATION INVESTIGATIONS

The results obtained in the form of approximating polynomials of output quantities describing state of considered engine with unserviceable charge exchange system, were used for working out the set of learning data for particular sub-networks.

In the case in question the form of the polynomials is as follows :

$$[y_i] = [B_i] + [x_k] \cdot [A_{k,i}] \qquad (1)$$

where :

$[y_i]$ – column vector of parameters under diagnostic surveillance (i = 1, 2, … 5) :

y_1 – exhaust gas temperature – t_{g1},

y_2 – concentration of nitrogen oxides in exhaust gas - C_{NOx},

y_3 - concentration of carbon oxide in exhaust gas - C_{CO},

y_4 - concentration of hydrocarbons in exhaust gas - C_{HC},

y_5 - s concentration of oxygen in exhaust gas - C_{O2}.

$[B_i]$ – column vector of constants appearing in approximating polynomials:

$$B = \begin{bmatrix} 121,319 \\ 257,584 \\ 2584,68 \\ -114,491 \\ 10,67619 \end{bmatrix}$$

$[x_k]$ – row vector of input variables:

$$x = \begin{bmatrix} n & T_{tq} & p_f & p_s & S_u & S_z & I_{12} & I_{13} & I_{14} & I_{15} & I_{16} & I_{34} & I_{36} \end{bmatrix}$$

where:

I_{jk} – regression coefficients concerning interactions $y_j \rightarrow y_k$

$[A_{j,k}]$ –matrix of regression coefficients of approximating polynomials

	$C_{CO(k)}$	$C_{HC(k)}$	$C_{NOx(k)}$	C_{O2}	t_{g1}
n	-2,45	-0,207	-0,147	0,00528	0,070
T_{tq}	-23,55	-0,929	0,736	-0,03629	-0,661
p_f	2,72	0,108	3,205	0,00385	0,316
p_s	-8,05	-2,828	3,245	0,01413	1,380
S_u	-1682,73	10,855	-118,832	2,26151	46,546
S_z	-1760,37	-215,56	-206,267	3,79633	-127,80
I_{12}	0,04	0,003	0,001	-0,00004	0,003
I_{13}	0,01	0,001	-0,003	-0,00003	0,001
I_{14}	0,02	0,004	-0,002	-0,00004	-0,000
I_{15}	1,65	0,048	0,115	-0,00206	-0,046
I_{16}	2,01	0,284	0,176	-0,00428	0,155
I_{34}	-0,10	-0,003	-0,027	0,00059	-0,021
I_{36}	-6,35	-2,007	0,707	0,01807	-0,813

In connection with that five parameters subjected to real time control were selected, it become necessary , in line with the assumed concept , to form the same number of neural models representing relationship between the input variables : T_{tq} and n , and variables subjected to diagnostic surveillance in the state considered normal , i.e. the state s_0.

The first stage of the work consisted in running preliminary investigations aimed at selection of type and optimum structure of neural networks of particular models. To this end, were applied automatic tools of the software *STATISTICA Neural Networks v. 7.0* aiding in the testing of neural networks used for data analysis and prediction issues [15].

The aim of training the networks was to reach such state of them , which determines correct reaction in the broad range of input functions which , in this case, are various values of engine load (in the range of 0÷77 Nm) and rotational speed (850 ÷ 1100 rpm), introduced to inputs. The worked out – by using approximating polynomials - learning set covered 19578 cases in relation to each of the five parameters. The example realizations of changes in values (cases : C_{NOX} and t_{g1}) in function of engine torque and rotational speed are presented in Fig. 4 and 5.
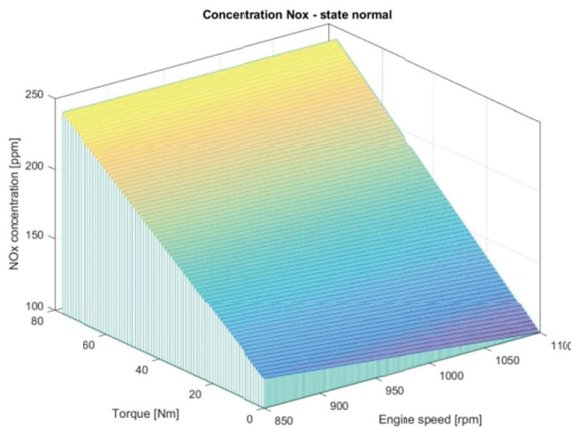

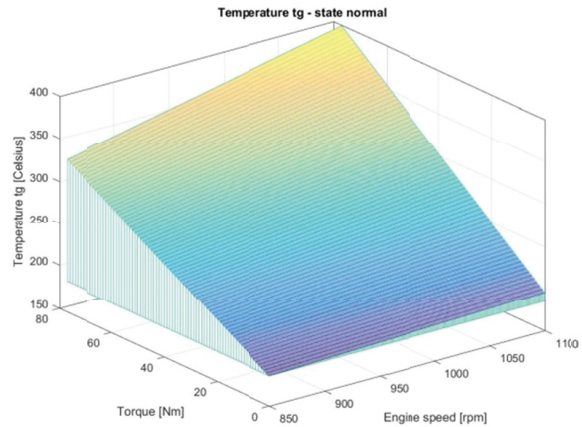Fig. 4. *The functional relationship between C_{NOX} and (T_{tq}, n)*

Fig. 5 *The functional relationship between tg1 and (Ttq, n)*

As a result of the performed simulations and analysis of their results, the network of the type : multilayer perceptron with one hidden layer, was selected.

The stage of preliminary investigations made it possible to perform the basic training of networks for each case of neural observer modelling changes in selected variables. The training and final architecture of the networks was realized by means of the software MATLAB 2015b and its dedicated extension „Neural Network Toolbox" [16].

Application of the basic quality measure for the worked - out neural models , i.e. values and distribution of residues and percentage errors between values expected at output from networks and its real response, showed adequate quality of representation and negligible , from practical point of view, differences. The next stage was aimed at the working out of structure and training of residues generator. For each of the considered class of states, the task of the residues generator is to determine values of differences between monitored output signals of the diagnosed engine, $y_i = f(T_{tq}, n)$, and values of responses, corresponding with them, from the side of the worked out neural observers bank , $y_{is} = f(T_{tq}, n)$. For the presented case of the class of states S_1:
– exhaust gas temperature t_{g1} - y_1,
– concentration of nitrogen oxides in exhaust gas, C_{NOx} - y_2,
– concentration of carbon oxide in exhaust gas , C_{CO} - y_3,
– concentration of hydrocarbons in exhaust gas , y_4,
– concentration of oxygen in exhaust gas, C_{O2} - y_5,
– neural model response, t_{g1s} - y_{1s},
– neural model response C_{NOxs} - y_{2s},
– neural model response C_{COs} - y_{3s},
– neural model response C_{HCs} - y_{4s},
– neural model response C_{O2s} – y_{5s},

The vector of residues $r = [r_1, r_2, r_3, r_4, r_5]$, obtained this way , may be considered a signal which contains information on occurred failures (in this case – untightness of sealing rings). During the engine running in the state taken as normal (the class of states S_0), components of the obtained vector of residues

should be close to zero , but in the case of failure occurrence the difference becomes significantly greater.
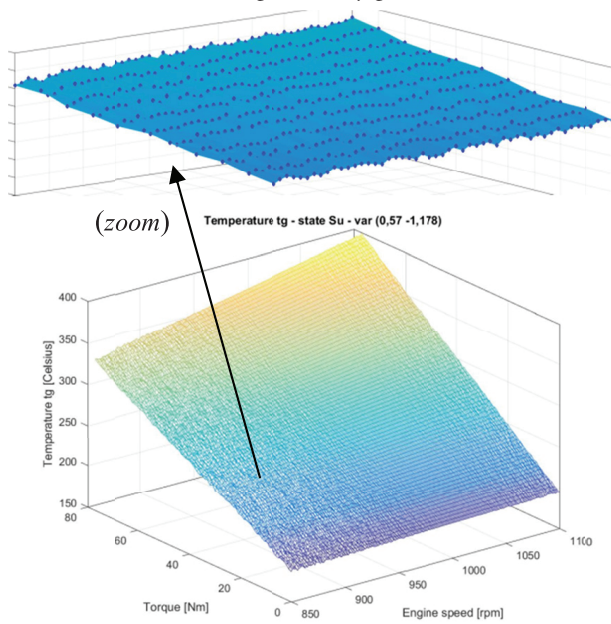

Fig. 6 The functional relationship between t_{g_1} and (T_{tq}, n) – class of states S_1 ($S_u \in <0,57, 1,178>$ [mm²])

The learning sets worked out with the use of approximating polynomials, contained about 20000 cases with reference to each of the five parameters. For the presented case of the class of states S_1 , the set of model responses $y_{is} = f(T_{tq}, n)$ was worked out for random changes in the values S_u within the range of $0,7 \div 1,178$ mm², n – values within the range of $850 \div 1100$ rpm, T_{tq} - values within the range of $0 \div 77$ Nm. Fig. 6 exemplifies the relationships $y_{1s} = f(T_{tq}, n)$ for the class of states S_1 .
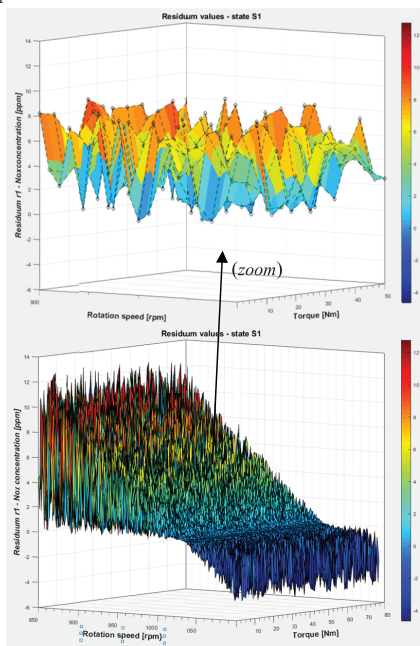

Fig. 7 Values of the residues r_2 (NO_x concentration) – the class of states S_1.

Based on experience dealing with optimum network structure and type , it was decided to select a linear neural network which models relations between its ten inputs (y_1, y_2, y_3, y_4, y_5, y_{1S}, y_{2S}, y_{3S}, y_{4S}, y_{5S}) and five outputs (r_1, r_2, r_3, r_4, r_5). The results achieved in the case of the class of states S_1 , are shown for the parameter C_{NOx} in Fig. 7.

Like in the case of the neural observers bank , the test of the network and application of its quality measure in the form of values and distribution of modules of the residues between values expected at network's output and its real response, showed very good quality of representation and negligible , from practical point of view , differences. Fig. 8 presents an example result for the class of states S_1 .
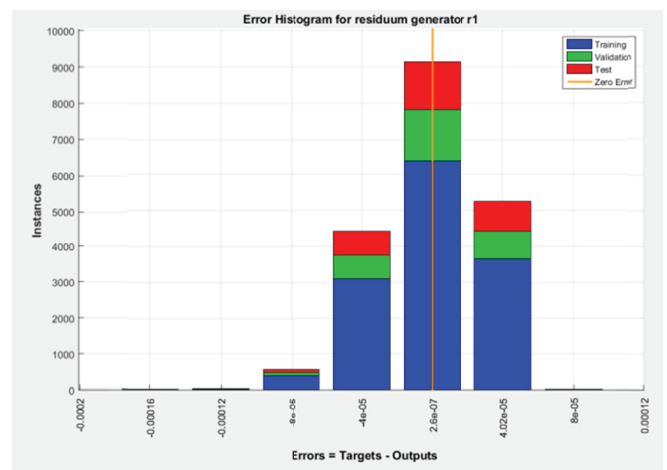

Fig. 8 Distribution of modules of absolute errors of residues generator – the class of states S_1

The task of the last element of failure detection and location system , i.e. the state classifier (block of residues evaluation), is to analyze residue's vector in order to determine whether a selected failure has occurred or not. This is a typical classification issue consisting in the matching of vector's symptoms to one of the distinguished classes of states.

Based on the 1st stage of investigations, to solve the presented issue , the network of the multilayer perceptron type with one hidden layer , was designed and trained, see Fig. 9.
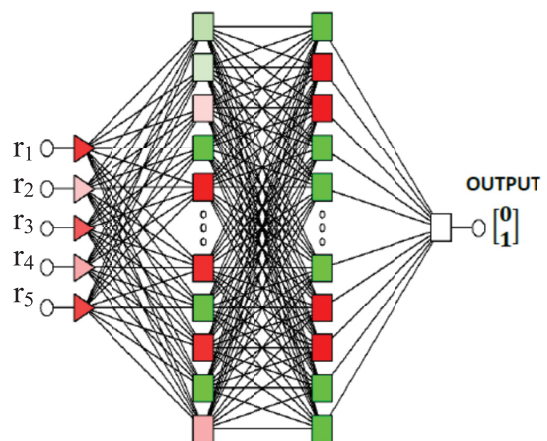

Fig. 9 Topological diagram of neural classifier of states

The classifier , sending to network's input, the vector $r = [r_1, r_2, r_3, r_4, r_5]$, triggers activation of one neuron of output layer – the value „*True*" (1) in the case of identification of the dedicated class of states , or the value „*False*" (0) – in the opposite case.

The learning sets intended for training the classifiers were worked out on the basis of the assumption that a change , by less than 10% , in values of particular classifiers , which results in transition of engine to a given class of states S_i (Tab. 2, row $3 \div 9$), triggers the response „*False*" at classifier's output . Otherwise, the response „*True*" is obtained at neural network's output.

The training, validation and test of the classifier, based on the learning set , showed its very good matching and negligible number of erroneously classified cases (below 1% during the testing phase).

TEST RESULTS OF NEURAL MODELS

The working-out of particular networks and positive completion of their training made it possible to test the presented system with the use of the testing set of simulated, determined cases of values of the exhaust gas temperature tg1 and the concentration of nitrogen oxides in exhaust gas C_{NOx} , concentration of carbon oxide in exhaust gas, C_{CO}, concentration of hydrocarbons in exhaust gas , C_{HC} , and concentration of oxygen in exhaust gas , C_{O2}.

The set of test cases containing 5000 sets of values (1000 cases for each of the class of states) were worked out on the basis of the prior obtained approximating polynomials which were randomly changed in each of the set by using a generator of pseudo-random numbers. The change concerned values of all the parameters appearing there, within the range of $\pm 5\%$;

The presented procedure had to show first of all susceptibility of the system on disturbances , and consequently, its potentially lower or greater usefulness for implementation in real ship power plant conditions. Fig. 10 shows an error matrix for the case of the class of states S_1 , and Tab. 4 summarizes generally results of the tests.

Fig. 10 State classifier's error matrix – the class of states S_1

Tab. 4 Results of testing the neural system for detection and location of errors

Subset of testing set	Correctly classified state (number of cases (%)	Erroneously classified state (number of cases (%)
State s_1	99,8	0,2
State s_2	98,4	1,6
State s_3	99,3	0,7
State s_4	98,9	1,1
State s_5	99,5	0,5
Mean	99,18	0,82

SUMMARY

The example investigation results, i.e. the values obtained during active experiment , indicate that the proposed "on-line" system for detection and location of failures correctly identifies a given class of engine states. From practical point of view its quality may be called excellent.

However it may also seem that specificity of use of especially responsible power systems such as ship power plant and its functional subsystems require higher percentage values of correct classification than those shown in Tab. 4 .

Another issue is empirical verification of the presented system. In the considered cases the set of data was relatively homogenous because it was obtained by means of algebraic relationships.

In case of investigations carried out directly on a real object, obtained results may appear quite different , that obviously requires to carry out further investigations whose main condition is to realize in practice , as to its program solutions and instrumentation, the system discussed in this paper.

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