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Problems of modelling toxic compounds emitted by a marine internal combustion engine for the evaluation of its structure parameters

The paper presents the possibility of using an analytical study of the engine exhaust ignition to evaluate the technical condition of the selected components. Software tools available for the analysis of experimental data commonly use multiple regression model that allows the study of the effects and iterations between model input quantities and one output variable. The use of multi-equation models gives a lot of freedom in the analysis of the measurement results, as it allows the simultaneous analysis of multiple effects and iterations of output variables. It can also be used as a tool for the preparation of experimental material for other advanced diagnostic tools, such as models using neural networks, which allow, in contrast to multi-equation models, the recognition of the state with the number of classes of more than two-class, thus enabling diagnostic reasoning. Assuming that there is a strong correlation and unambiguous nature of the changes in the concentrations of toxic compounds analyzed in the course of the experiment can be seen as symptoms of the technical condition of the engine and with the known values of the output signals (including concentrations of toxic compounds) and their estimates, the values of residuals can be determined, which may indicate the type of damage. The authors show the advantages of using these analytical tools on the example of research conducted on the engine test bench.

Key words: *engine exhaust components, marine engines, engine diagnostics*

Problemy modelowania emisji związków toksycznych okrętowego silnika spalinowego dla oceny jego parametrów struktury

W artykule przedstawiono możliwość wykorzystania wyników badań składu spalin silnika z zapłonem samoczynnym do oceny stanu technicznego jego wybranych podzespołów. Dostępne programy narzędziowe służące do analizy danych eksperymentalnych powszechnie wykorzystują model regresji wielokrotnej, który umożliwia badanie efektów i interakcji pomiędzy wielkościami wejściowymi modelu a jedną zmienną wyjściową. Zastosowanie modeli wielorównaniowych daje wiele możliwości podczas analizy wyników pomiarowych, gdyż umożliwia jednoczesną analizę efektów i interakcji wielu zmiennych wyjściowych. Może być również wykorzystywane jako narzędzie do przygotowania materiału doświadczalnego dla innych zaawansowanych narzędzi diagnostycznych, takich jak modele wykorzystujące sieci neuronowe, które pozwalają, w przeciwieństwie do modeli wielorównaniowych, na rozpoznanie stanu przy liczbie klas większej niż dwuklasowa, umożliwiając tym samym wnioskowanie diagnostyczne. Przy założeniu bowiem, że istnieje silna korelacja oraz jednoznaczny charakter zmian stężeń analizowanych związków toksycznych w trakcie prowadzonego eksperymentu można traktować jako symptomy stanu technicznego silnika a przy znanych wartościach sygnałów wyjściowych (między innymi stężeń związków toksycznych) oraz ich estymat można wyznaczyć wartości residuów, które mogą wskazywać na rodzaj uszkodzenia. Autorzy w pracy przedstawiają zalety stosowania powyższych narzędzi analitycznych na przykładzie badań przeprowadzonych na stanowisku silnika badawczego.

Słowa kluczowe: *składniki spalin silnika, silniki okrętowe, diagnostyka silników*

1. Introduction

During the operation of every power plant, its functional sub-systems interact with a variety of internal and external factors that are causing irreversible degradation processes, resulting in changes in the technical and the most progressive deterioration of operating characteristics. Damaged components will therefore inevitably appear in those subsystems.

In the case of a marine ship, a change to the aforementioned state to one of the sub-sets of undesirable states can cause a threat not only to the engine room, but also the entire ship, which in extreme cases of losing the ability to move and maintain the course may, in difficult hydrometeorological conditions, suffer a serious accident including sinking [1].

During the operation of watercraft units, direct and indirect power plant users continuously make decisions concerning the use and handling of the devices - including in particular the powertrain - in this regard aiming to ensure the normal situation, in which safe movement is possible .

Making the correct decision, of course, is not a simple task and means to select one of the multiple possible paths to take, which is found to be the best. The choice of such a decision, which is necessary to determine the rational exploitation strategy, is possible after taking into account the wide variety of information, but it will never be the correct choice without considering the data and indicators concerning the condition of the main drive motor.

During the working process of the motor, parameters of the structure undergo changes. It has an effect on its performance, described with a set of output parameters. The mutual relationship between the structure and the parameters of the engine output parameters allows, under specified conditions, to treat the symptoms of output parameters as the technical condition of the engine, measured without removing it because physicochemical processes occurring during the working process and describing its size can generally be observed and measured from the outside. Among these values are, for example, the value of the emissions of exhaust gas components.

The proper combustion process in the engine cylinder depends primarily on well-functioning supply system, which aims to provide primarily the fuel injection process repeatability. Because of this very reproducibility not only is the start and the end of injection important, but also their course. The correctness of the first criteria (the beginning and end of injection), a classic power systems, is largely protected by the high-pressure fuel pump adjusting parameters such as: fuel delivery and injection timing, which should be regarded as a basic parameter determining the correctness of the course combustion-ignition engines, because even small variations result in the significant changes in the key indicators of engine operation, including indicators of emissions [6, 16, 17].

2. Assumptions

On the basis of the aforementioned points, an analysis of a set of values characterizing the engine fuel supply system was carried out and the initial version of the diagnostic table (Table 1) and the topological model, which is shown in Fig. 1 [10, 13].

Due to the occurrence of many cases of intuitive indication of changes, and not very strong links of indicators of toxicity of exhaust from the engine operating parameters listed in Table 1, and the parameters of structure (damage), essential is an empirical verification and experimental designation table based on the existing simulation studies.

Table 1. The initial diagnostic table on engine fuel supply system

Diagnostic parameter		Location and type of malfunction							
		injection pump			injector				
		wear of cylinder-injection pump piston surface	erosive wear of steering edges of the piston	discharge valve leakage loss	loss of tightness in the needle seat	surface wear of the guide needle	erosive wear of spray nozzles	coking (obstruction) of spray nozzles	loss of spring tension force
Fuel injection advance angle	α_{ww}	-	-	-	-	-	0	0	+
Fuel injection angle	α_w	-	-	-	-	-	-	+	+
injector opening pressure	p_{owtr}	0	0	0	0	0	0	0	-
Fuel injection (forcing) pressure	p_{wtr}	-	-	-	-	-	-	+	-
Intensity of pressure accumulation in the cylinder	$dp_p/d\alpha$	-	-	-	-	-	0	0	0
Fuel consumption	b	+	+	+	+	+	+	+	+
Charge air pressure	p_{ba}	+	+	+	+	+	+	+	-/+
Rotational speed of the turbocharger	n_t	+	+	+	+	+	+	+	-/+
Outlet exhaust temperature	t_{g1}	+	+	+	+	+	+	+	-/+
Compression pressure during the fuel injection	p_c	+	+	+	+	+	0	0	-
Nitrogen oxides concentration in the exhaust	C_{NOx}	-	-	-	+	-	+	+	+
Carbon monoxide concentration in the exhaust	C_{CO}	-	-	-	+	+	+	+	+/-
Hydrocarbon concentration in the exhaust	C_{HC}	0	0	0	+	+	+	+	-
Opacity of the exhaust gas	D	0	0	0	+	+	+	+	-

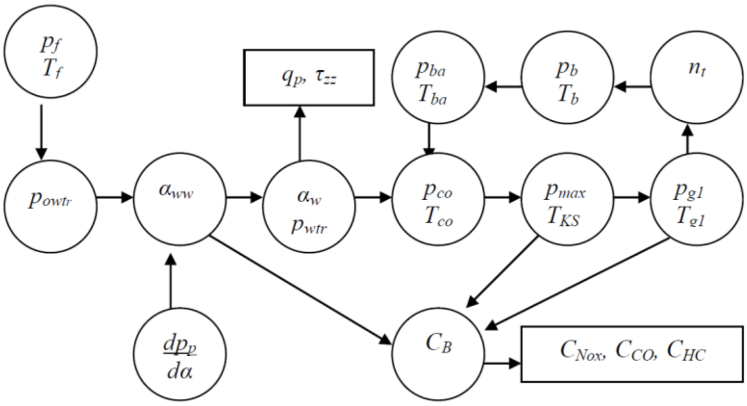

Fig. 1. Topological model of engine fuel supply system

3. The methodology of empirical simulation tests of the engine fuel supply system

The basic goal of the simulation tests is determining whether the identification of the technical state of the injection equipment is possible based on the changes in toxic compound components, including [4, 7, 13, 18]:

– verification of diagnostic parameters shown in Table 1;
– verification of the changes in diagnostic parameter values in relation to the place and the type of malfunction of the injection equipment elements;
– detecting (finding) relationships (dependencies) between parameters of the operating parameters of the engine, and the diagnostic parameters - indicators of toxic fumes;
– possible indicators of the toxicity of the fumes principal (main) diagnostic parameters and indicators of the auxiliary engine operation verifying the state of elements of diagnostic parameters of injection engine

  Those selected by the analysis of malfunction (damage) of engine fuel supply system components was simulated as follows:

– putting wear on the surface of the cylinder and piston injection pump by changing the geometric dimensions (grinding off the sealing portion of the piston) - the state of wear of the surfaces defined as the change of leakage S_{pw} [mm^2];
– the loss of the pump discharge valve leak by changing the geometric dimensions of the sealing seat and shoulder discharge (grinding off part of the valve seat and shoulder) – the state of wear was specified as a change of leakage S_{zt} [mm^2];
– wear of the conical part of the sealing needle in the pulverizer slot by changing the dimensions (grinding off part of the injector needle seat) - the state of wear of the surfaces defined as leakage S_r [mm^2];
– wear of the leading needle of the pulverizer by changing dimensions (grinding) – the state of wear specified as leakage S_i [mm^2];
– erosive wear of the atomizer nozzle caused by increasing the hole diameter - as defined by the increased amount of the cross-sections of pulverizer nozzles S_e [mm^2];
– coking of the pulverizer nozzles by partially obstructing the holes - the state of coking is defined by the decreased amount of the cross-sections of pulverizer nozzles S_k [mm^2];
– loss of the level of tension on the spring by decreasing it to a predetermined value by ΔP [MPa].

The approximate consumption values summarized in Table 2 are the basis to the preparation of so called worn parts, used in the basic simulations. The method of preparation is collecting, by grinding or machining, set amounts of material on the surfaces of the cooperating pairs of precision, which correspond to pre-calculated values of consumption, resulting from experimental data. Hence, the values of the factors specified below were initially adapted, which justified the results of calculation and analysis of the process of injection equipment wear.

It is assumed that the calculated total consumption value G = $0.296 \cdot 10^{-2}$ mm^3 vapor-precision plunger pump is incorporated into the sleeve (simulated) by a groove on the surface of the sealing portion of the piston in a plane perpendicular to the edge of the zero fuel delivery. The groove volume of 0.00296 mm^3 at this point has a cross-section F = $0.1141 \cdot 10^{-2}$ mm^2 and a length L = 6 mm. It can be made with a cutting tool of an equilateral triangle section and a side of a = 0.034 mm (h = 0.029 mm).

Wear of the leading pulverizer needle with a volume of V_1 = $1.1 \cdot 10^{-2}$ mm^3 was taken into account by creating a groove on the surface of the leading needle with a cross-section F = $0.487 \cdot 10^{-3}$ over its entire length L = 22.6 mm. This implies that the groove can be formed, for example, by a cutting tool with the cross-section of an equilateral triangle with side a = 0.0338mm (h = 0.029 mm).

Wear of the conical part of the sealing pulverizer needle of a volume $V = 1.48 \cdot 10^{-2}$ mm^3 was taken into account by making a groove on the surface F = 0.00529 mm^2 on the cone seat of length l = 2.8 mm. Implementation of the groove, similar to the previous ones, requires a cutting tool with a side a = 0.111 mm (h = 0.095 mm).

Wear of the discharge valve seat is assumed to be on the level of the needle spray nozzle, which means that the consumption V = 0.0148 mm^3 corresponds to the groove surface F = 0.0049 mm^2, made radially on the valve seat with a length l = 3 mm. Made similarly to the previous cases, the groove has a cross section of an equilateral triangle with side a = 0.106 mm (h = 0.092 mm).

Erosive wear of the pulverizer with seven nozzles with a diameter of 0.25 mm (the sum of the cross sections of nozzles being 0.3434 mm^2) was simulated by replacing it with eight spray nozzles of a 0.27 mm diameter (total cross 0.4578 mm^2), resulting in consumption that was established to be 0.1144 mm^2, which corresponds to the sum of the cross sections increasing by approximately 33%.

It is assumed that within a predetermined time, the coking has been done to one spray nozzle of a cross-sectional area of 0.0491 mm^2, which represents a reduction of 14% of the sum of all cross-sections of the basic pulverizer nozzles (7 x 0.25).

It is assumed that after 1000 hours of engine operation a reduction in tension of the spring cylinder injectors occured at 14%, which corresponds to its decrease from 21 MPa to 18MPa.

The values of input variables describing the object of study are summarized in Table 2.

Table 2. Summary of input variables in the experience engine fuel supply system plan

Lp.	Size of input	Indication	Dimension	Factor values		Notes
				min (–1)	max (+1)	
1	Rotational speed	n	rpm	850	1100	
2	Torque	T_{tq}	N·m	0	77	
3	Leak of the piston-sleeve set	S_{pw}	μm^2	0	1.14	The groove on the sealing portion of the piston l = 6 mm
4	Leak of the discharge valve of the needle	S_{zt}	μm^2	0	4.9	The groove on the valve seat l = 3 mm
5	Leak of the skirt of the needle	S_i	μm^2	0	0.487	The groove on the surface of the needle l = 22.6 mm
6	Leak of the cone needle seat	S_r	μm^2	0	5.29	The groove on the needle seat l= 2.8 mm
7	Erosive wear of the nozzle	S_e	μm^2	0	114	The use of the pulverizer 8 x 0.27
8	Coking of the pulverizer nozzle	S_k	μm^2	0	49	The coking of one nozzle
9	Reducing the tension of the injector spring	ΔP	MPa	0	3	The reduction of the tension

For the adopted model of paired interactions, determined were approximating polynomials for variables describing the state of a test on a defective engine fuel supply system [18]. Also determined were the statistical correlations of input and output variables of the object of research, indicating the significance of the individual interactions. Designated approximating polynomials allow to determine any relationship between the individual variables, as well as to calculate and evaluate the impact of introduced (simulated) damage (wear) of the elements of the fuel injection system and toxicity indicators of the engine, which allows for specifying the relationship (correlation) between the structure parameters and indicators of toxic fumes directly or indirectly through indicators of the engine operation. It is assumed that this way one will be able to determine from the exhaust components the diagnostic parameters of particular elements or assemblies of motor fuel equipment. The reality of this assumption is confirmed by the correlation values of the individual components of designated approximation equations which indicate the existing relationship between the consumption of fuel elements and the concentration of toxic components in the exhaust outlet of the engine [11, 12, 14, 15].

4. The concept of neural system diagnostics

Taking into account the complicated form of the polynomials approximating the output values describing the state of the tested engine with a defective fuel supply system, an applicable alternative may be a neural approximating model which basing on the experimental results and the set coefficients of approximating polynomials can be used to model any non-linearities and has a high resistance to interference [2, 3, 8, 9].

The condition for correct answers used in neural networks is an appropriately high number of training data collection. The development of such a set becomes possible through the use of approximating polynomials described earlier.

For the purpose of simulation tests, the results of which are presented later in this paper, a general scheme of neuronal damage detection system with the following assumptions was developed:

- system identifies the following classes of technical conditions of the engine:
  - class of states S_1 – technically sound engine,
  - class of states S_2 – leak of the sleeve-piston pump,
  - class of states S_3 – leak of the discharge valve of the pump,
  - class of states S_4 – leak of the leading part of the needle,
  - class of states S_5 – leak of the cone needle seat,
  - class of states S_6 – erosive wear of pulverizer nozzle,
  - class of states S_7 – coking of pulverizer nozzle,
  - class of states S_8 – reducing the spring tension of the injector,
- as independent variables (input parameters) were adopted the torque of the engine - T_{tq} and the speed - n,
- important parameters subjected to diagnostic supervision were concluded to be (Table 2):
  - exhaust temperature – t_{g1},
  - nitrogen oxides concentration in the exhausts - C_{NOx},
  - carbon monoxide concentration in the exhausts - C_{CO},
  - hydrocarbon concentration in the exhausts - C_{HC},
  - oxygen concentration in the exhausts - C_{O2},
- for each of these parameters will be developed a neural model, and all models developed in this way will form a so called bank of neural observers [2], modeling the examined parameter values in normal (not damaged) engine operating condition,
- by comparing the signal at the output of the model and the diagnosed engine will be determined residues - signals reflecting the discrepancies between the model and the engine,
- the resulting vector of residuals will be analized by neural residual classifier, whose task will be to determine whether there is damage - in which case, the output generated will be set to "True" (1), otherwise the system will generate a value of "False" (0)

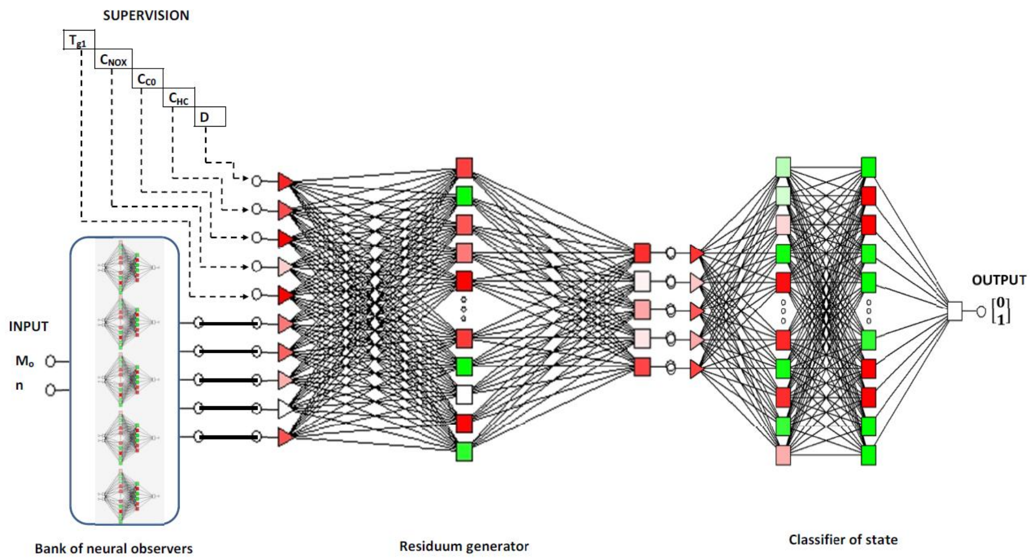

Fig. 2 Diagram of neural subsystem state detection S_i $(i = 1, 2, \dots 8)$

- for each class of states of the technically faulty engine will be developed a separate neural subnet (7 subnets total) generating at its output value of "True" (1) - in the case of identification of a dedicated class of states, or, otherwise, the value "False" (0). Single subnet scheme is shown in Fig. 2.
- obtained in result of the entire system (7 subnets) being in action, vector a $= [w_1 \cdots w_7]$ ($w_i = 0 \cup 1$) will be the source of diagnostic information.

The results presented in the following part of the article will be limited to one subnet - in this case, a network identifying the occurrence of the S_8 state.

5. The course and the results of simulation

The results obtained in the form of approximating polynomials of variables describing the state of the tested engine with a defective fuel supply system were used to develop a set of training data for each subnet.

In the presented case, the form of polynomials is as follows:

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

where:

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

- y_1 - exhaust temperature – t_{g1},
- y_2 - nitrogen oxides concentration in the exhausts - C_{NOx},
- y_3 - carbon monoxide concentration in the exhausts - C_{CO},
- y_4 - hydrocarbon concentration in the exhausts - C_{HC},
- y_5 - oxygen concentration in the exhausts - C_{O2}.

$[B_i]$ - column vector of constants occuring in approximating polynominals:

$$B = \begin{bmatrix} 46.15 \\ 84.3 \\ 2218.45 \\ 44.7 \\ 18.6195 \end{bmatrix}$$

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

$$x = \left[n\ T_{tq}\ S_{pw}\ S_{zt}\ S_i\ S_r\ S_e\ S_k\ \Delta P\ I_{12}\ I_{13}\ I_{15}\ I_{18}\ I_{19}\right]$$

$[A_{k,i}]$ – coefficient matrix of polynomials

$$A = \begin{bmatrix}
0.1735 & 0.027 & -1.787 & 0.0455 & -0.00302 \\
-1.3208 & 2.682 & -3.44 & 0.1669 & -0.06942 \\
-40.7018 & -10.175 & -892.061 & 3.114 & 1.23816 \\
-3.1888 & 1.99 & -67.449 & -4.5663 & 0.01786 \\
291.9918 & -371.253 & 3345.072 & 47.5359 & -1.79569 \\
-14.9527 & 27.505 & -655.132 & 1.0302 & 0.36002 \\
0.2686 & -0.235 & 4.432 & -0.0779 & -0.00088 \\
-0.8082 & -0.655 & -22.734 & 1.6724 & -0.00019 \\
68.3333 & 22.767 & 121.017 & -19.95 & -0.64250 \\
0.004 & -0.002 & 0.025 & 0.0001 & 0.0 \\
0.043 & -0.004 & 1.011 & -0.0202 & -0.00135 \\
-0.3018 & 0.386 & -3.322 & -0.0185 & 0.00189 \\
0.0172 & -0.026 & 0.63 & -0.0032 & -0.00034 \\
0.0008 & 0.001 & 0.024 & -0.0016 & 0.0 \\
-0.0717 & -0.019 & -0.176 & 0.0203 & 0.00073
\end{bmatrix}$$

Because of having five parameters identified and controlled in real time, it has become necessary, in accordance with a predetermined concept, that the creation of the same number of neural models be made, mapping relationship between input variables - T_{tq} and supervision of diagnostic variables in the engine operating condition that was defined as normal - the state S_1.

As the first phase of the work, preliminary studies were carried out, designed to determine the type and the optimal structure of the different models of neural networks. Used for this purpose were the automated tools *STATISTICA Neural Networks v.7.0*, supporting the development and testing of a neural networks used in the data analysis and predictive issues [18].

The purpose of the network training was to obtain the status which determines the correct response in a wide range of input functions, which are in this case fed to the various inputs (in the range of 0–77 Nm), the engine load and speed (850–1100 rpm). Prepared using the approximating polynomials, the training set counts 7.700 of cases for each of the 5 parameters. Exemplary embodiments of the changes in the value (cases of C_{NOx} and t_{g1}) as a function of torque and engine speed are shown in Fig. 3, 4 and 5.

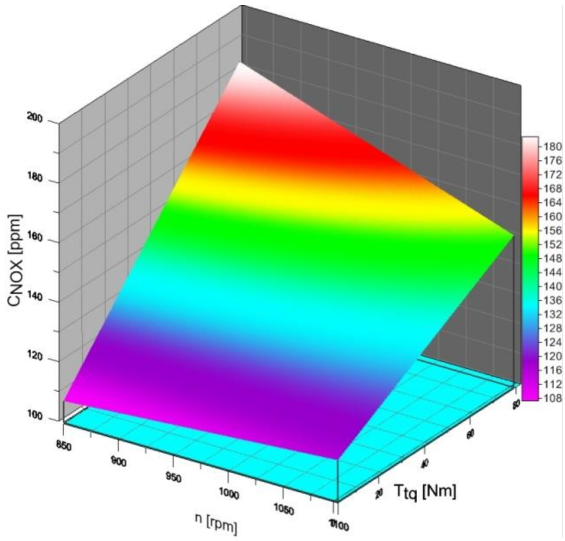

Fig. 3. The functional relationship between C_{NOx} and (T_{tq}, n)

As a result of the simulations and the analysis of the results a selection of the multilayer perceptron networks with one hidden layer was made.

Preparatory study allowed to conduct basic training networks for each neural observer modeling the changes of selected variables. Training and final network architecture was implemented using MATLAB 2014b and dedicated its extension "Neural Network Toolbox" [19].

The use of the basic measure of the quality of developed neural models, ie. the value and the distribution of residuals and the error rate between the expected values at the output of the network and its actual response showed the quality of representation and negligible, from a practical point of view, differences.

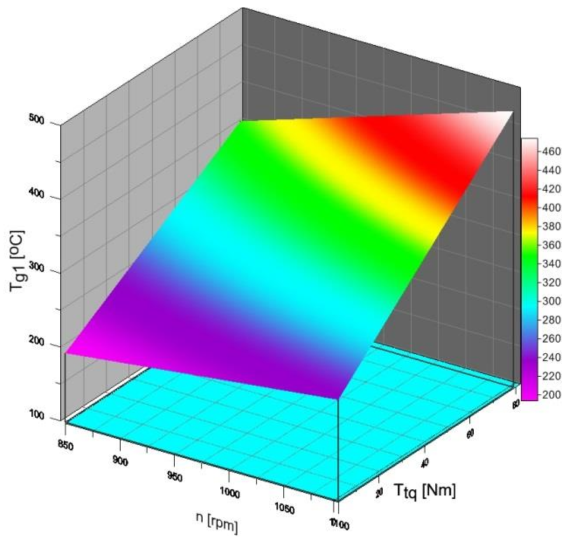

Fig. 4 The functional relationship between T_{g1} and (T_{tq}, n)

The use of the basic measure of the quality of developed neural models, ie. the value and the distribution of residuals and the error rate between the expected values at the output of the network and its actual response showed the quality of representation and negligible, from a practical point of view, differences.

The aim of the next stage was developing of structures and training of the residuals generator. For each of the state classes, the generator's task is to determine the value of the differences between the monitored output signals of the diagnosed engine - $y_i = f(T_{tq}, n)$ and the corresponding response of the developed models of neural observers bank - $y_{is} = f(T_{tq}, n)$ - Fig. 4. For the presented case S_8 are these class states:

– exhaust temperature t_{g1} - y_1,
– nitric oxide concentration in the exhausts - C_{NOx} - y_2,
– carbon monoxide concentration in the exhausts - C_{CO} - y_3,
– hydrocarbon concentration in the exhausts - C_{HC} - y_4,
– oxygen concentration in the exhausts - C_{O2} - y_5,
– the answer of neural model t_{g1} - y_{1s},
– the answer of neural model C_{NOx}- y_{2s},
– the answer of neural model C_{CO} - y_{3s},
– the answer of neural model C_{HC} - y_{4s},
– the answer of neural model C_{O2} – y_{5s},

Thus obtained residual vector $r = [r_1, r_2, r_3, r_4, r_5]$ may be considered as a signal containing information about the existing damage (in this case - reduction of the spring tension of the injector). During operation, the state defined as normal (class of states S_1), the resulting residual vector components should be close to zero, while in the case of taking damage, this difference is significantly increased.

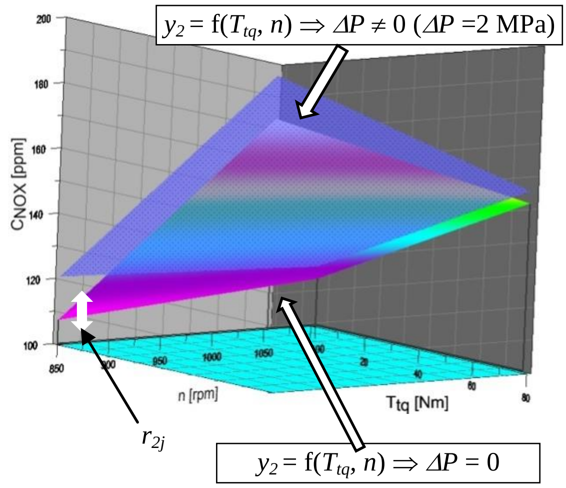

Fig. 5 The concept of neural residuals generator (for example, C_{NOx} concentration)

Developed using the approximating polynomials, teaching collections numbered from 20.000 to 30.000 cases with respect to each of the 5 parameters. For the presented class of states S_8, a collection of model answers $y_{2s} = f(T_{tq}, n)$ for random changes in the value of ΔP in the range of 0.5–3 MPa, the value of n in the range 850–1100 rpm, T_{tq} values in the range 0–77 Nm were developed - totaling to 22.000 cases.

Using the experience involving the optimal structure of the network and its type, it was decided to choose the linear neural network modeling mapped between ten of its inputs (y_1, y_2, y_3, y_4, y_5, y_{1S}, y_{2S}, y_{3S}, y_{4S}, y_{5S}) and five of its outputs (r_1, r_2, r_3, r_4, r_5).

Like in the case of a neural observer bank, the network test and the use of its quality meter in the form of modules and distribution of residues between the expected values for the network output and the actual response indicated a good fidelity and negligible, from the practical point of view, differences.

The task of the last element of the detection and location system of faults, ie. classifier state (block evaluation of residues – Fig. 6), is the analysis of vector residue to determine whether there is a typed damage. It is, therefore, a typical classification problem involving matching vector symptoms to one of the separate classes of conditions.

On the basis of the first stage of research, to solve the problem presented a multilayer perceptron network with one hidden layer was designed and underwent training.

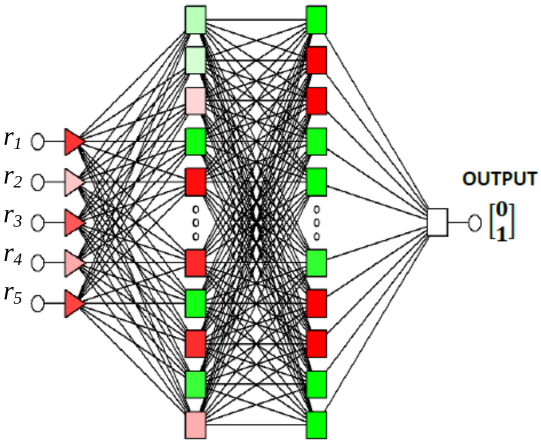

Fig. 6 Block of evaluation of residues

Initial administration of the classifier network input vector $r = [r_1, r_2, r_3, r_4, r_5]$ activates one neuron in the output layer - the "True" (1) value for identifying the dedicated class of conditions or, otherwise, the "False" (0) value.

Learning sets for training classifiers are based on the assumption that the change in the value of individual parameters resulting in moving the engine up to a certain class of S_i states (Tab. 2, items 3 - 9), less than 10% of the classifier output activates the answer "False". Otherwise, the output of the neural network gets the answer "True".

Training, validation and classifier test based on the training set, all showed a very good adjustment of the set and a negligible - less than 4% at the stage of testing - number of cases classified incorrectly.

6. The results of testing the neural models

The development of the structure of individual networks and the positive conclusion of their training enabled the present test system using a simulated test set, specific cases of the flue gas temperature - tg_1 and the concentration of nitrogen oxides in the exhaust - C_{NOx}, the concentration of carbon monoxide in the exhaust - C_{CO}, the concentration of hydrocarbons in the exhaust - C_{HC} and oxygen concentration in the exhaust gas - C_{O2}.

The set of test cases counting 4.000 sets of values (500 cases for each class of states) are based on previously obtained polynomial approximation that, using the pseudo-random number generator, changed in each set at random. Change related to the value of all existing parameters there was within ± 5%;

The following procedure was mainly to showcase the vulnerability of the system to interference and thus its potential, to a greater or lesser extent, suitability for use in the realities of the engine room.

The results of testing are presented in Table 3.

Table 3 The results of testing the neural system of detection and location of malfunctions

Subset of the test	Properly classified state (number of cases /%)	Poorly classified state (number of cases /%)
State S_1	492/98.4	8/1.6
State S_2	486/97.2	14/2.8
State S_3	480/96.0	20/4.0
State S_4	491/98.2	9/1.8
State S_5	479/95.8	21/4.2
State S_6	478/95.6	22/4.4
State S_7	490/98.0	10/2.0
State S_8	487/97.4	13/2.6
Total	3883/97.1	117/2.9

5. Summary

The results gotten from the values obtained during the active experiment indicate that the proposed system for detection and fault location in the "on - line" mode identifies quite well a specific class of engine conditions. From a practical point of view, the quality can even be described as perfect.

It would also appear possible that the specificity of an extremely responsible use of energy systems, and such is undoubtedly a power plant for ships and its functional subsystems, requires a higher percentage of correct classifications than those shown in Table 3.

A separate problem is the empirical verification of the presented layout. In the discussed cases, the collection of data was relatively homogenous, as it was obtained from algebraic relations.

In the case of an active experiment and research realized directly on the real object, the results may differ from those generated by the model adopted by the researchers. It will of course require further study. Nonetheless, the results presented above are encouraging and the authors are going to focus their attention on the more advanced methods of determining metrics of diagnostic parameters and their normalization for further use in the diagnostic field.

Nomenclature/*Skróty i oznaczenia*

n Rotational speed/*prędkość obrotowa*
T_{tq} Torque/*moment obrotowy*
S_{pw} Leak of the piston-sleeve set/*nieszczelność zespołu tulejka-tłoczek pompy*
S_{zt} Leak of the discharge valve of the needle/*nieszczelność zaworu tłocznego pompy*
S_i Leak of the skirt of the needle /*nieszczelność części prowadzącej iglicy*
S_r Leak of the cone needle seat/*nieszczelność przylgni stożka iglicy*
S_e Erosive wear of the nozzle/*zużycie erozyjne dysz rozpylacza*
S_k Coking of the pulverizer nozzle/*zakoksowanie dysz rozpylacza*
ΔP Reducing the tension of the injector spring/*zmniejszenie napięcia sprężyny wtryskiwacza*
α_{ww} Fuel injection advance angle/*kąt wyprzedzenia wtrysku paliwa*
α_w Fuel injection angle/*kąt wtrysku paliwa*
p_{owtr} Injector opening pressure/*ciśnienie otwarcia wtryskiwacza*
p_{wtr} Fuel injection (forcing) pressure/*ciśnienie wtrysku (tłoczenia) paliwa*
$dp_p/d\alpha$ Intensity of pressure accumulation in the cylinder /*intensywność przyrostu ciśnienia w przewodzie*
b Fuel consumption/*jednostkowe zużycie paliwa*
p_{ba} Charge air pressure/*ciśnienie powietrza doładowującego*
n_t Rotational speed of the turbocharger/*prędkość obrotowa turbosprężarki*
t_{g1} Outlet exhaust temperature/*temperatura spalin wylotowych*
p_c Compression pressure during the fuel injection/*ciśnienie sprężania w momencie wtrysku paliwa*
C_{NOx} Nitrogen oxide concentration in the exhaust/*stężenie tlenków azotu w spalinach*
C_{CO} Carbon monoxide concentration in the exhaust/*stężenie tlenku węgla w spalinach*
C_{HC} Hydrocarbon concentration in the exhaust/*stężenie węglowodorów w spalinach*
D Opacity of the exhaust gas/*zadymienie spalin wylotowych*

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