POLISH MARITIME RESEARCH 4(84) 2014 Vol. 21; pp. 57-65
10.2478/pomr-2014-0042

Problems of modelling toxic compounds emitted by a marine internal combustion engine in unsteady states

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ABSTRACT

Contemporary engine tests are performed based on the theory of experiment. The available versions of programmes used for analysing experimental data make frequent use of the multiple regression model, which enables examining effects and interactions between input model parameters and a single output variable. The use of multi-equation models provides more freedom in analysing the measured results, as those models enable simultaneous analysis of effects and interactions between many output variables. They can also be used as a tool in preparing experimental material for other advanced diagnostic tools, such as the models making use of neural networks which, when properly prepared, enable also analysing measurement results recorded during dynamic processes.
The article presents advantages of the use of the abovementioned analytical tools and a sample application of the neural model developed based on the results of examination carried out on the engine research rig.

Keywords: technical diagnostics, Diesel engine, dynamic processes, neural network

Introduction

Unsteady states are specific states of internal combustion engine operation. They appear as a result of the loss of thermodynamic equilibrium in engine cylinders, which is generally preserved during constant-load operation. These states disturb the combustion process by introducing instantaneous changes of, first of all, the rate of fresh charge delivered to the cylinder, but also of the amount of the delivered fuel. As a consequence, the fuel/air ratio is subject to temporary changes, which lead to changes of the excess air number and to the increased emission of combustion products generated at local oxygen deficiency. A further consequence of the appearance of larger amounts of carbon monoxide CO and non-combusted hydrocarbons HC is the decrease of the combustion temperature, which decides about the scale of the emission of nitrogen oxides NO_x.

A factor which decides about the amount of toxic compounds emitted in unsteady states is, most of all, the intensity of excitations which provoke these states. However, there is an additional factor which is to be taken into account, namely, the technical condition of the engine. When the engine executes the technical process, parameters of its structure change, which affects its performance defined by the set of output parameters. Mutual relation between the parameters of the structure and the output parameters of the engine allows, in certain conditions, the output parameters to be considered as symptoms of technical condition of the engine. These symptoms can be obtained without engine disassembling, as the physicochemical processes taking place during the working process and the relevant parameters can be, in general, observed and measured from outside. The volumes of the emitted exhaust gas components belong to the group of these parameters.

This simple association remains within the area of authors' interest and is oriented on analysing the applicability of exhaust gas emission indices and characteristics for evaluating parameters of engine's structure. However, a comment is needed here that in classical approach any output parameter can only be considered a diagnostic parameter when it simultaneously reveals certain properties, which are: unambiguousness, sufficient width of the field of changes, and availability. Therefore a question can be raised whether the emission indices and characteristics can be considered diagnostic parameters.

Authors have made an attempt to give a positive proof of this statement by analysing sample unsteady states of engine operation. Although short-lasting, these processes are so dynamical that the initial concentrations of toxic compounds (ZT) exceed by many times the levels characteristic for steady states. In this context we can expect that the engine with the structure parameters changed due to wear will be more sensitive to the action of unsteady states, thus providing opportunities for easier evaluation of technical condition of the engine. [7, 12].

EXAMINATION OF DYNAMIC PROCESSES OF ENGINE FUEL SUPPLY SYSTEM

A correct course of combustion in the engine cylinder depends most of all on correct operation of the supply system, the main task of which is to ensure repeatability of fuel injection. Because of this repeatability, of high importance is not only the beginning and end of the injection, but also its entire course. In classical supply systems, the correctness of these two criteria (beginning and end of injection) is to a large extent ensured by the high-pressure fuel pump with certain controlled parameters, such as the fuel dose and the injection advance angle. This latter parameter can be considered a basic parameter which decides about the correctness of the combustion course in Diesel engines, as even its small shift results in remarkable changes of the main parameters of engine operation, including exhaust gas emission indices.

The reported examination has been performed on the research rig for one-cylinder test engine [15]. The experimental material was collected according to the developed complete trivalent plan [8]. High repeatability of the dynamic processes for particular measuring systems (measuring points) of the above plan of experiment was obtained by the use of a programmable controller, installed in the control system for the eddy current brake being a part of the research rig equipment. The time of the dynamic process was the time elapse between the beginning of the reverse of the injection system elements and the renewed stabilisation of the output parameters. The above time, lasting about 106 seconds, was selected based on past experience gained by the authors.

In order to identify the effect of technical condition of the fuel supply system on engine power parameters during dynamic processes, sets of input quantities (set parameters) and sets of output quantities (observed parameters) were defined. For the purpose of the present work, the set of input quantities X was limited to three elements, which were: x_1 - engine rotational speed n [rpm]; x_2 – engine torque M_o [N×m],and x_3 – fuel injection advance angle $\boldsymbol{\alpha}_{ww}$ [°OWK]. The examination was performed in accordance with the adopted complete plan for three rotational speed values, which were: 850, 950 and 1100 [rpm]. For each rotational speed, the torque T_{tq} was increased, thus generating the unsteady state successively for the loads of 10, 20, 30, 50 and 70 [Nm]. For the rotational speed of 850 rpm, to avoid excessive engine load it was decided to resign from the loads of 50 and 70 Nm. The same decision was made for the rotational speed of 950 rpm and the load of 70 Nm. The fuel injection advance angle was changed by **±5°*OWK,*** thus obtaining three values, i.e. the nominal angle – N, the advanced angle – W, and the delayed angle – P. This way 36 repeatable unsteady states were obtained. Graphical interpretation of the examination programme is shown in Fig. 1.

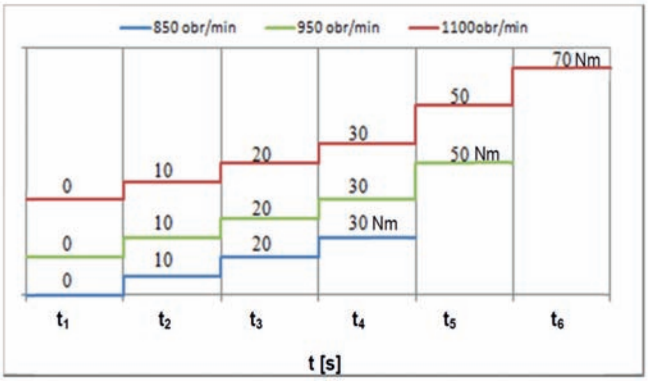

Fig.1. Scheme of implementation of the examination programme

A similar procedure was applied to the set of output quantities Y in which the number of elements was limited to basic toxic compounds in the exhaust gas manifold. These elements included: y_1 – concentration of carbon monoxide in the exhaust gas manifold $C_{CO(k)}$ [ppm]; y_2– concentration of hydrocarbons in the exhaust gas manifold $C_{HC(k)}$ [ppm]; y_3– concentration of nitrogen oxides in the exhaust gas manifold $C_{NOx(k)}$ [ppm], y_4– exhaust gas temperature t_{sp} [°C], y_5– $C_{O2(k)}$ [%].

The collected empirical material has made the basis for creating multi-equation models which enabled to analyse dynamic processes, adopting an assumption resulting from earlier experience that the process of changes of exhaust gas toxicity is time-dependent, i.e. has its dynamics [13, 14, 15, 16, 17, 18, 19]. As a consequence, the multi-equation model was developed using a system of linear difference equations. Since the measurement of concentration of toxic compounds is discrete by nature, a time-discrete signal (time series) has the form of a function in which the domain is the set of integers. Consequently, the time-discrete signal is a sequence of numbers in the functional notation of the $x[k]$ type. This notation reflected the tendency to minimise errors resulting from, among other sources, inevitable function approximation in cases when a continuous function was used.

The time-discrete signal $x[k]$ is frequently determined by sampling the time-continuous signal $x(t)$. If the sampling is uniform, than $x[k] = x(kT)$, where T is the sampling period. The time-history of the dynamic process depends not only on the value of excitation at a given time instant, but also on the past values of those excitations. Therefore the dynamic process (system) has memory in which the effects of past actions are collected [6, 8].

The relations between the input signals:

$$x_1[k], x_2[k], \cdots, x_n[k],$$

and the output signals:

$$y_1[k], y_2[k], \cdots, y_m[k]\ ,\ \ k = 0,1,2,\ldots,$$

have been described using a set of linear difference equations, the matrix form of which is:

$$\mathbf{y}[k+1] = \mathbf{A}\mathbf{y}[\mathbf{k}] + \mathbf{B}\,\mathbf{x}[\mathbf{k}] + \xi$$

where:

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} \cdots & a_{1m} \\ a_{21} & a_{22} \cdots & a_{2m} \\ \cdots & \cdots \quad \cdots & \cdots \\ a_{m1} & a_{m2} \cdots & a_{mm} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} b_{11} & b_{12} \cdots & b_{1n} \\ b_{21} & b_{22} \cdots & b_{2n} \\ \cdots & \cdots \quad \cdots & \cdots \\ b_{m1} & b_{m2} \cdots & b_{mn} \end{bmatrix}$$

$$\boldsymbol{y}[k] = \begin{bmatrix} y_1[k] \\ y_2[k] \\ \cdots \\ y_m[k] \end{bmatrix}, \ \boldsymbol{x}[k] = \begin{bmatrix} x_1[k] \\ x_2[k] \\ \cdots \\ x_n[k] \end{bmatrix}, \ \boldsymbol{\xi} = \begin{bmatrix} \xi_1 \\ \xi_2 \\ \cdots \\ \xi_m \end{bmatrix}$$

i.e.:

y[k]- matrix of output signal values at time *k, i = 1, 2, ..., m*

x[k]- matrix of input signal values at time k, *j = 1, 2, ..., n*

A – matrix of coefficients at output signal, ,

B - matrix of coefficients at input signal in *i*-th equation at -th element, *i = 1, 2, ..., m, j = 1, 2, ..., n,*

ξ - matrix of non-observable random component in *i*-th equation.

Statistical identification was performed using the code GRETL [5]. Coefficients in the equations for particular input variables were estimated using the least squares method. The estimation was oriented on verifying the relevance of particular parameters and rejecting negligible values, all this finally leading to remarkable simplification of the models.

The presented analysis of the results of examination accentuates essential advantage of multi-equation models, which is their capability of performing multi-criteria analysis of the input variables in case when these variables are intercorrelated with each other. Analysing these relations in one model reflects more precisely the reality (as there are obvious interactions between, for instance: concentrations of CO and HC on the one hand, and concentration of O_2 or the excess air number λ on the other hand), thus enabling wider interpretation of the problem. In the examined case substantial interactions were observed between the concentrations of CO and HC, while negative correlation was recorded between the concentrations of these compounds and the concentration of NO_x. These results seem to be logical taking into account processes of formation of these compounds in the cylinder.

Despite obvious advantages, the multi-equation models do not provide direct quantitative information on the analysed changes, here: changes in concentrations of particular toxic compounds resulting from the change of the fuel injection advance angle. Only a collection of time-histories recorded in the experiments, or obtained from the analysis of the developed models, provides opportunities for creating a possible pattern of the phenomenon. The concentrations of particular toxic compounds emitted during an unsteady state depend to a large extent on the intensity of the excitation which has provoked the appearance of this state. Nevertheless, these concentrations reveal certain regularities and repeatabilities, which can be observed in the time-histories of the states. Generally, two phases can be named in the time-history of a typical unsteady state. The first phase is characteristic for extremely high dynamics of changes and is accompanied with rapid increase of concentrations of ZT's, which, as a rule, exceed by many times the steady-state levels. The second phase of the unsteady state has much less dramatic course, is monotonic in nature and asymptotically nears the steady-state concentration levels.

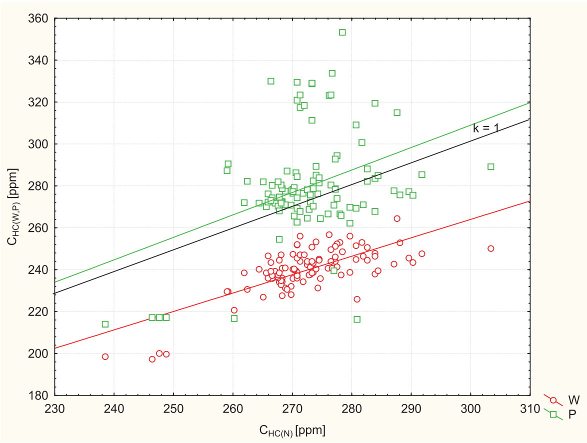

Fig. 2. Concentration of hydrocarbons HC for unsteady state at n = 1100 rpm and load change from M_o = 30 Nm to M_o = 50 Nm: P – delayed injection advance angle, W - advanced injection advance angle, CHC (N, W, P) – HC concentration for (N) nominal, (W) advanced, and (P) delayed injection advance angle

A method which can be used for relatively precise and objective description of the nature of individual concentrations of toxic compounds is the analysis of correlations of particular unsteady states, aimed at determining the correlation between the currently analysed state and the state assumed as the reference pattern for the examined phenomenon. The analysis of correlation functions enables to assess the level of correlation and its nature. Analysing components of the function also enables to conclude about the nature of the unsteady state, i.e. the contribution and intensity of its particular phases. Figure 2 shows the dispersion diagram being graphical illustration of the analysis of correlation.

Strong correlation with simultaneous unambiguous nature of concentration changes of the analysed toxic compounds during unsteady states can be considered symptoms of the technical condition of the engine. Moreover, the known values of the output signal (concentrations of ZT's, among others) and their estimates can make a basis for determining the values of residuals, which can indicate the type of damage.

CONCEPT OF NEURAL DIAGNOSTIC SYSTEM

Bearing in mind difficulties in analytical modelling of complex systems, an interesting alternative can be a neural diagnostic model which, based solely on experimental results, can be applied to modelling arbitrary nonlinearities. The neural models reveal high resistance to disturbances [9, 10, 11].

Basic data on the structures and possible applications of the artificial neural networks can be found in numerous manuals and publications, for instance in [3, 4, 10].

For the purpose of the simulation tests the results of which are presented further in the article, a general scheme of the neural system of damage detection was developed, adopting the following assumptions:

- parameters of substantial importance which are the objects of diagnostic monitoring are:
- exhaust gas temperature - T_{ex},
- contents of O_2, CO, HC, and NO_x in the exhaust gas
- for each of these parameters, a neural model will be developed, and all models created in this way will compose a so-called bank of neural observers [3] which model the values of the monitored parameters in the normal state of engine operation (without damages),
- comparing the signals at the outputs of the model and the diagnosed engine will make the basis for determining residuals – signals which reflect the discrepancy between the model and the engine,
- the obtained vector of residuals will be analysed using a neural classifier of residuals, the task of which is to decide whether the damage has taken place and, if so, to indicate the type of damage.

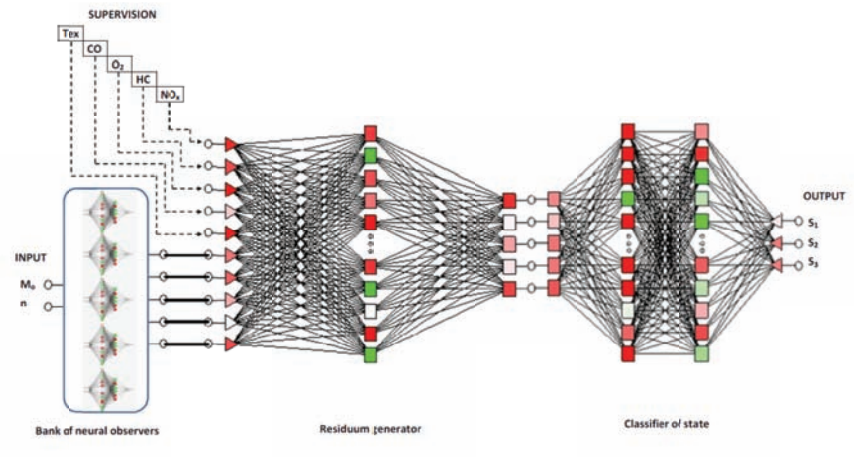

Fig. 3. Scheme of neural damage detection system. M_o – engine torque, n – engine rotational speed, T_{ex} – exhaust gas temperature, CO – content of carbon monoxide in the exhaust gas, O_2 – content of oxide in the exhaust gas, HC – content of aromatic hydrocarbons in the exhaust gas, NO_x – content of nitrogen oxides in the exhaust gas

THE COURSE AND RESULTS OF SIMULTION TESTS

The results obtained in the experimental examination were elaborated as the time-histories of the analysed quantities (Fig. 4) for each rotational speed.

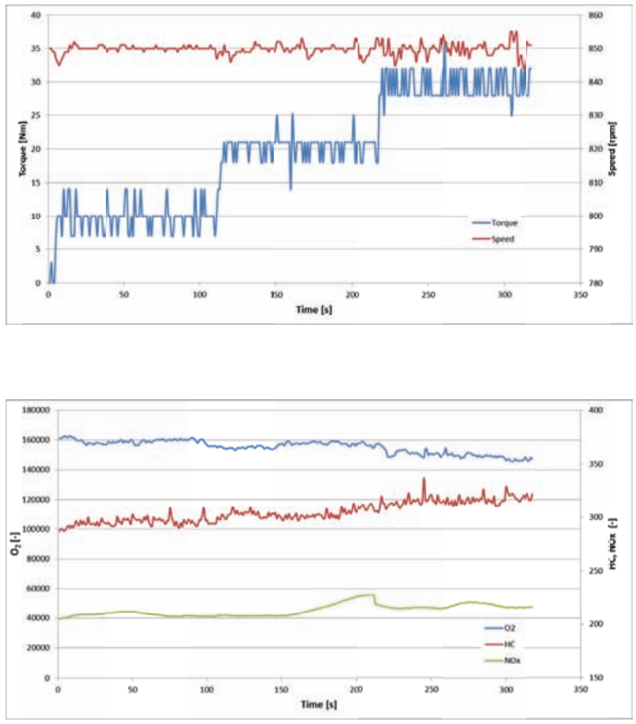

Fig. 4. Time-histories of changes of diagnostic parameters for engine rotational speed n = 850 rpm (for example the contents of O_2, HC, NO_x)

To facilitate practical use of the neural damage detection system shown in Fig. 3, the quantities assumed as independent variables (input parameters) were: the engine torque M_o and the engine rotational speed - n.

Then, referring to the results of experimental examination, three classes of technical condition of the engine were assumed:

1. Class of states S_1 – normal state of operation – the values of the fuel injection advance angle defined by the engine producer.
2. Class of states S_2 – damage manifesting itself by the increased value of the fuel injection advance angle (with respect to the nominal value) – injection too early.
3. Class of states S_3 – damage manifesting itself by the decreased value of the fuel injection advance angle (with respect to the nominal value) – injection too late.

Banks of neural observers

Since, according to the adopted concept, five output parameters were selected as the objects of on-line control, the same number of neural models were to be developed to model the relations between the input variables: Mo and n, and the output variables being the object of diagnostic supervision in the engine operation condition referred to as normal – state s_1.

The first stage of examination has the form of preliminary tests oriented on selecting the type and optimal structure of the neural networks for particular models. For this purpose, automatic tools included to the package STATISTICA Neural Networks v. 7.0 which support construction and testing of neural networks used in data analyses and predictive issues, were applied [20].

The goal of network training was to achieve the state which returns correct responses within a wide range of excitations, having in this case the form of different (ranging within 0 – 70 Nm) engine loads for corresponding steady-state rotational speeds (850, 950 and 1100 rpm). The teaching set, prepared based on experimental results, included 1272 cases referring to each of 5 parameters. Sample realisations of changes of the analysed variables (CO and T_{ex}) as functions of engine torque and rotational speed are shown in Fig. 5.

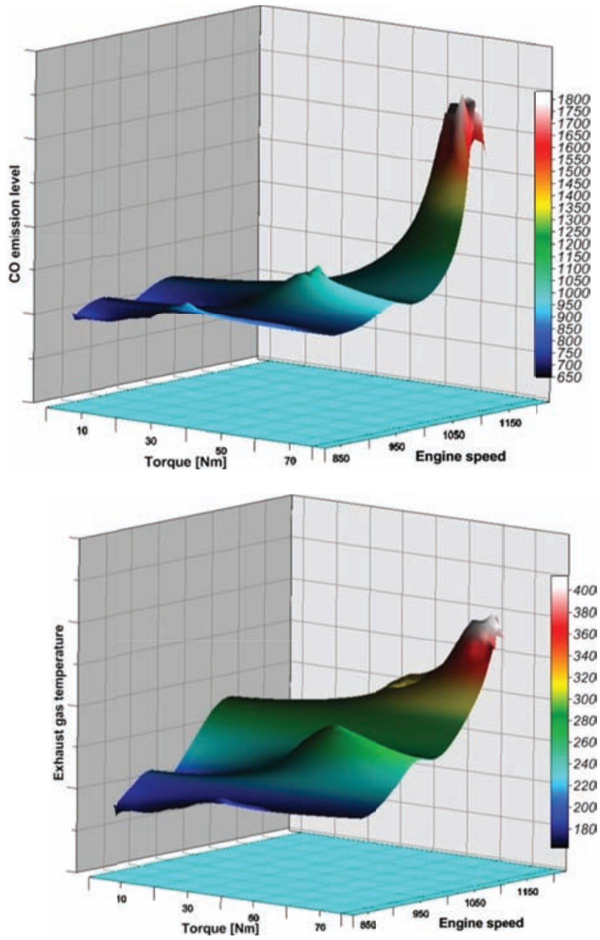

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Fig. 5. Changes of CO emission and exhaust gas temperature vs. engine speed and torque

The performed simulations and the analysis of the obtained results have led to selecting the neural network of multilayer perceptron type with one hidden layer.

The preliminary examination stage has made it possible to perform basic training of the networks for each neural observer which modelled changes of the assumed input variables, i.e. T_{ex}, O_2, CO, HC, NO_x. Training was performed and final architecture of the network was created using the package MATLAB 2014b and its dedicated extension "Neural Network Toolbox" [21]

Analysing basic measures of quality of the developed neural models, i.e. the values and distributions of the residuals, and the percentage errors between the values expected at the network output and its real responses, has revealed good quality of modelling and practically negligible differences. Sample values of these differences for models of T_{ex} and NO_x are shown in Figs. 6 and 7.

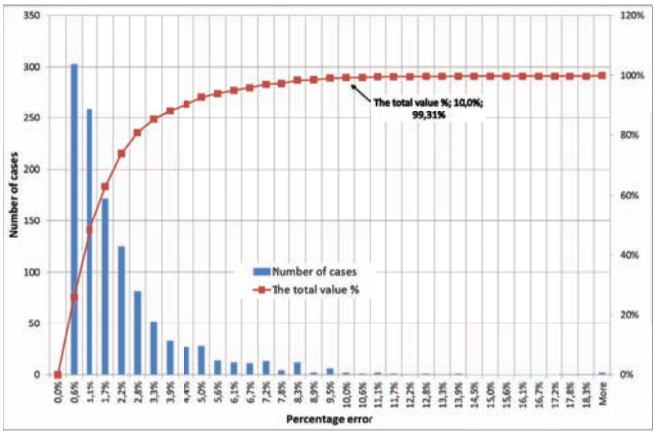

Fig. 6. Distribution of percentage errors of neural network response – model T_{ex}.

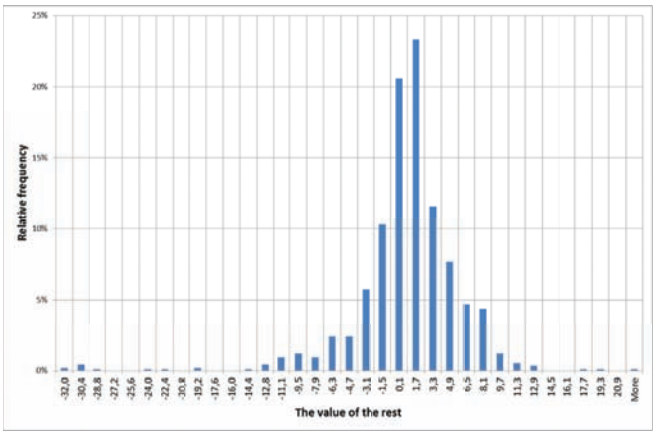

Fig. 7. Distribution of residuals (NO_x - NO_{xs}) for the neural model NO_x. NO_x = f(M_o, n) – experimentally measured content of NO_x in the exhaust gas, NO_{xs} – neural network response obtained for the set values of (M_o, n)

Generation of residuals

The task of the residual generator is to calculate the differences between the monitored output signals of the diagnosed engine, V_k, and the corresponding responses of the developed models of the bank of neural observers, V_{ks}. Figure 8 shows relevant values for the case of NO_x. In the analysed case:

- exhaust gas temperature $T_{ex} = V_1$
- content of oxygen in the exhaust gas $O_2 = V_2$,
- content of hydrocarbons in the exhaust gas $HC = V_3$,
- content of carbon monoxide in the exhaust gas $CO = V_4$,
- content of nitrogen oxides in the exhaust gas $NO_x = V_5$
- neural model response $T_{ex} - T_{exs} = V_{1S}$,
- neural model response $O_2 - O_{2s} = V_{2S}$
- neural model response $HC - HC_s = V_{3S}$
- neural model response $CO - CO_s = V_{4S}$
- neural model response $NO_x - NO_{xs} = V_{5S}$

The vector of residuals $r = [r_1, r_2, r_3, r_4, r_5]$ obtained in the above way can be considered a signal which contains the information about damages [3]. In this case:

$$r_k = V_k - V_{kS},$$

where:
$k = 1, 2, \dots, 5$,
V_k – diagnostic parameter value $V_k = f(M_o, n)$,
V_{kS} – parameter value generated by the neural model $V_{kS} = f(M_o, n)$.

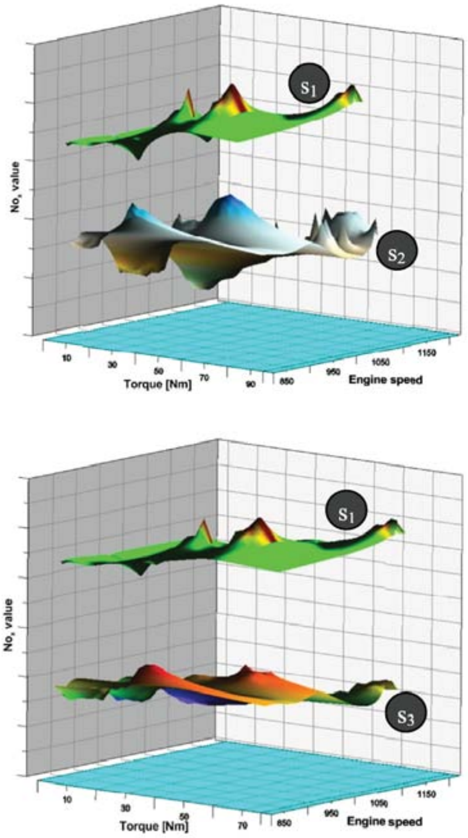

Fig. 8. Content of NO_x as the function $NO_x = f(M_o, n)$ for state classes s_1, s_2, s_3.

In the analysed case three classes of technical condition of the diagnosed engine were defined. During the engine operation referred to as normal, the components of the obtained vector of residuals should be close to zero, while the appearance of damage increases remarkably these differences.

The experimentally obtained reference patterns of the components r_k for states s_1, s_2 and s_3 as functions of engine load and rotational speed are shown in Figs. 6, 7 and 8 for residuum r_2.

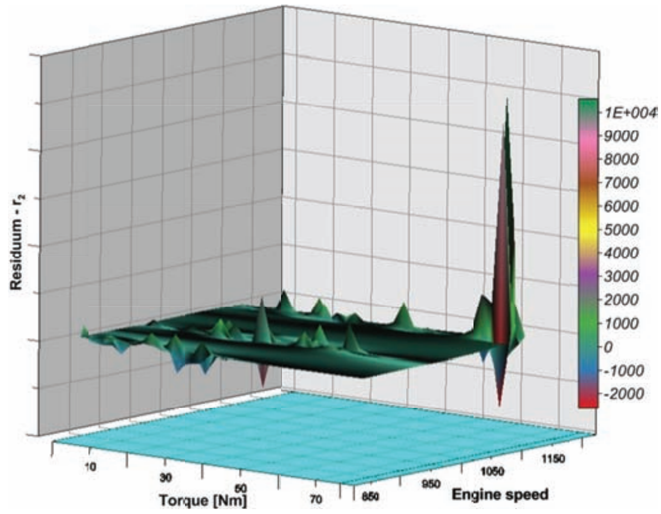

Fig. 9. Residual vector component r_2 as the function $r_2 = f(M_o, n)$ – state s_1

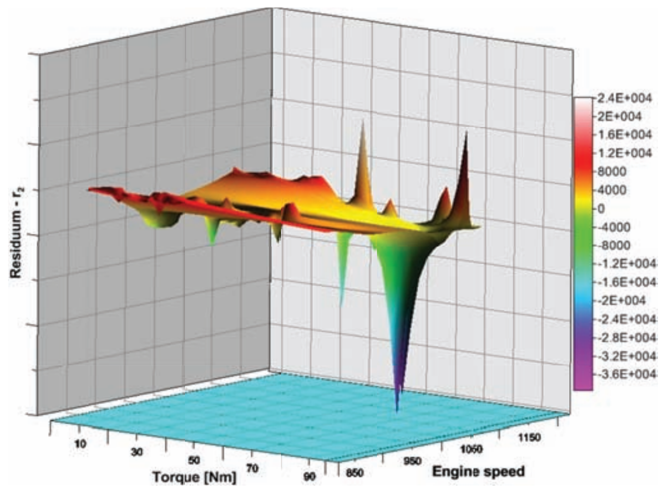

Fig. 10. Residual vector component r_2 as the function $r_2 = f(M_o, n)$ – state s_2

Preliminary tests oriented on selecting the type and optimal structure of the neural network for the residual generator enabled selecting a linear neural network which models the relations between ten inputs (V_1, V_2, V_3, V_4, V_5, V_{1S}, V_{2S}, V_{3S}, V_{4S}, V_{5S}) and five outputs (r_1, r_2, r_3, r_4, r_5).

Like for the bank of neural observers, the performed tests and the applied quality measures, having the form of values and distributions of modules of residuals between the expected network outlet values and the real network responses, have proved very good quality of modelling and practically negligible differences. Figure 12 shows the adjustment of the residual generator response to real values.

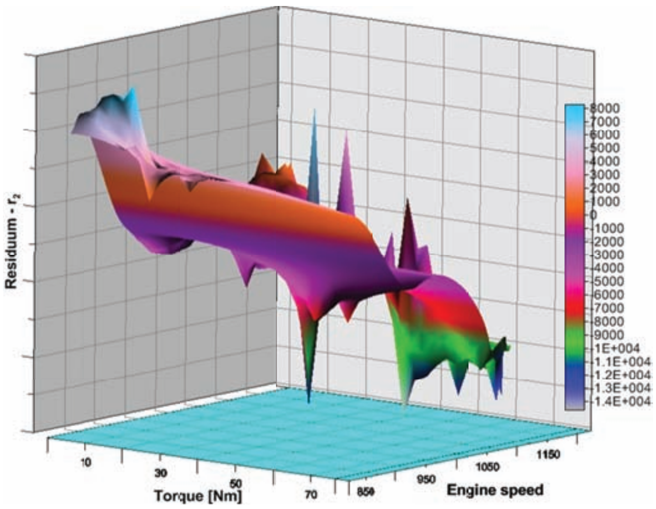

Fig. 11. Residual vector component r_2 as the function $r_2 = f(M_o, n)$ – state s_3

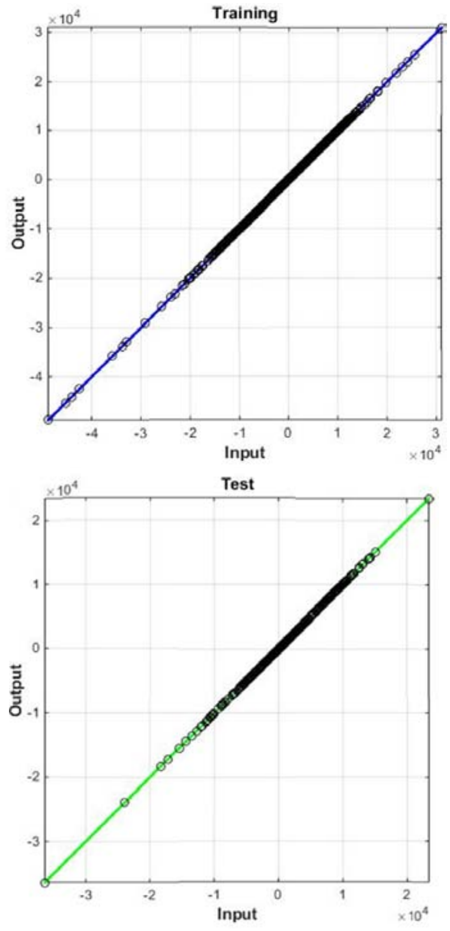

Fig. 12. Adjusting the residual generator response during network training and test stages

Neural classifiers of installation condition

The task of the installation condition classifier (the residual evaluation block), being a part of the damage detection and localisation system, is to analyse the residual vector and recognise whether and where the damage took place. Thus, it solves a typical classification problem consisting in adjusting the vector of symptoms to one of the separated classes of states.

Based on the first stage of examination, the neural network constructed and trained to solve the presented problem had the multilayer perceptron structure with one hidden layer.

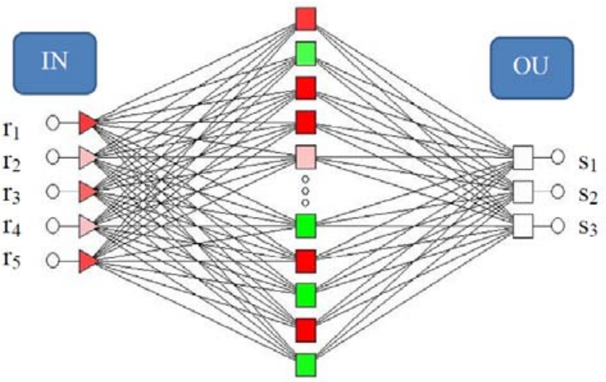

Fig. 13. Classifier – neural network of multilayer perceptron type. IN – input layer (5 neurons), OU – output layer (3 neurons); r – input excitations, s_i – network responses, i = 1, 2, 3.

Setting the vector $r = [r_1, r_2, r_3, r_4, r_5]$ at the input of the classifier network activates one of the three neurons in the output layer, thus indicating the presence of certain damage and passing of the installation to the state si.

Training, validation and tests of the classifier, performed with the aid of the training set, have revealed its very good adjustment, and the infinitesimal number of incorrectly classified cases, below 2% at the testing stage. Figure 14 shows the obtained results in the form of confusion matrix.

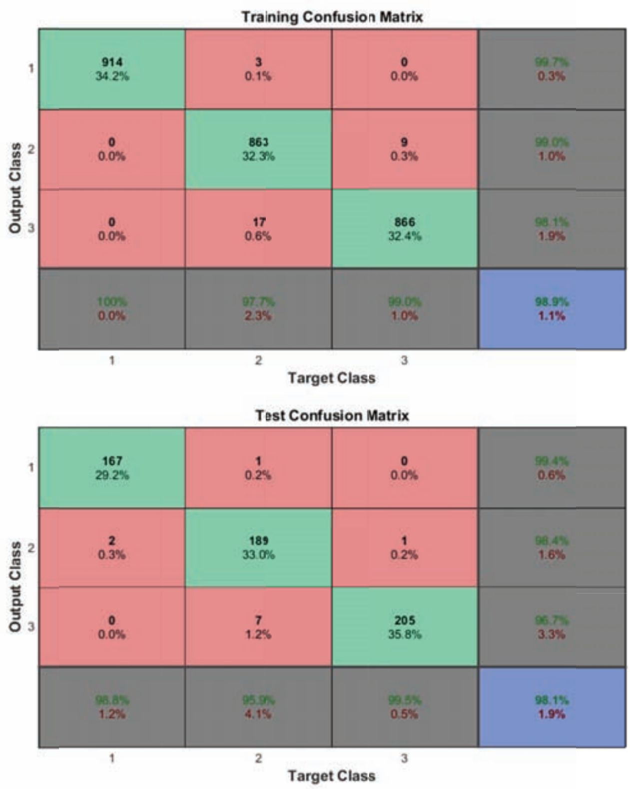

Fig. 14. Confusion matrix obtained during network training and test stages

RESULTS OF NEURAL MODEL TESTS

Working out the structure for particular networks and successful finalisation of their training enabled to test the system using a set of selected simulated cases of the exhaust gas temperature, T_{ex}, and the contents of O_2, CO, HC, NO_x in the exhaust gas.

The set of test cases, comprising 3816 sets of values (1272 cases for each state), was worked out based on the results obtained in empirical examination, which were randomly changed in each set using the pseudorandom number generator. The imposed changes referred to the values of all parameters within the range of ±5%.

The presented procedure aimed, first of all, at assessing the sensitivity of the system to disturbances, and the resultant scale of applicability in marine power plant reality.

The results of the performed tests are given in Table 1.

Table 1. Results of tests of the neural damage detection and localisation system.

Subset of the test set	Correct state classification (number of cases / %)	Incorrect state classification (number of cases / %)
State s_1	1271 / 99,9%	1 / 0,1%
State s_2	1187 / 93,3%	85 / 6,7%
State s_3	1212 / 95,3%	60 / 4,7%
Total	95,97%	4,03%

CONCLUSIONS

The results obtained based on the values recorded in the active experiment reveal that the proposed system of on-line damage detection and localisation relatively well identifies the certain class of engine condition states. From the practical point of view, its quality can even be evaluated as excellent.

However, it may be expected that the specific nature of operation of such extremely responsible power systems as the marine power plant and its functional subsystems, should require higher percentages of correct classifications than those presented in Table 1.

The solution to the above problem can consist, in the simplest case, in undertaking two types of actions:

1. Increasing the number of parameters being the objects of continuous diagnostic monitoring. In the analysed case the number of the selected diagnostic parameters was five (the exhaust gas temperature - T_{ex}, and the contents of O_2, CO, HC, NO_x in the exhaust gas) due to the tendency to simplify, as much as possible, the developed structures of the neural networks. However in authors' opinion, introducing only one additional reliable parameter (for instance the charge air pressure) would remarkably improve the results, as the six-element vector of residuals would unarguably contain more unmistakable information about the condition of the installation.
2. Introducing cases of deformed values of the parameters being the objects of diagnostic monitoring to the teaching sets. The course of neural network teaching will take much longer in this case, but the resistance of the trained networks to disturbances, which in real conditions can turn out very intensive, should be improved. However, confirmation of this statement requires further research oriented on determining whether this is a universal regularity and whether it results from the presence of certain rules and principles.

The presented results are undoubtedly good motivation for further research and possible application of neural networks in operating practice, most of all by developing their software or hardware realisations in the form, for instance, of dedicated electronic systems. An additional favourable factor here is possible use of VLSI systems with large integration scales, as these systems provide opportunities for practical construction of parallel data processing systems, i.e. the type of systems which includes neural networks [4]).

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