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ANN based evaluation of the NOx concentration in the exhaust gas of a marine two-stroke diesel engine

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ABSTRACT

The article presents results of a study on the possible application of artificial neural networks (ANNs) to the evaluation of NOx concentration in the exhaust gas of a marine two-stroke Diesel engine. A concept is presented how to use the ANN as an alternative to direct measurements carried out on a ship at sea. Methods of proper ANN selection, configuration and training are presented. Also included are the results of laboratory tests, performed to obtain data for ANN training and tests, and the results obtained from modelling certain processes with the aid of selected ANNs. As a result of the performed investigations, an ANN was constructed and trained to calculate NOx concentration in the Diesel engine exhaust gas based on the engine operation parameters measured with an average error of 1.83% , and the fuel consumption measured with an average error of 1.12%.

Keywords: artificial neural network; marine two-stroke engine; NOx concentration; Annex VI to Marpol Convention

INTRODUCTION

Chemical compounds of oxygen and nitrogen (NOx) emitted to the atmosphere with the exhaust gas from a ship engine are a source of pollution of the marine environment. In order to prevent negative effects on the environment, the International Marine Organisation adopted Annex VI to the MARPOL 73/78 Convention. This Annex forces the ship owners to reduce the emission of NOx down to the agreed limits defined in the NOx Technical Code [1]. According to these regulations, each ship engine with power exceeding 130 kW is to have a certificate which confirms the compliance of the level of NOx emitted by the engine with the limits in force. Obligatorily, this certificate is to be prolonged after a certain time period, which is done by comparing selected engine parameters which are decisive for NOx emission with the records collected in a technical file specially created for this purpose. Any changes in the engine structure or control system which go beyond the scope defined in the technical file require new measurements performed directly on the ship. Unfortunately, the ship power plant is not equipped, as a rule, with a proper exhaust gas analyser, which makes performing these measurements extremely difficult. Moreover, the measurements of NOx concentration are to be done at precisely defined engine operation points. For the main engine, this means withdrawal of the ship from operation for the time of measurement, a requirement which leads to remarkable increase of operating costs. The regulations of the NOx Technical Code make it possible to use a simplified method of measurement, compared to that used in land applications, which requires the measurements at 4 points of engine operation only. This approach, however, results in decreased accuracy of the measurements. That is why Code regulations permit the possibility to exceed the assumed emission limits by 10% in case of measurements performed on an engine supplied with diesel oil, and 15% for an engine supplied with heavy fuel oil.

The above situation is the reason why numerous research centres search for alternative methods for evaluating the level of NOx emitted by an internal combustion engine. Kyrtatos at al. [2] proposed a "*software sensor for exhaust emissions estimation"* built based on a multi-zone, thermochemical model of NOx production in the cylinder chamber of an engine. This model takes only into account the Zeldowicz mechanism of NOx production [3]. A continuation of this method is a zero-dimensional, thermochemical model proposed by the author of this article [4, 5]. It was worked out based on the Konnov model [6] and includes 724 chemical reactions between 83 compounds taking part in the fuel combustion process in the engine cylinder. The results of the investigations confirm the applicability of the model for evaluating the NOx emission level, but only with respect to a given engine. Extending the model application range requires the implementation of more complicated calculation algorithms, which goes beyond calculating abilities of the computers available on ships. The cost of modelling can be reduced by the use of an Artificial Neural Network (ANN) as a general-purpose approximator of complicated calculation algorithms. The ANN training method proposed by Werbos [7] and bearing the name of the error back propagation method makes it possible to use the ANN in various branches of knowledge. Wang et al. [8], Oladsine et al. [9], and Hafner et al. [10] used ANNs for adjusting piston engines, while Stephan et al. [11] - for controlling the combustion process in the power plant boiler. Yang et al. [12] and Ramadhas et al. [13] used ANNs for predicting the cetane number for the mixtures of fuels, while Lee et al. [14] used ANNs for modelling the range of fuel injection to the engine cylinder chamber. ANNs were also used in the combustion process models to reduce the cost of the algorithm calculation [15] – [21], and for determining specific fuel consumption [22, 23], combustion process temperature [24], air/fuel equivalence ratio [25], the emission of carbon oxide and hydrocarbons [26] – [28], and even failures of piston engines [29].

The article presents the application of the ANN to modelling the combustion process in a two-stroke piston engine in order to assess the level of NOx emission in the exhaust gas. Selection of the model input data is described, along with the ANN structure and the method used for its training. The description of laboratory tests and results of calculations performed using selected ANN configurations are included.

NOX PRODUCTION IN THE ENGINE CYLINDER CHAMBER

Compounds belonging to the NOx group are produced in the engine cylinder chamber as a result of oxidation of the nitrogen, taken from the air and combusted fuel, in high-temperature and high-pressure conditions. The nitrogen oxidation reactions are reversible, but the rate of the NOx decomposition reaction is relatively slow and decreases with the decreased temperature of the combustion process. This factor is a source of „freezing" of the NOx's, which, undecomposed, are released to the atmosphere as a result of engine cylinder scavenging. Many years' investigations over the NOx production Combusted mixtures with diverse parameters revealing various chemical mechanisms the chemical mechanisms which explains the process of production of those compounds during combustion. Based on the thermal mechanism, named the Zeldowicz mechanism [30], we can conclude that the main parameter affecting the amount of NOx compounds produced during the combustion process is the temperature. The Zeldowicz mechanism, consisting of only 3 reversible chemical reactions, has a clearly dominating effect on the amount of NOx produced in the conditions observed during the combustion in the cylinder chamber of a supercharged piston engine. Among other facts, this is confirmed by the results of investigations presented in [30] and [31]. Prolonging the process of combustion of the combusted mixture in high-temperature conditions increases the amount of produced NOx, until the equilibrium concentration is reached [32]. According to the conclusions formulated in [33], the next parameter in the combustion process which affects the amount of the produced NOx is the pressure, the increase of which results in the decrease of molar NOx concentration in the burned mixture. The investigations performed by Lyle at al. [34], show the effect of the air content in the burned mixture on the amount of the produced NOx's. For rich mixtures, the dominating mechanism of NOx production in the engine cylinder chamber regions in which relatively small air content is observed is the Fenimore prompt mechanism. But increasing the air content above the stoichiometric mixture level leads to the increase of the NOx content in the burned mixture, caused by the domination of the thermal mechanism. Further increase of the air content results in cooling the burned mixture and the resultant decrease of the NOx content. Kuo [35] presented the dependence of the NOx concentration in the burned mixture on fuel composition and combustion rate. The obtained results confirm the effect of the fuel composition on the combustion rate and NOx concentration in the mixture, but this effect is not unambiguous.

Based on the above presented discussion we can conclude that the amount of NOx produced in the burned mixture is mostly affected by:

- temperature of the combustion process
- pressure of the combustion process
- time duration of the combustion process
- composition of the burned mixture.

During the combustion process, these parameters change periodically in the piston engine and cannot be measured directly on-board. That is why, leaving aside direct measurements, the evaluation of the level of NOx emission in sea conditions should be executed by measuring other engine operation parameters which affect the above listed combustion process parameters. Author's investigations in this area [36] confirm that the measurements of engine operation parameters, performed at sea using a standard measuring instrumentation, are sufficient for evaluating the level of NOx emission from the engine when a relevant thermochemical calculation algorithm is applied. Unfortunately, the application of such an algorithm requires large computing powers, usually unavailable on-board [6], [37] – [39]. Consequently, the application of a calculation algorithm to replace direct measurements of NOx concentration in the engine exhaust gas seems to be questionable. On the other hand, the use of a properly trained ANN as a approximating the thermochemical algorithm can provide opportunities for evaluating the NOx concentration with a predetermined accuracy in the exhaust gas emitted by the engine in operation.

MODEL INPUT DATA

According to the ANN theory [40], the ANN input data should reveal mutual independence. That means that any change of the value of one input data must not affect another data delivered to the ANN model input. That is why the ANN input data which model the amount of the NOx emitted by the engine are to be selected in such a way that they describe the above-named engine combustion process parameters, which affect NOx concentration in the engine exhaust gas, in a most comprehensive way. The selected parameters should also be able to be measured on the ship at sea, and should be mutually independent. The complexity of the physicochemical processes taking place during engine operation can make meeting these conditions, especially the last one, impossible. When analysing the above selected parameters which affect the amount of NOx produced in the burned mixture we can conclude that the composition of the burned mixture in the engine cylinder depends directly on initial mixture concentration, defined by the parameters of the air and fuel delivered to the cylinder. Of high importance is also the concentration of the components in the burned mixture, which depends on the injection characteristics, available in modern designs of two-stroke engines with electronic valve timing [41] in a form of injection pressure measurement results. The time of mixture combustion in the cylinder depends on the rotational speed of the engine, for the assumed constant setting parameters of the valve timing or camshaft timing. The pressure of the combustion process can be indirectly determined by engine indication. Only selected indicator diagram parameters characterising the quality of the combustion process were used for modelling purposes. The temperature of the combustion process, different in different regions of the cylinder chamber and changing with angular crankshaft position, cannot be directly measured during engine operation at sea. Therefore it is to be described by the parameters of fuel injection and cooling system, and the temperature of the engine exhaust gas.

Following the abovementioned discussion, 15 model input data were selected:

★ temperature of the scavenging air
★ humidity of the scavenging air
★ fuel consumption
★ air/fuel equivalence ratio
★ rotational speed of the engine
★ mean indication pressure
★ maximum indication pressure
★ angular crankshaft position at the maximum indication pressure
★ maximum injection pressure
★ angular crankshaft position at the maximum injection pressure
★ fuel temperature before the injection pump
★ exhaust gas temperature
★ water temperature at cooling system inlet
★ water temperature at cooling system outlet
★ water pressure in the cooling system.

It is noteworthy that for the ship at sea the fuel consumption is frequently determined in a very inaccurate way, by checking levels in fuel tanks every 24 hours. Although sufficient for fuel management purposes, such a measurement may turn out too inaccurate to be used in the proposed model. That is why a fuel consumption analysis oriented of engine combustion process parameters was done. This analysis made it possible to select parameters which can be used as ANN input data to determine the fuel consumption. In this case 16 model input data were selected, which were:

☆ temperature of the scavenging air
☆ pressure of the scavenging air
☆ fuel temperature before the injection pump
☆ fuel pressure before the engine
☆ exhaust gas temperature
☆ exhaust gas pressure
☆ mean indication pressure
☆ maximum indication pressure
☆ pressure in the cylinder at the initial injection point (7° before the top dead centre position of the piston)
☆ angular crankshaft position at the maximum indication pressure
☆ maximum injection pressure
☆ angular crankshaft position at the maximum injection pressure
☆ range of angular crankshaft positions during fuel injection
☆ water temperature at cooling system inlet
☆ water temperature at cooling system outlet
☆ water pressure in the cooling system.

The input data for ANN training, and the output data for the verification of the results of modelling were collected during tests performed on the L-22 laboratory engine installed in the Marine Engine Laboratory, Gdynia Maritime University. This is a one-cylinder two-stroke crosshead Diesel engine with loop scavenging, supplied with Diesel oil (Lotos EuroDiesel EKO Z, the density of which is 829.6 kg/m^3 at the temperature of 15ºC) and supercharged by an independently driven Roots blower. A detailed description of the laboratory stand is given in [42] and the basic engine parameters are collected in Tab. 1.

***Tab. 1.** Basic engine parameters*

Nominal power [kW]	73.5
Maximum rotational speed [rev/min]	600
Cylinder bore [mm]	220
Piston stroke [mm]	350
Compression ratio [-]	18.5

The data were recorded during 3 investigation sessions, each of which included 10 observations of engine operation at two rotational speeds equal to 200 rpm and 360 rpm. The measurements in those sessions were done:

⇨ every 5 minutes from engine start, during its cold start with the load of 25% of the nominal torque
⇨ when the engine was loaded from 75% down to 25% of the nominal torque, according to the schedule presented in Tab. 2
⇨ during engine operation at the load equal to 25% of the nominal torque, for changing air/fuel equivalence ratio.

The engine loads (T), as percents of the nominal torque (Tn) and engine rotational speeds (n) are given in Tab. 2.

***Tab. 2.** Engine operation cycles during data recording*

No.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
T [% Tn]	75	70	65	60	55	50	45	40	35	30	25
n [rpm]	200										
No.	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**
T [% Tn]	75	70	65	60	55	50	45	40	35	30	25
n [rpm]	360										

During the laboratory tests, 228 data sets were collected for different engine operation points.

ANN CONSTRUCTION AND TRAINING

Evaluating the emission level from a marine piston engine can be classified as a regressive problem [40], which can be solved using the ANN of multilayer perceptron (MLP) or radial basis function network (RBF) type. The application of these two networks was tested by the author [43]. The obtained results made it possible to formulate conclusions which then were used for selecting the MLP ANN as most suitable for further investigations. The structure of the selected ANN, shown in Fig. 1. consists of the input layer, the hidden layer, and the output layer. The input and output layers are composed of

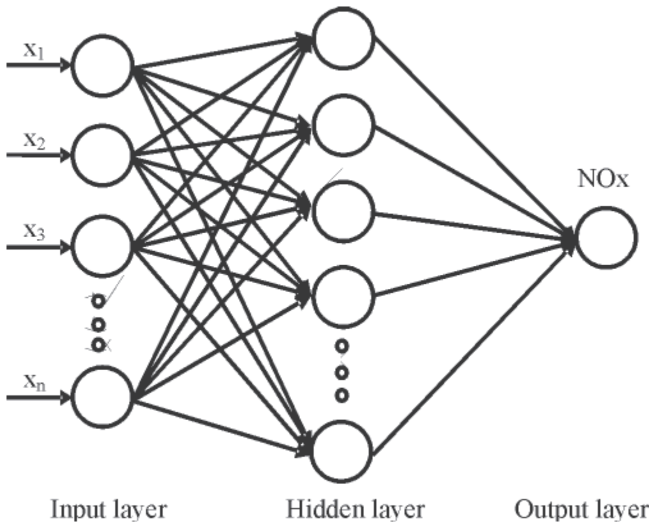

***Fig. 1.** Structure of MLP ANN*

neurons: one neuron for each input and output parameter. The hidden layer can have an arbitrary number of neurons. It is noteworthy that a number of hidden layers can be used, but the proof presented in [40] accepts one hidden layer as sufficient for good approximation of each continuous function.

Each neuron in the ANN converts the input signals by adding them up, taking into account the weight coefficients, according to the following formula:

$$y = f\left(\sum_{i=1}^{n} w_i x_i\right) \quad (1)$$

where:
f – nonlinear function, named the activation function
x – input signal value
w – input signal
n – input signal number
y – output signal value.

ANN training consists in adjusting input signal weights in a way which makes it possible to obtain the assumed output signal.

The presented investigations included construction, training and tests of three ANN variants:

a. for evaluating the level of NOx emitted by the test engine
b. for evaluating the fuel consumption in the test engine
c. for evaluating the level of NOx emitted by the test engine with the aid of the resultant fuel consumption obtained from ANN variant b as input data.

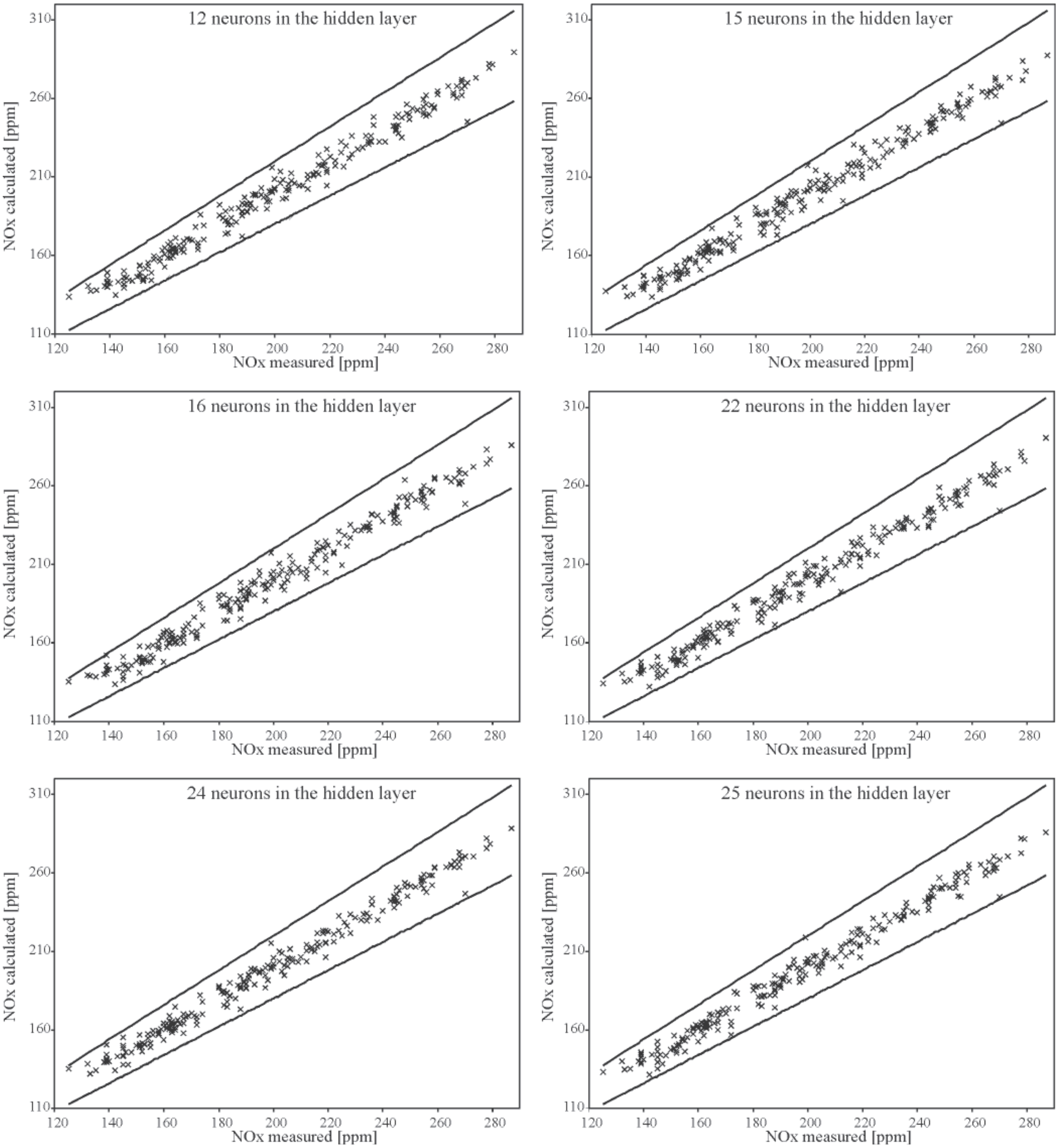

Fig. 2. Results of calculations for the ANNs meeting the adopted criteria

Each ANN consisted of 15 neurons in the input layer (16 neurons in variant b) corresponding to particular input data, one neuron in the output layer corresponding to the output signal, and from 10 to 25 neurons in the hidden layer. The data collected during the laboratory tests were standardised to the value between 0 and 1 and then randomly divided into two sets, in proportion 80% to 20%. The first set was used as training data and the second - as verifying data. The ANN was trained using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) method, one of fastest quasi-Newtonian methods of ANN training [44, 45]. The logistic function was used as the activation function in the hidden layer, and the linear function - in the output layer. Each ANN configuration corresponding to a different number of neurons in the hidden layer was trained 10 times, and each time the training and verifying sets were randomly selected. Such an approach made it possible to reduce the possibility of incorrect ANN training, as caused by possible presence of local extrema in the approximated functions. The calculations were performed using the code STATISTICA. In total, 480 ANNs were trained and tested in these variants.

RESULTS OF INVESTIGATIONS

For analysing purposes, one best trained ANN was selected from each tested ANN configuration using the following criteria:

- the error must not exceed 10% for a possibly large number of data sets,
- the mean square error calculated for all collected data sets is the smallest.

Fig. 2 shows the results of calculations for all analysed engine load variants, obtained using the ANNs meeting both of the above formulated criteria. These ANNs are best trained, and include, respectively, 12, 15, 16, 22, 24, and 25 neurons in the hidden layer.

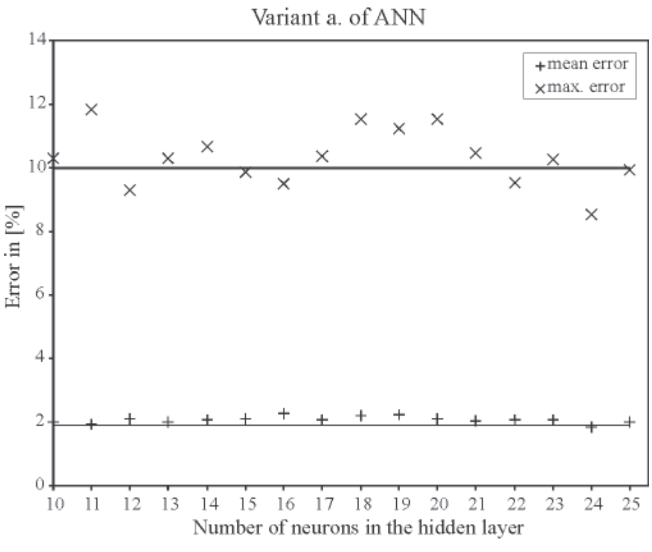

Fig. 3. Mean square errors and maximum errors of the results of ANN calculations: variant "a", different numbers of neurons in the hidden layer

Fig. 3 presents mean square errors and maximum errors of the results of calculations approximating NOx concentration in the engine exhaust gas. The calculations were done with the aid of the best trained ANNs, one from each tested configuration, using the measured fuel consumption as the input data (variant a). Horizontal lines in the figure represent the 10% error criterion. Marks are also added to facilitate the selection of the best ANN with respect to the mean error.

According to the presented criteria, it turned out that the best ANN is that with 24 neurons in the hidden layer, for which the mean square error within the entire analysed range of engine loads did not exceed 1.83% and the maximum error was 8.5%. It is noteworthy that changing the number of neurons in the MLP ANN hidden layer within the 10-25 range does not visibly increase the accuracy of modelling, as no clear trends connected with these changes were observed both for the mean square error and the maximum error.

An inaccurate fuel consumption measurement, performed on a ship, was a motivation for approximating this parameter using ANN. Fig. 4 presents mean square errors and maximum errors of these calculations done using the best trained ANN from among all ANN configurations used for approximating the fuel consumption based on 4 engine operation parameters discussed in Section 4.

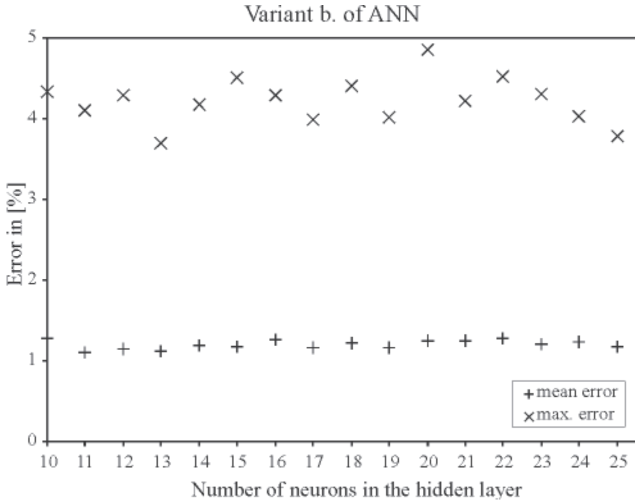

Fig. 4. Mean square errors and maximum errors of the results of ANN calculations: variant b, different numbers of neutrons in the hidden layer.

The results presented in Fig. 4 suggest selecting the ANN with 13 neurons in the hidden layer as most suitable for approximating the fuel consumption in the test engine. The mean square error of the results obtained using this ANN was 1.12% while the maximum error was 3.7%.

Fig. 5 presents mean square errors and maximum errors of the results of calculations done using the best trained ANNs to approximate the NOx concentration in the engine exhaust gas, one ANN from each tested configuration. Two horizontal lines

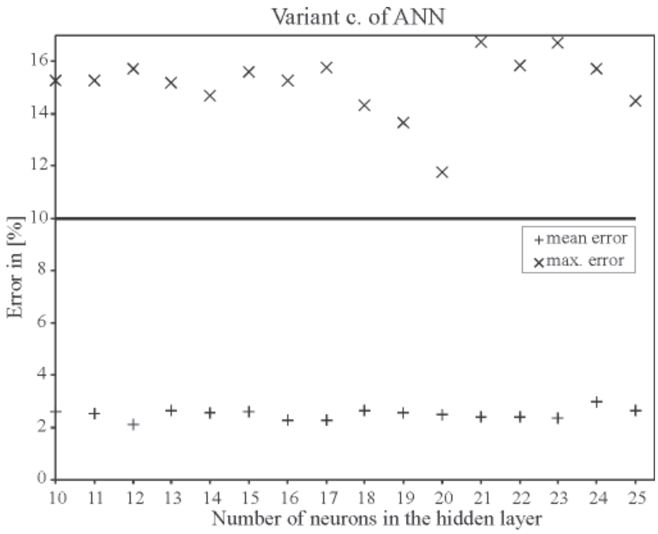

Fig. 5. Mean square errors and maximum errors of the results of ANN calculations: variant c, different numbers of neutrons in the hidden layer

limit the area of 10% error criterion. These ANNs were trained and tested using the data obtained from the measurements on the test engine, in which the measured fuel consumption was replaced by the results obtained using the best trained ANN from variant b (ANN with 13 neurons in the hidden layer).

The smallest mean square error was obtained for the ANN with 12 neurons in the hidden layer. This error was equal to 2.1% with respect to the measured values. Unfortunately, in each analysed ANN at least one calculated result error exceeded 10%, i.e. the level permitted by the regulations of the NOx Technical Code [1]. It is the ANN with 20 neurons in the hidden layer which is the closest to meet this requirement. For this ANN only one result error from among all analysed engine loads exceeded 10% and was equal to 11.74%. For this ANN, Fig. 6 shows the results of calculations for all analysed engine load variants. The continuous lines mark the assumed error limits. The presented results of calculations show that only one result error exceeds the assumed limit. This situation may be explained by the presence of a gross error, possibly generated during the measurements and then not eliminated, or, what is more likely, excessively small number of input data used for ANN training.

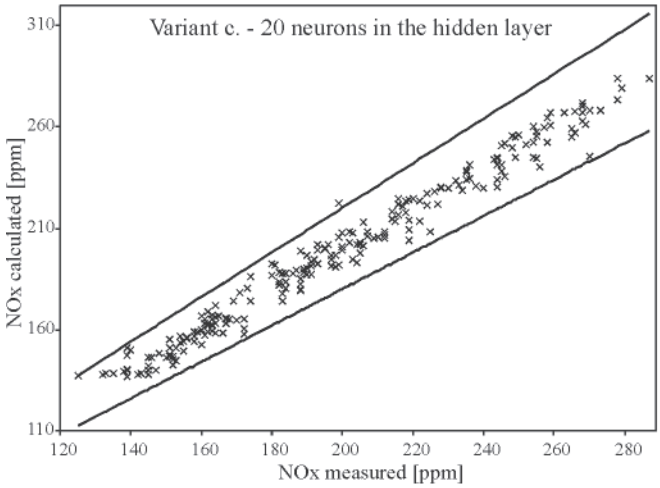

Fig. 6. *Results of calculations for the best trained ANN with 20 neurons in the hidden layer, variant c.*

CONCLUSIONS

The article presents a concept and structure description of the ANN approximating the NOx concentration in the exhaust gas of a marine Diesel engine. The presented results provide opportunities for formulating the following conclusions:

- ❍ The ANN constructed for the given input data is sufficient for approximating the NOx concentration in the exhaust gas of the marine Diesel engine working under the analysed load conditions.
- ❍ An ANN was constructed which makes it possible to calculate the NOx concentration in the exhaust gas of the marine Diesel engine with an error not exceeding 10% for all examined loads. Six ANN's of this type, with 12, 15, 16, 22, 24, and 25 neurons in the hidden layer, were constructed and properly trained. The results closest to the measured data were obtained for the ANN with 24 neurons in the hidden layer.
- ❍ An ANN was constructed which makes it possible to calculate engine fuel consumption with an error not exceeding 3.7% for all analysed loads. This ANN had 13 neurons in the hidden layer.
- ❍ An attempt to construct an ANN calculating NOx concentration in the engine exhaust gas in which the applied fuel consumption would be obtained from ANN approximation with 13 neurons in the hidden layer ended with failure. The ANN which most accurately approximated NOx concentrations had 20 neurons in the hidden layer, and for one engine operation point, from among all analysed load variants, produced an error exceeding 10% of the measured value.

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