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AN ARTIFICAL NEURAL NETWORK USAGE IN MEASUREMENTS OF EXHAUST GAS EMISSION FROM MARINE ENGINES: CASE STUDY

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Abstract

The paper presents the case study of using the artificial neural network to predict the main propulsion marine engine load. Mentioned load of the engine is important parameter to assess the emission level of toxic compounds into the atmosphere according to ISO standard and MARPOL convention. The engine load depends on the ship speed, rotational speed of the engine, propeller blades settings, the direction and the speed of wind, the condition of sea and the direction and the speed of sea currents and construction parameters of the ship. The realization of the aim of the work requires the direct measurement of presented parameters and measurement of exhaust gas composition. The experiment was carried out onboard STS "Pogoria". Obtained results are enough to use the ANN to predict engine load to measure the emission level of toxic compounds.

Keywords: marine engine, emission, neural network, measurement, power approximation

1. Introduction

The introduction of Annex VI to the MARPOL Convention entails certification of marine diesel engines due to emissions of nitrogen oxides (NOx). Mentioned certification is connected with the necessity of the periodic check of the NOx emission using generally understood analysis of technical parameters of the engine or, in extreme cases, direct measurements. Obtaining the NOx emission, normatively expressed in g/kWh, imposes the necessity to define i.e. the engine power during measurements of the composition of exhaust gas. This task is technically problematic for ship operators due to the lack of appropriate measuring devices on board installed. Systems of measurement of the engine output torque i.e. the ETNP-10 system manufactured by Enamor, are unpopular and relatively expensive. For this reason, there is a need to determine the main propulsion engine load. However, it is possible to measure this parameter indirectly, basis on current weather and motion of the ship parameters. We may make an assumption, that the main propulsion engine load is proportional to the ship speed, rotational speed of the engine, propeller blades settings, the direction and the speed of wind, the condition of sea and the direction and the speed of sea currents. All mentioned parameters are measured by the standard ship equipment. For this reason presented data and parameters comes from the ship construction could be useful to determine actual the engine load. It should be remembered that detailed calculation algorithm of the presented problem is not completely known. According to this situation convenient tool to solve this problem should be an artificial neural network (ANN). ANN is simple tool to approximation complex determined algorithms. Oladsine et al. [1] and Hafner et al. [2] use ANN to control piston engines and Stephan et al. [3] use ANN to control the combustion process in the power plant furnace. Yang et al. [4] and Ramadhas et al. [5] use ANN to predict cetane number in fuel mixtures and Lee et al. [6] use ANN to predict fuel injection range to the combustion chamber in the engine. ANN is useful to estimate the specific fuel consumption [7], [8] temperature of the combustion process in the engine [9], the air/fuel excess ratio [10], the NOx emission approximation [11] and faults of piston engines [12].

Presented works tend to conclude that it is possible to effectively use the ANN to assess the marine engine load. The main target of the work is presentation of the case study about possibility of the ANN use to predict the main propulsion engine load to direct measurements of the emission of toxic compounds.

2. Measurement procedure

Measurements were taken on the sailing vessel STS ”Pogoria”. She is a barkentine, about 48 meters of length and the deadweight of 340 tons. Mentioned ship is equipped with main propulsion engine, which through a reduction gear drives the controllable biplane propeller with nominal speed 356 rpm. Detailed parameters of the engine are presented in Tab.1.

Tab.1. Main engine technical data

Engine designation: VOLVO PENTA TAMD103A		
No.	Name of parameter	Value
1.	Method of operation	4-stroke, direct-injected, turbocharged diesel engine
2.	No. of cylinders and configuration	6 cylinders, in-line
3.	Bore	120.65 mm
4.	Stroke	140 mm
5.	Displacement	9.6 dm^3
6.	Compression ratio	17.0
7.	Minimal shaft rotatin speed	530 rpm
8.	Nominal crankshaft rotatin speed	1800 rpm
9.	Nominal power torque	1353 Nm (at 1800 rpm)
10.	Maximal torque	1580 Nm (at 1250 rpm)
11.	Specific fuel consumption	212 g/kWh

The exhaust gas composition has been measured by TESTO350XL exhaust gas analyser with ranges and accuracy presented in [13]. The procedure of measurement needs an information about fuel consumption and actual the engine load.

The fuel consumption has been measured by volumetric methodology, and the engine load was calculated by properly learned ANN.

3. **Artificial neural network usage**

As mentioned earlier the power output of the engine was calculated by the ANN. The input data of the ANN were the rotational speed of the engine, pitch propeller settings and the nautical and the meteorological data. Presented ANN was prepared in Matlab Neural Toolbox. The multi-layer perceptron with 7 neurons in the input layer, 2 hidden layers and 1 neuron in the output layer was used. The ANN input data are presented in Tab.2.

Tab. 2. Input variables of the ANN

Variable name	Unit	Recording method
fuel consumption	[dm^3/h]	Direct measurement
wind speed	[knots]	Weather Station PB150 made by Airmar, installed on the vessel.
wind direction	[^{o}]	Weather Station PB150 made by Airmar, installed on the vessel.
sea current speed	[knots]	tide tables and GPS
sea current direction	[^{o}]	tide tables and GPS
sea state	[^{o} of Douglas]	Douglas scale
rotational speed of the engine	[rpm]	Main engine speed indicator
propeller pitch setting	[pitch scale]	Scale of pitch propeller setting lever

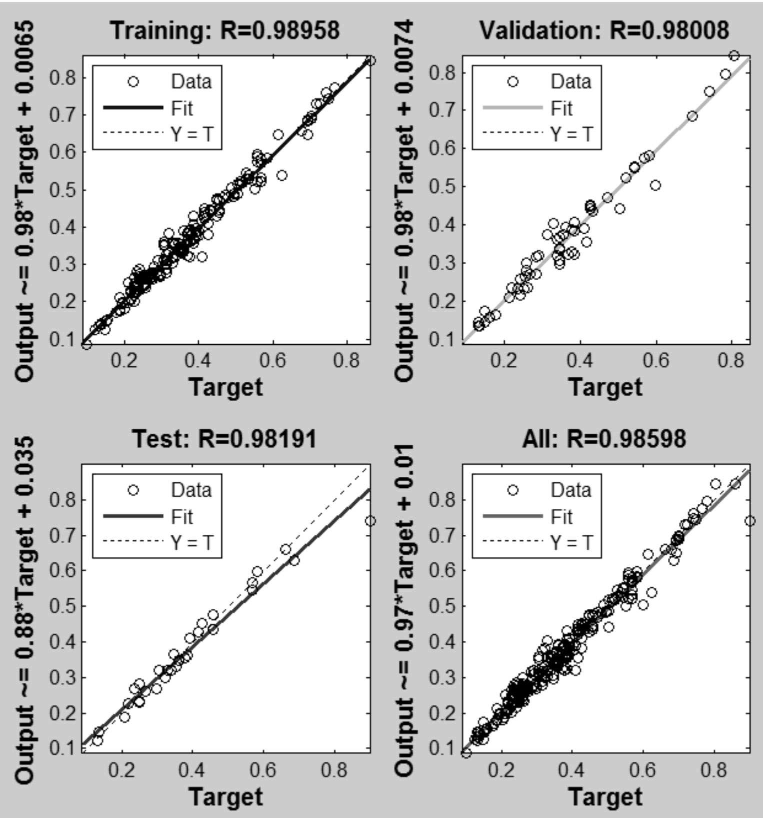

Fig.1. Screenshots from Matlab Neural Network Toolbox

Backpropagation algorithm was used to learn the ANN. There are many variations of the backpropagation algorithm. In this study the Gradient Descent with Momentum algorithm was implemented. Fig.1 presents the screen capture of the learning results summary. Detailed description of the ANN model is presented in [19], [20]. On the fig.1 target shows normalized torque at crankshaft. According to presented results the mean square error value (R) for all considered results is over 0.98. It means that the ANN model well-fits the measured data.

4. **Obtained results**

The use of ANN allows to direct measurement of the gaseous emission from the main propulsion engine of STS „POGORIA" ship. According to this, the direct measurement of exhaust gas composition with fuel consumption and parameters of the surrounding air was measured. The required information about the engine load was taken from proper learned ANN.

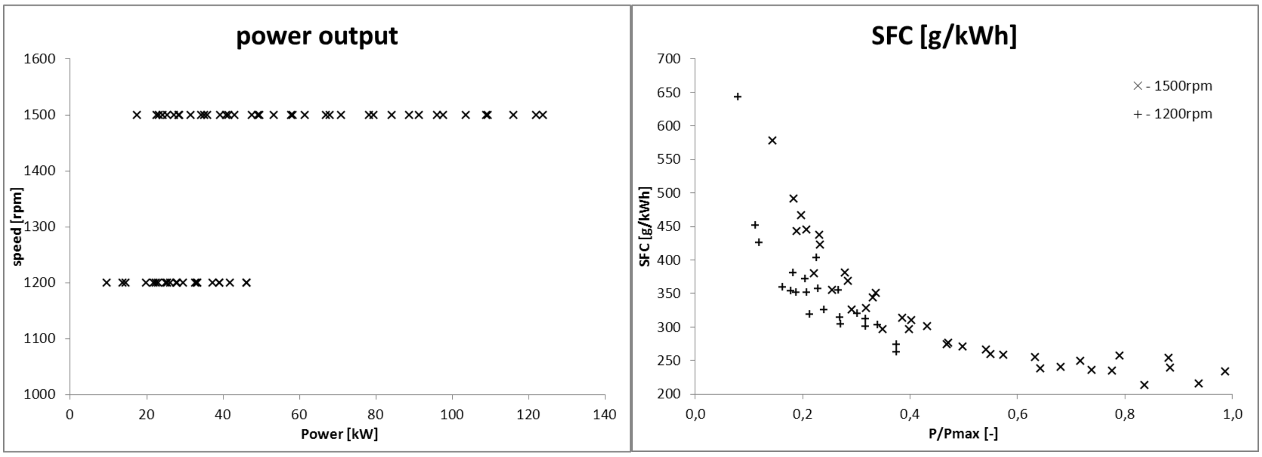

Fig.2. Obtained power output from the main propulsion engine and specific fuel consumption

Left side of Fig.2 presents the calculated power output of the main propulsion engine obtained from the ANN for all considered points of measurements. According to presented results, despite identic settings of values of both the engine speed and propeller's blades the value of obtained power output is different. Observed results are expected due to changes in values and the direction of wind and sea waves. Right side of Fig.2 presents the specific fuel consumption (SFC) calculated for all considered loads of the engine. Presented calculation results are based on measured fuel consumption and obtained from ANN results of power output. According to results presented in Tab.1 the SFC for nominal power output of the engine equals 212g/kWh. The obtained minimal value of SFC for the maximum power output equals 233g/kWh. Naturally, value of the SFC increases with the decrease of the power output. The maximum value of the SFC was obtained for idle load of the engine and it equals 643g/kWh.

Fig.3 presents results of the direct measurement of exhaust gas composition. Obtained results are qualitatively convergent to results presented in literature for similar constructions of marine engines [14], [15], [16]. The increase of the power output causes the decrease of oxygen (O_2) in exhaust gas and the increase of the carbon dioxide (CO_2). Presented results are expected. The increase of the power output and the increase of the fuel consumption in the same quantity of combustion volume cause the increase of the CO_2 in exhaust gas. Largest differences between measurements are observed in the case of the carbon monoxide (CO) content in exhaust gas. The result difference for 88% of the maximum power output for the CO equals 14% for two measurement points. The cause of this phenomenon wasn't recognized due to the lack of additional information, but the difference in the humidity of air and parameters of the engine cooling process may be suspected. According to presented results the increase of the power output causes the increase of both the CO and the NOx composition in exhaust gas. Observed dependences are expected. The increase of the power output causes the increase of combustion temperature and the acceleration of the nitrogen oxidation according to the Zeldovich thermal mechanism.

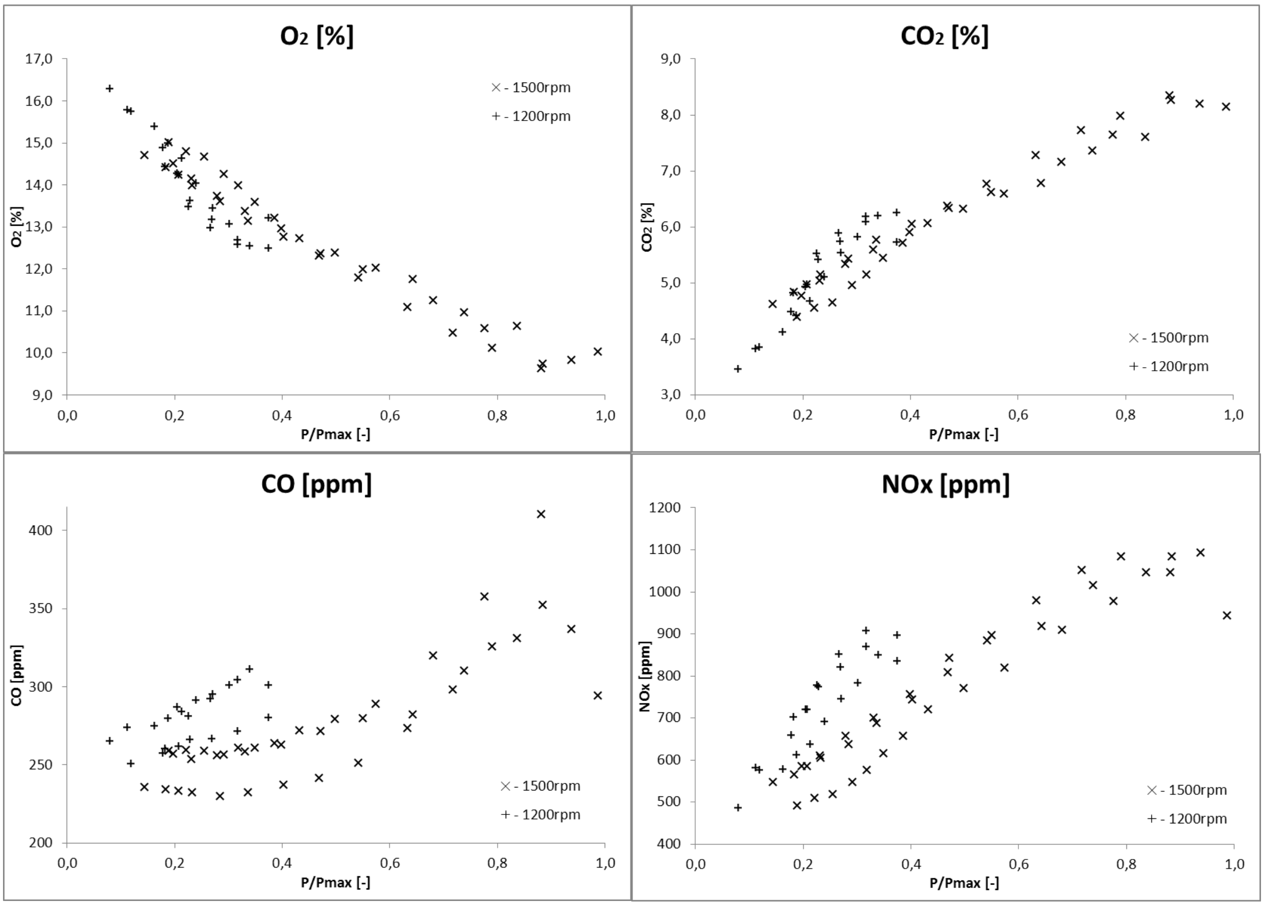

Fig.3. Measured composition of exhaust gas for all considered loads of the engine

Fig.4 presents results of the NOx and the CO emissions for all considered loads of the engine. Presented emissions are obtained with use of the engine power output, calculated by presented ANN. According to presented results, the increase of the engine power output causes the decrease of the CO and the NOx emissions. It should be noted that the increase of the power output of the marine engine causes the increase of its efficiency. According to this observed decrease of the CO emission is expected [17].

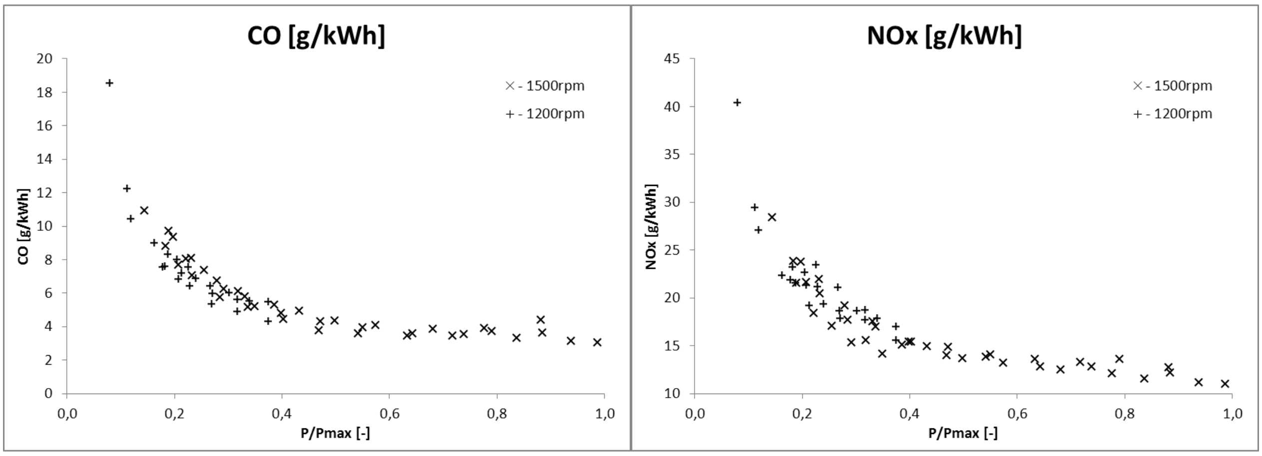

Fig.4. Emission of CO and NOx in exhaust gas for all considered loads of the engine

It should be noted that the increase of the engine speed causes the decrease of the CO and the NOx emissions. According to mentioned Zeldovich mechanism the quantity of nitrogen oxidation depends on temperature but time of combustion also.

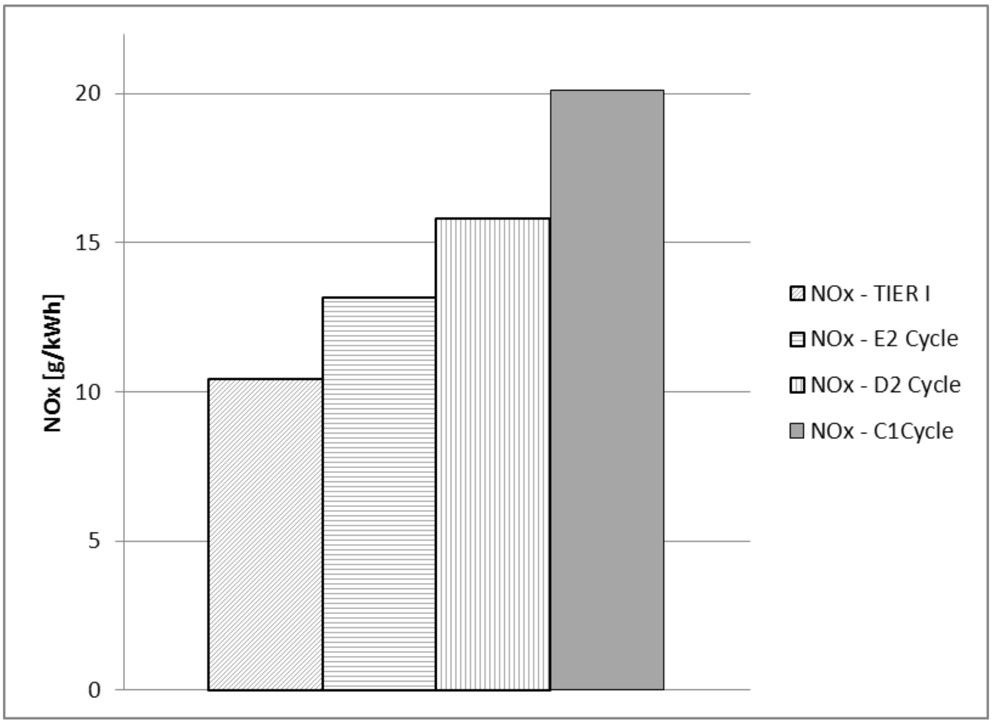

Fig.5. NOx emission levels for the E2, D2 and C1 cycle and the NOx emission limit according to Tier I of the MARPOL convention.

Calculated results of the NOx emission was used to the NOx emission presentation according to ISO8178 standard regulations. Obtained results may be used to the NOx calculation according to E2, D2 and C1 cycle of measurements. The E2 cycle is used for measurement the emission for marine engines operated as main propulsion marine engines operated at constant speed. D2 and C1 cycles are useful for marine engines operated as an auxiliary propulsion. Obtained results are presented in Fig.5.

Fig.5 presents the limit of the NOx emission according to Tier I of MARPOL convention [18] also. According to presented results, used type of cycle for the engine testing during the direct measurement of the NOx emission level, influences on obtained results. Differences between obtained results equal 34%. It should be noted that observed engine, according to the manufacturer declaration, should be used as either the main propulsion engine or the auxiliary propulsion onboard.

5. Conclusions

The paper presents the case study of possibility the ANN use to the engine load approximation during direct onboard measurements of the exhaust gas emission. The rotational speed of the engine as well as the fuel consumption and parameters of wind and sea state were used to properly learning the ANN. Calculated by ANN load of the engine has been used to NOx emission calculation according to ISO8178 standard regulation. Prepared observations allow to express the following conclusions.

- obtained ANN calculates the power output of the engine with accuracy not exceeded 2% ,
- the increase of the engine power output causes the decrease of the CO and the NOx emissions. Presented results are expected because the increase of the power output of the marine engine causes the increase of its efficiency,
- the increase of the engine speed causes the decrease of the CO and the NOx emissions,
- used type of cycle for the engine testing during the direct measurement of the NOx emission level, influences on obtained results. Differences between obtained results equal 34% for different types of measurement cycle.

Acknowledgments

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References

[1] Oladsine M., Bloch G., Dovifaaz X., *Neural modelling and control of a diesel engine with pollution constrains*, J. Intel. Robotic Systems, Vol. 41, Kluwer Academic Publishers, 2004,

[2] Hafner M., Schuler M., Nelles O., Isermann R., *Fast neural networks for diesel engine control design*, Control Engineering Practice, Vol. 8, Pergamon 2000.

[3] Stephan V., Debes K., Gross H-M., Wintrich F. Wintrich H., *A new control scheme for combustion processes using reinforcement learning based on neural networks*, Int. J. Comput. Intel. Appl. Vol. 1, No 2, Imperial College Press, 2001.

[4] Yang H., Ring Z., Briker Y., McLean N., Friesen W., Fairbridge C., *Neural network prediction of cetane number and density of diesel fuel from its chemical composition determined by LC and GC-MS*, Fuel Vol. 81, Elsevier, 2002.

[5] Ramadhas A. S., Jayaraj S., Muraleedharan C., Padmakumari K., *Artificial neural networks used for the prediction of the cetane number of biodiesel*, Renewable Energy Vol. 31, Elsevier, 2006.

[6] Lee S. H., Howlett R. J., Crua C., Walters S. D., *Fuzzy logic and neuro-fuzzy modelling of diesel spray penetration: A comparative study*, J. Intel. Fuz. Sys. Vol. 18, IOS Press, 2007.

[7] Sayin C., Ertunc H. M., Hosoz M., Kilicaslan I., Canakci M., *Performance and exhaust emissions of a gasoline engine using artificial neural network*, Applied Thermal Engineering Vol. 27, Elsevier, 2007,

[8] Al-Hinti I., Samhouri M., Al-Ghandoor A., Sakhrieh A., *The effect of boost pressure on the performance characteristics of a diesel engine: A neuro-fuzzy approach*, Applied Energy Vol. 86, Elsevier, 2009.

[9] Parlak A., Islamoglu Y., Yasar H., Egrisogut A., *Application of artificial neural network to predict fuel consumption and temperature for a diesel engine*, Applied Thermal Engineering Vol. 26, Elsevier, 2006.

[10] Wang S., D.L. Yu., *Adaptive RBF network for parameter estimation and stable air–fuel ratio control*, Neural Networks Vol. 21, Elsevier, 2008.

[11] Kowalski J., *ANN based evaluation of the NOx concentration in the exhaust gas of a marine two-stroke diesel engine*, Polish Maritime Research, No 2(60), Vol. 16, pp. 60 – 66, Gdańsk 2009.

[12] Wu J-D., Liu C-H., *An expert system for fault diagnosis in internal combustion engines using wavelet packet transform and neural network*, Expert Systems with Applications Vol. 36, Elsevier, 2009.

[13] Kowalski J., *Concept of the multidimensional diagnostic tool based on exhaust gas composition for marine engines*, Applied Energy, Vol. 150, pp. 1-8, Elsevier 2015.

[14] Ming Zheng, Reader G.T., Hawley J.G., *Diesel engine exhaust gas recirculation–a review on advanced and novel concepts*, Energy Conversion and Management, Vol. 45, pp. 883 – 900, Elsevier, 2004.

[15] Kowalski J., *Wpływ wybranych niesprawności układu paliwowego na skład emitowanych spalin z czterosuwowego silnika okrętowego*, Zeszyty Naukowe AMW w Gdyni, Vol. 178A pp. 133 – 138, Gdynia 2009.

[16] Kowalski J., *Wpływ wybranych niesprawności układu doładowania na skład emitowanych spalin z czterosuwowego silnika okrętowego*, Zeszyty Naukowe AMW w Gdyni, Vol. 178A, pp. 139 – 144, Gdynia 2009.

[17] Sarvi A, Fogelholm C-J, Zevenhoven R., *Emissions from large-scale medium-speed diesel engines: 2. Influence of fuel type and operating mode*, Fuel Process Technol, Vol. 89, No. 5, pp. 520 – 527, Elsevier, 2007.

[18] *Technical code on control of emission of nitrogen oxides from marine diesel engines*, International Maritime Organisation, Resolution MEPC.251.(66), 2008.

[19] Rudzki K.: *Dwukryterialna optymalizacja nastaw silnikowego układu napędowego statku ze śrubą nastawną z wykorzystaniem sztucznych sieci neuronowych*. Rozprawa doktorska, Akademia Morska w Gdyni, Gdynia 2014.

[20] Rudzki K., Tarełko W.: *Optymalizacja nastaw układu napędowego statku ze śrubą nastawną*, 2014, Logistyka, Zeszyt 6, pp. 1103-1108.