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THE ARTIFICIAL NEURAL NETWORK: A TOOL FOR NOx EMISSION ESTIMATION FROM MARINE ENGINE

Jerzy Kowalski

Gdynia Maritime University
Department of Engineering Sciences
Morska Street 81-87, 81-225 Gdynia, Poland
tel.+48 58 6901484, fax: +48 58 6901399
e-mail: jerzy95@am.gdynia.pl

Abstract

The paper presents the preliminary investigations of nitric oxides (NOx) estimation from marine two-stroke engines. The Annex VI to Marpol Convention enforce to ship-owners necessity of periodical direct measurements of the NOx emission from the ship engines. It is very expensive procedure but with a low accuracy. Presented investigations show the possibility of estimation the NOx emission without direct measurements but using the artificial neural network (ANN). The paper presents method of choice the input data influenced on NOx emission and configuration of ANN and effects of calculations. The input data poses 15 parameters of engine working, influencing on NOx emission. The output data, necessary to learning the network, were NOx concentration in engine exhaust gases. We take into account two types of ANN; the 3-layer perceptron (MLP) with number of neurons in the hidden layer from 10 to 20 and the radial basis function neural network (RBF) with number of neurons in the hidden layer from 10 to 80. The input, validation and verification data was obtained from laboratory tests. After procedure of network configuration, the chosen ANN was learned by back propagation and conjugate gradient methods. During this operation the weights of neurons were changed to minimize the root mean square error. We obtained four ANN's, which allow us to estimate the NOx emission from laboratory engine with accuracy, comparable with Annex VI regulations.

Keywords: *emission, NOx, Artificial Neural Network, Marpol Convention, marine diesel engine*

1. Introduction

The nitric oxides (NOx) contained in exhaust gases, emitted from ship engines causes' high level of health hazard. To prevent of sea environment from this pollutant International Maritime Organization introduced Annex VI to MARPOL 73/78 convention in 1997. This Annex forces ship owners to limit nitric oxides emission from ship engines. The allowable level of this emission is defined in NOx Technical Code [11]. According to this Code, every introduced to operation onboard engines above 130 [kW] are obligated to have the valid certificate confirming the acceptable NOx emission. If ship engines are subjected some alterations during their operation period, they will have to extend such a certificate. Its prolonging consists in checking of parameters and structural parts of the engine influencing the NOx emission. Changes of engine structural parameters could entail the necessity of carrying out the direct onboard measurements of the NOx emission. Usually, the standard equipped engine rooms have not installed any appropriate analyzer of exhaust gases. Therefore, such direct measurements lead to significant expenses for ship owners. Moreover, these measurements have to be carried out for strictly determined points of engine load. Such situation can also cause to withdrawing the ship with operation in order to perform these measurements, which are additionally not precise. According to the NOx Technical Code regulations, we can apply the simplified method during the onboard measurements. These regulations allow us to overcome the acceptable levels of emission even about 10% comparing with methods using on the shore. For the heavy fuel, these regulations allow to exceed this limit even up to 15%.

In order to make these regulations more applicable, many research centers work on alternative methods of nitric oxides estimations from onboard operated diesel engines. Kyrtatos et al. [16] proposes the "*software sensor for exhaust emissions estimation*" based on multi-zone thermochemical model of nitric oxides formation in combustion chamber of the engine. This sensor includes only Zeldovicz's model [10] of nitric oxides creation. Developing this method of nitric oxides estimation the mono-zone multi-component, thermochemical model was proposed [14]. It's based on Konnov's model [13] and consists of 724 reactions between 83 chemical species. The conclusions formulated after researches on this model, shows enough accuracy of nitric oxides estimation only for one engine. Moreover, the complexity of nitric oxides formation in combustion chamber of engine required very expensive computational power, not onboard accessible. According to this, it's necessary finding of the appropriate method, allowing to the lowering of the costs of modeling without limiting her accuracy. Such method can be an approximation of the NOx composition model, possible to calculation by the PC class computer. The useful and universal approximator, being suitable to this aim, is the artificial neuronal network (ANN). Proposed by Werbos method of ANN learning [29], called the back propagation method, allows using the ANN in the various fields of knowledge. Wang et al. [28], Oladsine et al. [20] and Hafner et al. [8] uses ANN to control parameters of the piston engines and Stephan et al. [25] to control the power plant. Yang et al. [30] and Ramadhas et al. [22] proposes use ANNs to modeling of cetane number for blended fuels and Lee et al. [17] use ANN to modeling of fuel spray penetration in combustion chamber of the engine. The ANN was also applied to the lowering of the costs of the modeling of the combustion process reactions [3], [5], [12], [24], [26] specific fuel consumptions of the engine [23] and the temperature of the combustion process [21].

Presented works shows, that using the ANNs is effective and not expensive alternative to modeling of the combustion process parameters. According to this situation we would like to propose a method of the NOx estimation from the onboard diesel engine based on the measurements of working engine parameters like pressures, temperatures, etc. Moreover, we assume that these parameters measured in the standard equipped engine room are sufficient for developing the mentioned method. This, in turn, requires developing the appropriate model connecting these parameters into a function allowing for assessing a level of the NOx emission. In order to reduce the high cost of modeling the artificial neural network is proposed.

2. Formation of the NOx in combustion chamber of the engine

The main reason of nitric oxides formation is reactions of the nitrogen oxidization in environment of high temperature and high pressure in a combustion chamber. The nitrogen oxidized in these reactions comes from air and fuel injected to a cylinder. The process of the nitrogen oxidation is reversible. Unfortunately, the quickness of reactions opposite to the oxidation is too low in conditions of the combustion chamber. It causes to release some parts of the nitric oxides to atmosphere during the scavenging process of a cylinder. Long-term investigations of the NOx formation carried out during a combustion process of various flammable mixtures bring into being many mechanisms allowing for estimating the amount of the emitted NOx. Basing on thermal mechanism [9], we can state that the most important parameter of this process is its temperature. This statement is supported by results of experimental investigations presented in [2]. According to conclusions contained in [7], the second important parameter is pressure of causing for decreasing of NOx molar concentration. Investigations of Lyle and al. [18], shows us the considerable influence of relation between the molar concentration of fuel and air on the NOx emission level. According to results of these studies, the prompt mechanism predominates in rich mixtures. After exceeding a stoichiometric air concentration in a mixture, the rapid growth of the

NOx concentration occurs due to a thermal mechanism domination. However, the further increase of the air concentration causes for decreasing of the NOx concentration due to decreasing the combustion process temperature. Kuo [15] gives also dependences between the fuel composition and burning velocity, and the NOx concentration. According to results, a fuel molecular structure depends on burning the velocity and NOx concentration, but this dependence is ambiguous.

According to these considerations the most important parameters influenced on NOx formation are:

- Composition of burned mixture in the combustion chamber,
- Time of combustion,
- Pressure of combustion,
- Temperature of combustion.

Values of these parameters are changed during the combustion process in the engine cylinder. Moreover, presented parameters couldn't be measured during sea operation of the engine. It means that estimation of the NOx emission requires measurement some another parameters of the engine working influencing on temperature, pressure, time of combustion and composition of the combusted mixture. The author's research demonstrates [14], that measurement of the engine parameters during the sea operation conditions, are enough to the NOx emission estimation. The prediction of NOx emission by the direct calculation of NOx formation during combustion process is very expensive and difficult process [1] [4] [6], [13], requiring large computational power not attainable onboard. In this situation the direct calculation of the NOx formation to estimation of the level of the emission onboard is problematic. On the other hand properly learned neural network, may be sufficient tool to assess the level of the NOx emissions.

3. The preparing of the ANN's

According to the ANN theory [19] the enter data inserted to the ANN model has to comply appropriate requirements. The most important is the mutual independence of the enter data. It means that chosen entered data couldn't influence each other.

The earlier considerations show that the enter data to the ANN must represent the parameters influenced on NOx formation in the combustion chamber. The composition of the burned mixture in the combustion chamber may to be estimated by the parameters of the air and fuel at the inlet to the engine and the parameters of the injection system. We choose the following parameters: temperature and humidity of the scavenging air and a fuel consumption of the engine. Dependence between quantity of fuel and air in the combustion chamber is represented by an air/fuel ratio. Time of combustion is represented in enter data by speed of the engine and pressure of combustion is represented by the mean cylinder pressure, the maximum cylinder pressure and the crankshaft position at the maximum cylinder pressure. Temperature of the combustion process is represented in enter data by parameters of the injection process; the maximum injection pressure, the crankshaft position at the maximum injection pressure and temperature of the fuel before the injecting pump and temperature of the exhaust gas. The cooling system of the engine influences on temperature of combustion process that has way the pressure and temperatures in the inlet and outlet of the cooling system were added to the enter data. According to these considerations 15 independent parameters of the combustion process are taken like the enter data to ANN.

The problem of NOx emission estimation from the diesel engine is classified as regressive problem. General two types of ANN may to be used to solve this class of problems. The first, most popular, network is multilayer perceptron (MLP) [23] and the second the radial basis function network (RBF) [27].

During the investigations both, the MLP and RBF networks are considered. The networks consist of 15 input neurons in input layer for 15 enter data, one neuron in output layer for NOx emission estimation and neurons in one hidden layer. The number of neurons in the hidden layer was changed from 10 to 20 for MLP network and from 10 to 80 in RBF network. The input, validate, and the test data were collected during direct measurements on two stroke, one cylinder, loop scavenged, laboratory engine. The 212 sets of data are collected to teaching the networks after measurements. The cross validation was used because of a small quantity of the data sets. During the teaching process 162 data sets was randomly assigned as the teaching data, 20 to validation the networks, while the remaining 30 was employed for verification the performance of the ANN prediction. The logistic function as an activation function was used and the data sets before using were standardized to values from 0 to 1. The learning rate was set on 0,1.

The teaching process for all considered ANNs consists of few stages:

- weights of all neurons were randomly assigned,
- inputs were presented to the input layer, and the output was calculated,
- weights were calculated by minimizing the error in back propagation process, this process was repeated to assign all data sets,
- data sets were mixed and the second epoch was started,
- after 200 epochs weights were calculated by minimizing the error in the conjugate gradient method by 500 epochs,
- the cross validation was used and repeated 5 times,

4. The description of the laboratory test

We have carried out the laboratory test using the engine L-22 installed in Gdynia Maritime University laboratory. It is a crosshead, single-cylinder, and two-stroke diesel engine with loop scavenging. Roots' blower driven independently by an electric motor with an infinitely variable adjustment of rotational speed charges this engine. The tested engine is loaded by a water brake. Basic parameters of the L-22 engine are presented in Tab.1. and a schematic diagram of the laboratory stand is presented in Fig.1.

The measuring equipment installed on the tested engine permitted on the continuous recording of the considered parameters of the engine with approximately 0,5 second samplings.

Tab.1. Parameters of the test engine

Nominal Power [kW]	73,5
Rotational Speed [rpm]	600
Cylinder bore [mm]	220
Piston Stroke [mm]	350
Compression Ratio [-]	18,5
Fuel consumption at maximum load* [kg/h]	7,33
Specific fuel consumption at maximum load* [g/kWh]	277,6

* – maximum load considered during laboratory tests (see description below)

The fundamental stage of our research consists of 10 observations. We loaded the tested engine in a range from 25% to 65% of its nominal load with two rotational speeds namely 200 and 360 rpm. The larger load of the engine was not possible because of the admissible load of the used water brake and too small efficiency of the Roots' blower. The measurements have been carried out for the working engine with:

- its constant rotational speed and changeable loads for a constant value of air/fuel equivalence ratio,
- its constant rotational speed and load for changeable values of air/fuel equivalence ratio.

In this research, the air/fuel equivalence ratio [9] was understood as a ratio of a mass amount of air delivered to a cylinder to amount of air necessary to combustion of a fuel dose injected to this cylinder whereas the changeable loads realized by means of using a water brake. Values of the engine loads (*M*) described like percent of nominal momentum M_n and rotational speeds (*n*) are presented in Tab.2.

During our research, the engine has been supplied by the diesel fuel with its known specification obtained from its producer (Lotos EuroDiesel EKO Z with density at 15ºC equal 829,6 kg/m^3).

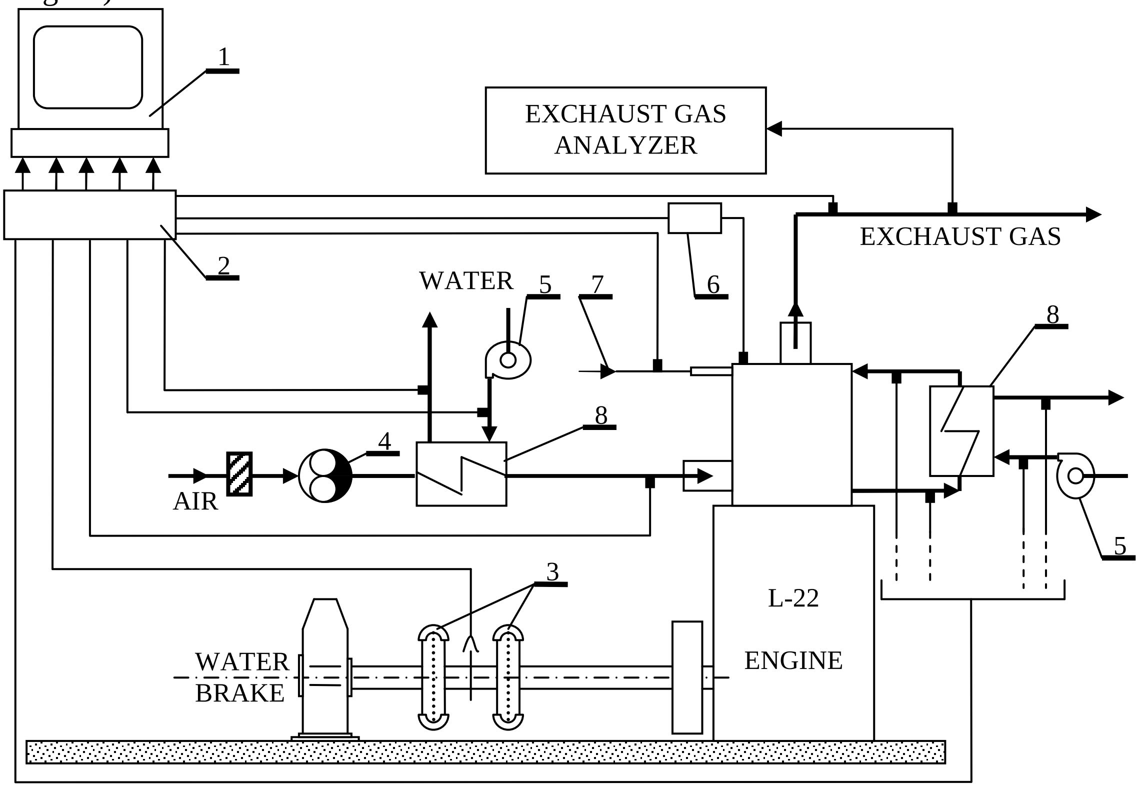

Fig.1. A schematic diagram of the laboratory stand: 1 – a recording computer, 2 – A/C converter, 3 – rubber flexible couplings, 4 – Roots' blower, 5 – a fresh water pump, 6 – an electronic indicator of pressure, 7 – fuel installation, 8 – a heat exchanger

Tab.2. Values of the tested engine loads and rotational speeds

No.	1	2	3	4	5	6	7	8	9
M [% of M_n]	65	60	55	50	45	40	35	30	25
n [rpm]	200								
No.	10	11	12	13	14	15	16	17	18
M [% of M_n]	65	60	55	50	45	40	35	30	25
n [rpm]	360								

5. The results of the investigations

The learning processes of ANNs were prepared in STATISTICA 7.1 computer code. The root mean square errors for best ANNs after cross validation for all considered networks were presented in Fig.2.

According to presented in Fig.2 results, the MLP networks have littlest root mean square errors than RBF networks. Increasing of number of neurons in hidden layer cause decrease considered error, but increasing number of neurons in the hidden layer of RBF network over 70 neurons decreases the error only imperceptibly. The changing of the neurons number in the MLP hidden layer between 10 and 20 neurons doesn't influence improvement of the quality of modeling significantly. The values of the maximum errors for all considered ANNs are presented in Fig.3.

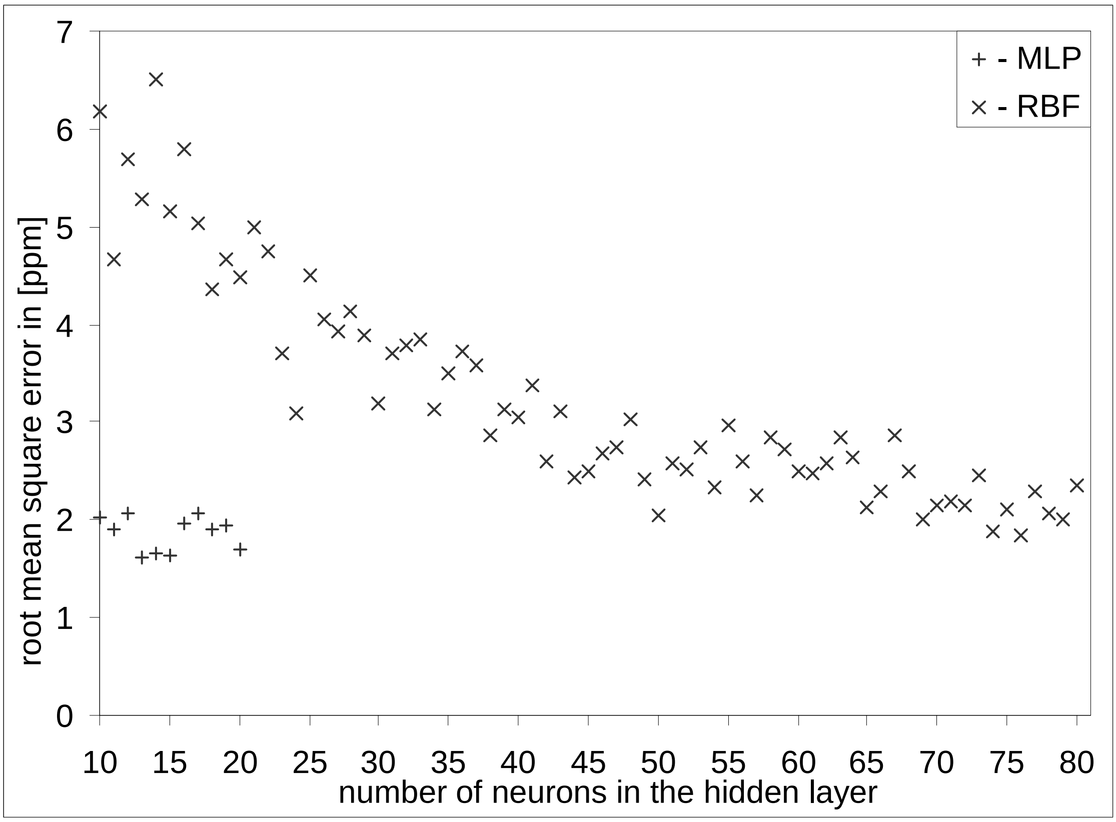

Fig.2. the root mean square error for all considered ANNs

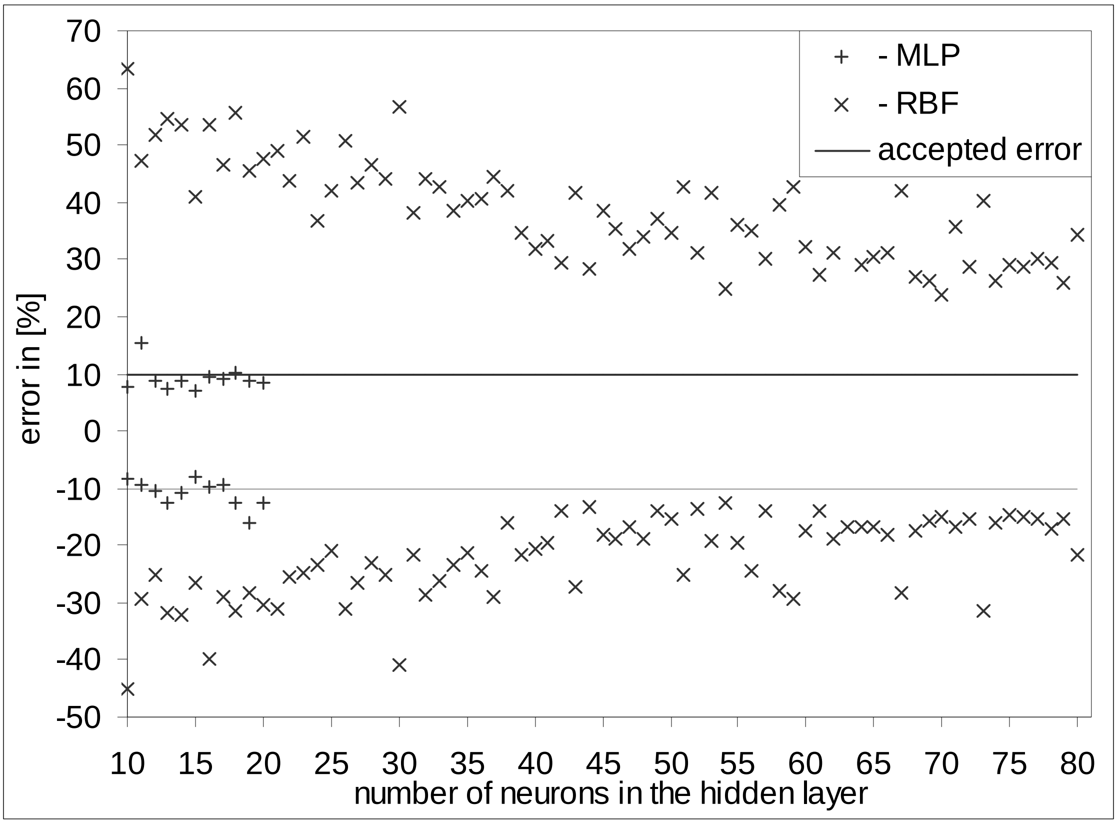

Fig.3. the values of maximum errors for all considered ANNs

Results, presented in Fig.3. shows, that only four MLP networks estimate the NOx emission in errors not excided 10% for all considered points of load the engine. There are the MLP networks with 10, 15, 16, and 17 neurons in the hidden layer. According to these considerations the presented MLP networks are sufficient to NOx emission from engine with accuracy specified in Technical Code.

5. Conclusions

This paper describes the method of ANN preparing to NOx emission estimation from the ship diesel engine during onboard working. The presented results of this work enable the following conclusions to be drawn:

- The possibility of the enter data collecting to the NOx formation model in the ship engine exists without the installation of the additional measuring equipment in the engine room.
- Four MLP networks with 10, 15, 16, and 17 neurons in the hidden layer successful estimate the NOx emission with error not exceeded 10% for all considered points of the engine load.
- The preparing of artificial neural network with considered enter data is sufficient to NOx emission estimation from the ship diesel engine. However the network was learned only for one engine and more studies are necessary.

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