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The Use of Neural Networks for the Faults Classification of a Marine Diesel Engine Fuel Injection System*

Rafał Pawletko
Gdynia Maritime University
ul. Morska 83, 81-962 Gdynia, Poland

In this article, the author presents the diagnostic possibilities of the marine diesel engine fuel injection system. This method is based on an indicator diagram analysis. The algorithm of the faults detection was constructed with the use of neural networks. The data collected during the test of the Sulzer 3Al 25/30 engine has provided valuable experience. An indication diagram has been recorded by the electronic indicator Unitest 201. In the article, the author also presents the following stages of a diagnostic research: the diagnostic data acquisition during the active experiment, the diagnostic model's construction, the automatic classificator's construction and the verification. The proposed diagnostic method can be utilised to provide an example of the automatic evaluation of an engine's technical state.

INTRODUCTION

Technical diagnostics play a very important role during the exploitation of marine machinery equipment, especially for diesel engines [1][2]. Automatic faults classification methods provide a very useful and helpful tool for a watchkeeping engineer, who is responsible for the unit's proper operation [3]. Practical knowledge about the construction and working principles of such a diagnostic method should be an important component in a marine engineer's education process.

The application of marine diesel engines is linked to frequent faults found in a fuel injection system. The technical state of this system, in turn, influences the level of combustion. The engine's performance, its durability and reliability, strictly depend on a proper course of the combustion process [4]. On the other hand, the condition of an injection system is linked with emissions from toxic combustion fumes and fuel consumption.

The fuel injection system is one of the most breakable parts of an engine. Notably, faults in this system do not usually stop the engine. However, engines that are in a bad technical state have the following features:

- Higher fuel consumption;
- Greater emission of gas and toxic particles;
- Problematic start-ups and a quicker use of the main tribologic systems of an engine [5].

Upon analysing the diagnostic methods utilised for the fuel injection system, it was found that most of them are based on the level of the fuel pressure in an injection pipe between a pump and a fuel injector [6][7]. This does impose some limitations, such as the pressure in the injection pipe is usually inaccessible in a ship's engine room (the engine needs to be equipped with some additional sensors and the measuring devices that record the pressure curve).

For this reason, there is a need to work out an algorithm that could be used as a diagnostic guide. It should be remembered that this diagnostic method is supposed to be a cheap alternative to other complex diagnostic systems. Indeed, it has to have parameters that are relatively and easily accessible for measuring and, at the same time, giving information about the condition of the fuel injection system [8].

Because of this, the pressure in a cylinder (measured

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behind the indicating valve with the use of an electronic indicator) was taken as a diagnostic signal.

The algorithm for the faults detection was constructed with the use of neural networks. They were also used to build the diagnostic model in order to classify the fuel injection system states.

NEURAL NETWORKS

Neural networks are algorithms whose architecture is modelled after the brain. They typically consist of many hundreds of simple processing units that are wired together in a complex communication network. Each unit or node is a simplified model of a real neuron, which calculates a new signal based on input signal from the other nodes to which it is connected. The strength of these connections may be varied in order for the network to perform different tasks.

Neural networks are a new method for the programming of computers. They are exceptionally good at performing pattern recognition and other tasks that are very difficult to program using conventional techniques. Programs that employ neural nets are also capable of learning on their own and adapting to changing conditions.

A Simple Artificial Neuron

Neural networks consist of many simple processing units (artificial neurons). A neuron is often called a node or unit. It receives input from some other units, or from an external source. Each input *x* has an associated weight *w*, which can be modified during the learning process. The unit computes some function *f* of the weighted sum of its inputs, as follows:

$$y = f\left(\sum_j w_j x_j\right)$$

Output *y*, in turn, can serve as an input to other units, as shown in Figure 1.

The weighted sum, å $w_i X_i$, is called the net input to unit *i*, often written as neti. The function *f* is the unit's activation function. In the simplest case, *f* is the identity function, and the unit's output is just its net input. This is called a linear unit.

Simple neurons can be arranged in a different topology – neural networks. From the point of view of the activation flowing between processing units, there are three architectures of neural networks, as follows:

- Single-layer feed-forward: one input layer and one output layer of processing units; there are no feedback connections;
- Multi-layer feed-forward: one input layer, one output layer, and one or more hidden layers of processing units; there are no feedback connections, and the hidden layers sit in between the input and output layers (for example, a multi-layer perceptron);
- Recurrent: any network with at least one feedback connection; this may, or may not, have hidden units [9][10].

Perceptron Neural Network

A perceptron is the most popular network architecture in use today – especially in the technical sciences. In this model, the artificial neurons are arranged into layers. The signal representing an input pattern is fed into the first layer. The nodes in this layer are connected to another layer (sometimes called the *hidden layer*). The firing of nodes on the input layer is conveyed via these connections to this hidden layer. Finally, the activity on the nodes in this layer feeds onto the final output layer, where the pattern of firing of the output nodes defines the response of the network to the given input pattern. Signals are only conveyed forward from one layer to a later layer. In a perceptron, there is no feedback from the output layer. Figure 2 displays a perceptron's neural network.

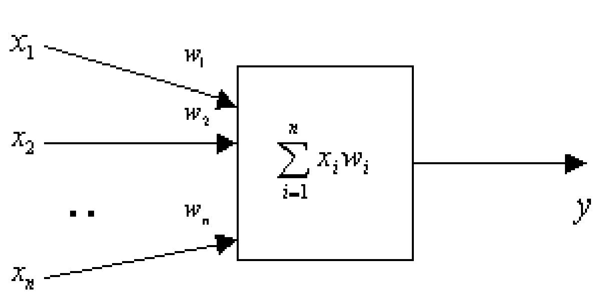

Figure 1: An artificial neuron.

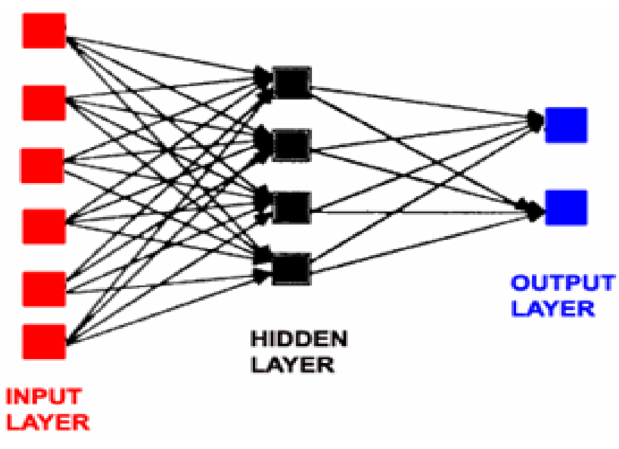

Figure 2: A perceptron's neural network.

A perceptron is capable of both recognising and classifying patterns. By utilising a large network with many nodes in the hidden layer, it is possible to classify patterns into one of two or more sets.

There is another important task that the perceptron can perform usefully: the network may be used to draw associations between objects.

Perceptron neural networks are a perfect tool for the modelling of non-linear objects, thanks to such features like the approximation of the optional, constant, non-linear relations and the ability to learn and adapt. Neural networks are also widely used in diagnostics [11][12].

OUTLINE OF THE DIAGNOSTIC METHOD

The idea of this method was based on the use of a model pressure changes in a cylinder for a fuel injection system technical state diagnosis. This model was utilised to calculate a standard pressure level for the engine without faults. After that, the residuum signal was calculated with the use of the standard pressure curve and the measured pressure. This signal showed some incompatibility between the nominal (without the faults) and faulty conditions of the fuel injection system. The course of the residuum signal was then analysed from the point of view of the fuel injection system technical state. The general structure of the diagnostic algorithm is shown in Figure 3.

The algorithm presented in Figure 3 consists of two main blocks: the generation and classification of residuum values. The generation block identifies the residuum signal by comparing the signals from the pressure model with the measured values. The residuum signal should be equal to zero while the system is working under nominal conditions, and in case there is a fault, it should be different from zero. The classification block distinguishes the damage in the fuel injection system based on the previously reckoned residuum signal. Because of the difficulties in the analytical modelling of the complex objects and their processes, neural network modelling was used instead.

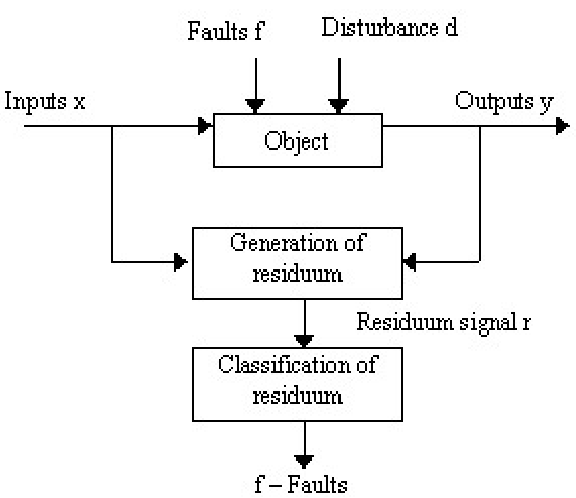

Figure 3: The general structure of the diagnostic algorithm.

Perceptron neural networks with one hidden layer were used. They were also used to model the course of pressure in a cylinder and to classify residuum signals. The error back propagation algorithm was utilised to teach students about the network.

At the beginning of the research, a neural model of the pressure course in a cylinder was generated. The model showed the curve of standard pressure behind the indicating valve as an engine load function. The load of the engine was estimated from the compression pressure curve. The relationship between the compression pressure and the engine load was typical for a turbocharged engine [13]. The compression pressures in the range of 55-50 crank angle degrees before top dead centre (TDC) were used as inputs.

Modelling and analysing was limited to 40 crank angle degrees (10 before TDC and 30 after TDC) (see Figure 4).

RESEARCH RESULTS

This experimental research was carried out on a four-stroke supercharged marine diesel engine, Sulzer 3A1 25/30 type. The electronic indicator Unitest 201 was used for the engine's indication.

In the first part of the research, the neural model of pressure course for a nominal state was developed. The model was based on the indicator graphs for the loads from 50 kW to 250 kW. It is possible to calculate an example pressure curve within the range from 10 crank degrees before TDC to 30 crank degrees after TDC. A comparison of the neural model with

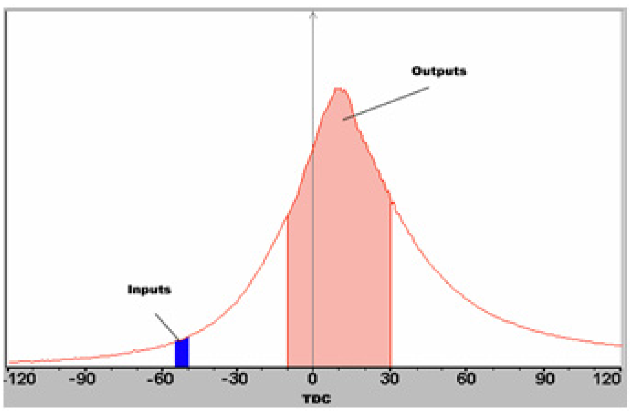

Figure 4: The range of the inputs and outputs of the neural model of the combustion course.

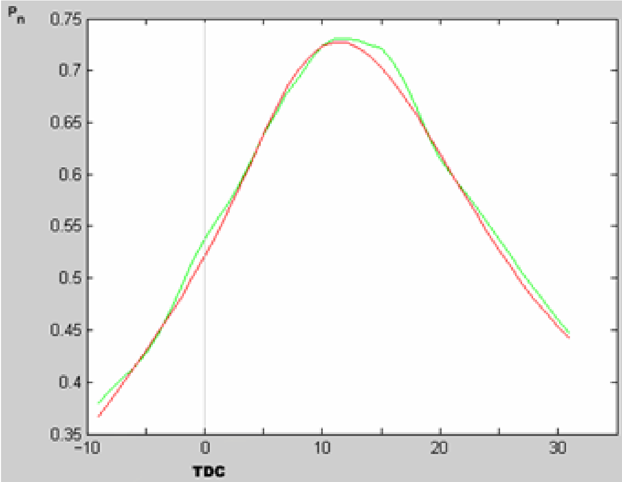

Figure 5: Example of the pressure courses: the dashed line shows calculations using the model, while the continuous line shows what was measured.

the real curve of pressure is presented in Figure 5.

The active experiment was carried out to verify the proposed diagnostic method. The following faults of the fuel injection system was simulated during the experiment:

- Reduced tension in the fuel injector spring;
- The injection pump wear;
- Decalibration of the fuel injector nozzles;
- Coked fuel injector nozzles.

During experiment, one level of the fault was simulated and then the pressure in the cylinder was measured, within the range of the engine load from 50 to 250 kW. For each simulated engine state, 42 pressure curves were registered.

Table 1 lists the simulated faults with their respective symbols. The implementation of several faults at the same time and various levels of given faults were not the focus of the experiment.

The experimental data were then used to classify the states of the fuel injection system. The main task of classification is to assign the patterns (states) to one of the possible classes. Two different images of states should to be assigned to the same class only if they are similar, and should be assigned to different classes if they are not similar. The notion of similarity depends strongly on the context of the task of classification.

Table 1: The simulated faults with their respective symbols.

Symbol	State of the Engine
K1	Nominal state without faults
K2	Fall of tension of the fuel injector spring
K3	Injection pump wear
K4	Decalibration of the fuel injector nozzles
K5	Coked fuel injector nozzles

Two terms were introduced in order to verify classificatory neural networks activity, namely: a *relative error* and a *wrong assign error*. The *relative error* defines how many examples from the certain class were wrongly identified. The *wrong assign error* defines how many negative examples to the certain class were assigned to it. The results of the faults classification are presented in Table 2.

Table 2: The results of the classification with the errors.

Classificatory network	The number assigned to the class					Relative error	Mean relative error	Wrong assign error	Mean wrong assign error
	K 1	K 2	K 3	K 4	K 5				
K2	2	**38**	4	5	2	10%	**12%**	4%	**3%**
K3	0	0	**39**	4	1	7%		2%	
K4	1	3	8	**30**	2	28%		5%	
K5	1	0	2	0	**41**	2%		1%	

CONCLUSIONS

The results of the study described in this article yielded the conclusions described below.

Using the developed method, it is possible to diagnose (with a relative error below 15%) such faults, like reduced tension in the fuel injector spring, wear in the injection pump and coked fuel injector nozzles. However, in the case of fuel injector nozzles' decalibration, the observed relative error was about 28%.

The low diagnosis quality can be caused by the following key factors:

- Errors in the measurement of the pressure in a cylinder;
- Errors in the representation of the pressure in a cylinder using a nominal neural model;
- Low sensitivity of the diagnostic signal to certain faults.

The developed diagnostic method can be utilised for practice for the classification of automatic, fuel injection system faults.

The article presents practical knowledge regarding the development, generation and working principles of a diagnostic method that should be considered an important component in maritime engineering education.

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BIOGRAPHY

Rafał Pawletko was born in 1975 in Torun, Poland. He graduated from Gdynia Maritime University (GMU), in Gdynia, Poland, with an MSc in marine engineering in 2000. He is presently an assistant at Gdynia Maritime University.

His professional interests lie in the application of measuring equipment for marine diesel engines, as well as automatic faults classification methods in technical diagnostics.

9th Baltic Region Seminar on Engineering Education: **Seminar Proceedings**

edited by Zenon J. Pudlowski, Romuald Cwilewicz & Józef Lisowski

The very successful *9th Baltic Region Seminar on Engineering Education*, conducted at Gdynia Maritime University (GMU), Gdynia, Poland, between 17 and 20 June 2005, was held in conjunction with the GMU's 85th Anniversary and, indeed, the 85th anniversary of maritime education in Poland. Contributions from ten countries are represented in the 50 papers, which include an informative Opening Address about the GMU by its Rector, three Keynote Addresses and various Lead Papers. These papers present a diverse scope of important issues that currently affect on engineering and technology education at the national, regional and international levels. The strong participation from academics at the GMU displays the University's enthusiasm to advancing engineering education for the benefit of students, staff, industry and society.

The paramount objective of this Seminar was to bring together educators from the Baltic region to continue dialogue about common problems in engineering and technology education under the umbrella of the UICEE. To consider and debate the impact of globalisation on engineering and technology education within the context of the recent economic changes in the Baltic region, and in the context of the strong revival of the sea economy, were also important objectives of this Seminar. Moreover, the other important objectives were to discuss the need for innovation in engineering and technology education, and to establish new links and foster existing contacts, collaboration and friendships already generated in the region through the leadership of the UICEE.

The papers incorporated in these Proceedings reflect on the international debate regarding the processes and structure of current engineering education. They are grouped under the following broad topics:

- Opening and keynote addresses
- New technologies and developments in maritime engineering education
- Case studies
- Simulation, multimedia and the Internet in engineering education
- Innovation and alternatives in engineering education
- Specific engineering education programmes
- New trends and approaches to engineering education
- Quality issues and improvements in engineering education

It should be noted that all of the papers published in this volume were subject to a formal peer review process, as is the case with all UICEE publications. It is envisaged that these Proceedings will contribute to the international debate in engineering education and will become a source of information and reference on research and development in engineering education.