

internal combustion engines; artificial neural networks; diagnostics

**Piotr CZECH\***, **Henryk BĄKOWSKI**

Silesian University of Technology, Faculty of Transport  
Krasinskiego 8, 40-019 Katowice, Poland

\*Corresponding author. E-mail: [piotr.czech@polsl.pl](mailto:piotr.czech@polsl.pl)

## DIAGNOSING OF CAR ENGINE FUEL INJECTORS DAMAGE USING DWT ANALYSIS AND PNN NEURAL NETWORKS

**Summary.** In many research centers all over the world nowadays works are being carried out aimed at compiling method for diagnosis machines technical condition. Special meaning have non-invasive methods including methods using vibroacoustic phenomena. In this article is proposed using DWT analysis and energy or entropy, which are a base for diagnostic system of fuel injectors damage in car combustion engine. There were conducted researches aimed at building of diagnostic system using PNN neural networks.

## DIAGNOZOWANIE USZKODZEŃ WTRYSKIWACZY W SILNIKACH SPALINOWYCH POJAZDÓW PRZY UŻYCIU ANALIZY DWT I SIECI NEURONOWYCH PNN

**Streszczenie.** W wielu ośrodkach naukowych na całym świecie trwają obecnie prace mające na celu opracowanie metod diagnozowania stanu technicznego maszyn. Szczególnego znaczenia nabierają metody nieinwazyjne, do których należą metody wykorzystujące zjawiska wibroakustyczne. W artykule zaproponowano wykorzystanie analizy DWT oraz energii lub entropii będących podstawą systemu diagnozującego występującą niesprawność wtryskiwaczy w silniku spalinowym samochodu. Przeprowadzono badania mające na celu budowę systemu diagnostycznego wykorzystującego sieci neuronowe typu PNN.

### 1. INTRODUCTION

As reported in literature for automotive services, many symptoms incorrect engine working is a result of bad injection system condition.

In workshop practice the most frequent symptoms are:

- unstable work at slow running,
- increased toxic components emission in exhaust,
- lower power of an engine,
- bad work of catalytic converter system and lambda probe,
- difficult start
- failure indication by MIL lamp.

Process of injection obstruction is an effect of sediment commutation, which are formed during burning process or it enters into the fuel during its production, storage, transport, distribution or use.

Besides injectors obstruction, sediments effects unfavourably causing abrasion and erosion usage of cooperating surfaces of an injection needle, an injection sprayer and eyelets of sprayer ending.

Workshop literature reports that injector fault occurrence causes:

- lower fuel outflow,
- changed shape of fuel stream,
- changed size of sprayed fuel drops,
- less engine performances,
- smaller fuel consumption,
- smaller vitality of lambda probe and catalytic converter system,
- increase of toxic components in exhaust,
- increase of exploitation costs,
- incorrect working of whole fuel injection system.

## 2. DESCRIPTION OF EXPERIMENT

The aim of the experiment was to detect damages in fuel inlets of internal combustion engine with the use of vibrations, which accompany it.

Object of researches was an internal combustion engine with spark ignition on 1,6 dm<sup>3</sup> capacity in Ford Focus.

Signals of engine head vibration were registered in the points near:

- intake valve 1<sup>st</sup> cylinder,
- exhaust valve 1<sup>st</sup> cylinder,
- exhaust valve 4<sup>th</sup> cylinder,
- gearbox.

Measurement were taken for:

- 3<sup>rd</sup> gear,
- 4<sup>th</sup> gear,
- 5<sup>th</sup> gear,

in three engine speed:

- 2000 rpm,
- 3000 rpm,
- 4000 rpm.

Each measurement was executed in two series, for efficient injector and injector with simulated damage.

A simultaneous analysis of the time and frequency related properties of signals by means of a wavelet transform are more and more frequently used in diagnosing combustion engines.

A wavelet analysis consists in signal decomposition and its presentation as a linear combination of the base functions known as wavelets. The features distinguishing this method of signal analysis from other methods are multilevel signal decomposition, variable resolution in time and frequency domains and the possibility of using base functions other than harmonic functions.

The discrete wavelet transform of a signal  $x(t)$  is determined as scalar products  $x(t)$  and a sequence of a base function  $\psi(t)$ :

$$DWT = \int_{-\infty}^{+\infty} \psi(t) \cdot x(t) dt . \quad (1)$$

The original signal  $x(t)$  passes through two complementary filters and emerges as low frequency (approximations signals  $A(t)$ ), and high frequency (details signals  $D(t)$ ). The decomposition process can be iterated, with successive approximations being decomposed in turn, such that a signal can be broken down into many lower-resolution components.

The signal  $x(t)$  can be represented by:

$$x(t) = A_n(t) + \sum_{l=1}^n D_l(t). \quad (2)$$

As the signal decomposition level increases, the share of details decreases, the result of which is a situation where a reduced resolution is accompanied by a reduced content of details in the signal approximation.

In the conducted experiments, the signals of vibration accelerations underwent decomposition at one to ten levels.

In order to describe the character of changes in decomposed vibroacoustic signal, with the use of wavelet analysis, two methods of conduct were chosen. First assumes the use of signal entropy as a measure which characterizes changes in signal  $x_j(t)$ . It can be calculated with the use of dependence:

$$E_{Sh} = - \sum_j x_j^2(t) \cdot \log(x_j^2(t)). \quad (3)$$

Second method of conduct assumes the use of signal energy to describe the changes occurring in vibroacoustic signal. It was assumed here, that according to a definition of discrete wavelet transform, the total energy of signal before decomposition is equal to the sum of approximation energy and further details. Total energy of signal after decomposition on defined number of levels was assumed as 100% and calculated which percentage of that energy is approximation signal and further details.

In the process of building the models it was essential to determine on how many levels the basic signal will be arranged and what basic wavelet will be used. The usefulness of 52 basic wavelets was checked in the tests. The wavelets from the following families were used: biorthogonal, coiflets, daubechies, discrete meyer, haar, reverse biorthogonal, symlets.

On the basis of such assumed two methods of conduct, two types of models used in the process of teaching and testing neural networks were applied.

In the experiment 720 pattern sets ("4 places of vibration" x "3 gears" x "3 speed" x "energy or entropy" x "10 decomposition levels") were created.

### 3. RESEARCH RESULTS

In reached researches decided to check usefulness of artificial neural network for diagnosing technical condition fuel injection system of combustion engine.

Input data for neural network constituted patterns build at information deriving from vibratory signals measured in different points of combustion engine and on a gear. Using signals measured in different measuring places aimed showing its influence on diagnostic results.

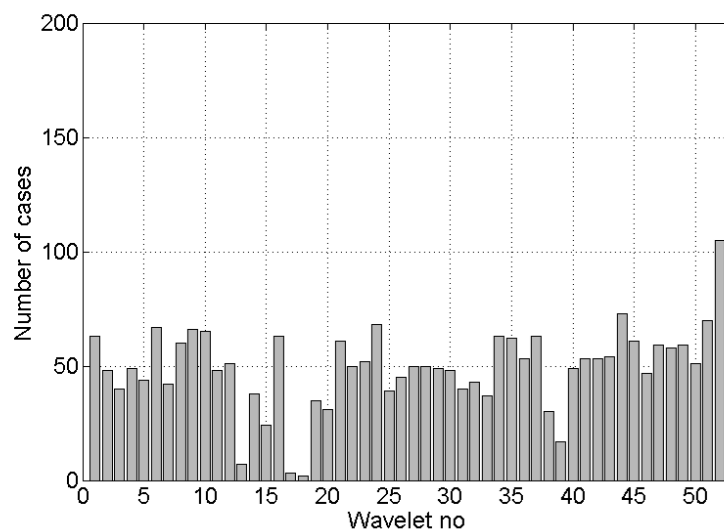
In this experiment probabilistic neural networks (PNN) were used [2, 9, 12, 13]. In conducted tests explored an influence of  $\gamma$  factor on test error. Experiments were conducted for 86 values of coefficient  $\gamma$ .

In order to check the possibilities of application of PNN neural networks to diagnose the damage of fuel injectors in car engine, a series of classifiers were built and tested to check their functioning. They were taught on data coming from vibroacoustic signals registered in a specific way (out of 4 ways), for engine working on one gear (out of 3 gears), with given speed (out of 3 speeds). Each of them was tested for models using energy or entropy of signal arranged in 10 different versions of the number of

decomposition levels. In total, the functioning of 720 versions of classifiers were tested, and each of them was tested for various parameters of coefficient  $\gamma$ .

In order to determine the best basic wavelet to build descriptors, such achieved arrangement of the number of cases was used, in which, with the use of given basic wavelet, the classifiers were characterised with the minimum error value. The best wavelet would be this one for which the number of cases was 360 (4 places of vibroacoustic signals measurement times 3 gears times 3 engine rotation speeds for which the signals were registered times 10 signal decomposition levels). It would equal to a situation where independently from the method of signal measurement and chosen number of decomposition levels used to build models, classifier would show minimum error with the use of given basic wavelet. In the experiment, however, such situation did not occur. The number of cases for which, with the use of given wavelet in the process of model building, the classifier reached minimum value is shown in figure 1.

a)



b)

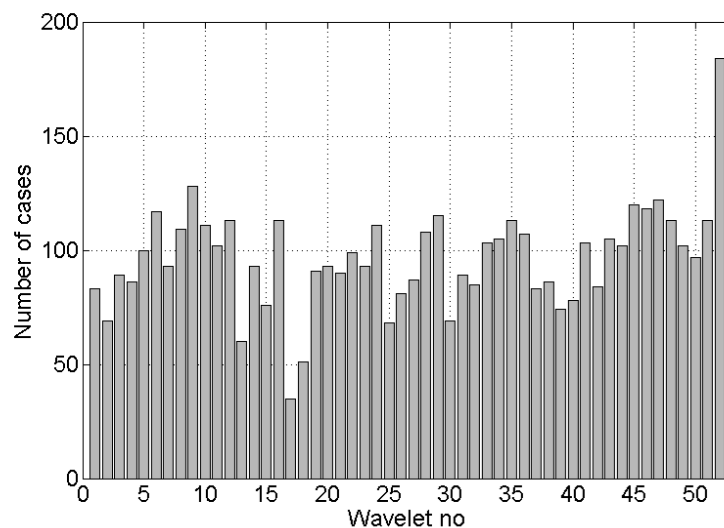


Fig. 1. Arrangements of number of cases in which the classification errors were minimum – models: energy (a), entropy (b)

Rys. 1. Rozkłady liczby przypadków, dla których błędy klasyfikacji były minimalne – modele: energia (a), entropia (b)

Depend on used building patterns variant, utility of relevant base wavelet was different. At the base on none wavelet it was possible to create pattern sets for which classifiers could always reach minima terror values.

Definitely the best choice is the wavelet under the name dmey. For this wavelet the created models allowed classifiers to reach the lowest error values independently from chosen option connected with the method of signal registration, method of initial signal processing or working parameters of tested object.

The worst choice were the wavelets: bior2.2, bior3.1 and bior3.3. For these cases the classifiers reached maximum errors.

In each cases if analysed options of PNN classifiers it was very important to choose the right value of coefficient  $\gamma$ . The example of obtained results, the dependence of coefficient  $\gamma$ 's influence on the classification error value are presented in figure 2.

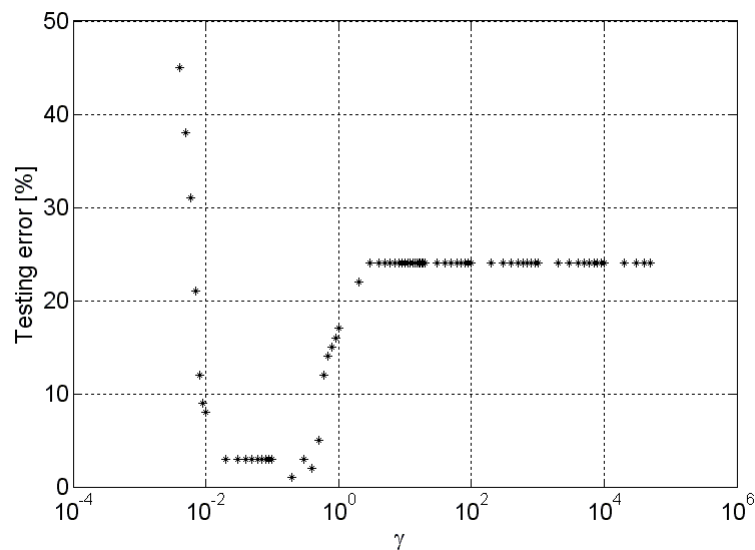


Fig. 2. Example of influence of parameter  $\gamma$  value on the error value

Rys. 2. Przykładowy wpływ parametru  $\gamma$  na wartość błędu

#### 4. CONCLUSIONS

World literature presents huge involvement of world of science by problems regarding different factors monitoring connected with machines operation [1-8, 10, 11, 14]. The vehicles of today are full of most modern systems, which serve to increase safety and comfort and reduce the negative impact on the environment. Development of branches connected with most modern technologies does not limit the conduction of basic research works which leads to similar measurable effects such as increase of safety by increase of the durability of the power transmission system elements.

Nowadays car condition diagnosis processes are mainly made in diagnostic and repair station and in the vehicle inspection station. New generation of diagnosis equipment, computerized diagnosis lines and obligation to install OBD on-board diagnosis system gives ability to use latest technologies to determine the technical condition of car combustion engines elements. The perfect solution could be measuring device which would measure some symptoms answering the question about occurring damage or using in vehicle whole complex self-diagnosis system which could diagnose engine individual elements.

The main idea in conducted researches is ability to expand used OBD system with diagnosis system using vibroacoustic signals. Because vibration signals were registered in actual car ride conditions it is no doubt that ability of practical using proposed way of diagnosis.

Presented results are preliminary study connected with ability to use vibroacoustic signals and neural networks to describe technical condition of car combustion engine. There are conducted researches connected with diagnosis other elements of different car combustion engines. Reached results permit to reduce number of needful experiments, which are necessary during building properly working diagnosis system based on neural networks and vibroacoustic signals. It is possible because of limiting the number of patterns sets – after choosing the best way of preliminary signals processing (also the choice of base wavelets) and number tested neural networks – after choosing range tested values for  $\gamma$  factors.

The studies have proven that it is possible to build a correctly working neuron classifier capable of recognizing different conditions of engine work, including those connected with car engine fuel injectors damage.

The descriptors calculated on the basis of the vibration acceleration signal registered on the engine were proposed to serve as the source of information on the engine condition. The results have corroborated effectiveness of using the entropy and energy, acquired from wavelet decomposition, as the base for building models of engine operation.

The use of a PNN neural network with a correctly selected value of coefficient  $\gamma$  enables obtaining a faultless classification.

The conducted experiments allowed constructing a faultlessly working neuron classifier.

## Bibliography

1. Bartelmus, W. & Zimroz, R. A new feature for monitoring the condition of gearboxes in nonstationary operating conditions. *Mechanical Systems and Signal Processing*. 2009. Vol. 23. P. 1528-1534.
2. Czech, P. & Łazarz, B. & Wojnar, G. *Detection of local defects of gear teeth using artificial neural networks and genetic algorithms*. Radom: ITE. 2007.
3. Czech, P. & Madej, H. Application of cepstrum and spectrum histograms of vibration engine body for setting up the clearance model of the piston-cylinder assembly for RBF neural classifier. *Eksploatacja i Niezawodność – Maintenance And Reliability*. 2011. No 4. P. 15-20.
4. Figlus, T. Diagnosing the engine valve clearance, on the basis of the energy changes of the vibratory signal. *Maintenance Problems*. 2009. Vol. 1. P. 75-84.
5. Grega, R. & Homišin, J. & Kaššay, P. & Krajňák, J. The analyse of vibrations after changing shaft coupling in drive belt conveyer. *Zeszyty Naukowe. Transport*. Gliwice: Politechnika Śląska. 2011. Z. 72. P. 23-31.
6. Komorska, I. Adaptive model of engine vibration signal for diagnostics of mechanical defects. *Mechanika*. 2013. Vol. 19 (3). P. 301-305.
7. Liu, B. Selection of wavelet packet basis for rotating machinery fault diagnosis. *Journal of Sound and Vibration*. 2005. Vol. 284. P. 567-582.
8. Madej, H. & Czech, P. Discrete wavelet transform and probabilistic neural network in IC engine fault diagnosis. *Eksploatacja i Niezawodność – Maintenance And Reliability*. 2010. No 4. P. 47-54.
9. Osowski, St. *Neural networks for information processing*. Warsaw: Oficyna Wydawnicza Politechniki Warszawskiej. 2000.
10. Peng, Z. & Chu, F. Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography. *Mechanical Systems and Signal Processing*. 2004. Vol. 18. P. 199-221.
11. Puškár, M. & Bigoš, P. & Puškárová, P. Accurate measurements of output characteristics and detonations of motorbike high-speed racing engine and their optimization at actual atmospheric conditions and combusted mixture composition. *Measurement*. 2012. Vol. 45. P. 1067-1076.

12. Tadeusiewicz, R. & Lula, P. *Introduction to neural networks*. Krakow: StatSoft. 2001.
13. Yu Hen Hu & Jenq-Neng Hwang *Handbook of neural network signal processing*. USA: CRC PRESS. 2002.
14. Zuber, N. & Ličen, H. & Klašnja-Miličević, A. Remote online condition monitoring of the bucket wheel excavator SR1300 – a case study. *Facta Universitatis. Series: Working and Living Environmental Protection*. 2008. Vol. 1 (5). P. 25-37.

Received 13.07.2012; accepted in revised form 27.08.2013