DIAGNOSING OF DISTURBANCES IN THE FUEL INFLOW TO CYLINDERS BY VIBROACOUSTIC SIGNALS AND SVM NEURAL NETWORKS

Czech P. PhD.
Faculty of Transport – Silesian University of Technology, Poland

Abstract: *Diagnostic systems used in modern combustion engines are intended for indicating the location of a component or system which can no longer perform its function assigned by the manufacturer, owing to its ordinary wear or damage. Increasing requirements regarding durability and reliability of combustion engines as well as cost minimization and unfavourable effect on the environment, make it necessary to acquire information on the condition of the engine during its operation. Introduction of the obligation of manufacturing motor vehicles compliant with the OBDII standard resulted in the possibility of accessing data stored in the drivers of individual systems. Owing to this solution, new possibilities of diagnosing the technical condition of those systems arise. An important issue in vibroacoustic examination of engines is a correct interpretation of complex measured signals by applying more and more proficient methods of their processing. The main tasks in diagnostics include: separation of a useful vibroacoustic signal and selection of characteristic, damage-sensitive features of the processed signal.At present, failure symptoms found in the signal, are more and more often studied with the aid of artificial intelligence methods. The major issue referred to in the literature related to methods of artificial intelligence is the method for creating data used in the process of neural network operations. The ability to set up models is the guarantee for a successful classifying process using neural networks.The paper presents an attempt of detecting lack of fuel inflow to a cylinder by measuring the engine block accelerations and noise based on these, building patterns for artificial neural networks.*

Keywords: DIAGNOSTIC SYSTEM, ENGINE, ARTIFICIAL NEURAL NETWORKS

1. Introduction

In modern internal combustion engines all the processes connected with charge exchange, the combustion, purification of fumes, are steered electronically by the steering unit [3]. Moreover, each steering unit is supplied with on-board diagnostic system OBD which continuously performs self-diagnosis of a given steering system. When any defect in any electronic part of the system appears, the system signalises it to the driver by switching on a light on the dashboard and often, additionally, by limiting the power of the engine. In order to diagnose the reason of the defect one should use the diagnostic tester and read the error codes saved in the memory of the controller and remove the reason of the defect. OBD systems made the work of the people diagnosing the vehicle much easier, because they show with high precision which element of the system is defected [4].

However, there are some defects in the engines of vehicles, which cannot be found by the OBD systems and which are sometimes harder to find, due to the existence of an OBD system and their ability to conceal their presence [2]. It is connected with mechanical defects of the driving unit. In such cases the OBD system does not register the defect, or registers only the defect which is the result of the wear of the given part. In the worst of cases, the steering system will not register the defect, due to its adaptive algorithms, but will try to level the work of the engine by camouflaging its mechanical defect. Such defect will become visible only when the adaptive system will no longer be able to camouflage the given worn part. If such a situation occurs, the engine usually requires expensive repairs.

In order to prevent such situations the modern OBD systems should be equipped with a part, which could diagnose the mechanical defects of the engine at an early stage and which could show it. According to preliminary research one could use vibroacoustic symptoms in such case [6].

The engine, as a complex unit, emits vibrations and acoustic signals. With modern development of digital technology such signal can be registered and, on its basis, one could determine the level of wear of the elements of driving unit and at the same time diagnose which part got defected.

An important issue in vibroacoustic examination of engines is a correct interpretation of complex measured signals by applying more and more proficient methods of their processing [10]. The main tasks in diagnostics include: separation of a useful vibroacoustic signal and selection of characteristic, damage-sensitive features of the processed signal [5].

The paper presents an attempt of detecting lack of fuel inflow to a cylinder by measuring the engine block accelerations, noise and based on these, building patterns for SVM artificial neural networks.

2. The description of the conducted tests

The main purpose of the research was to determine the effect of the lack of fuel inflow to individual cylinders on the vibration signal characteristics. Different states of engine operation were simulated as part of the studies, i.e.:
- fully operational engine;
- cylinder no. 1 off;
- cylinder no. 2 off;
- cylinder no. 3 off;
- cylinder no. 4 off;
- pair of cylinders no. 1 and no. 4 off;
- pair of cylinders no. 2 and no. 3 off.

The object of the tests was a four-cylinder, four-cycle engine of a Volkswagen Polo car with swept capacity 1.0 dm^3 with magneto ignition, adjusted to alternative power supply with the use of LPG gas fuel.

Before the tests began, the engine had been adjusted to them in the following way:
- the air filter had been dismantled and the air-escape of the crankcase of the engine had been led to the outside of the vehicle;
- for the test period the ventilation of the cooler had been switched off so that the noise of the working ventilator had not interrupted the measurement;
- a sensor of angular orientation of the crankshaft had been fixed with a spare wheel adjusted to cooperate with it. It enabled to mark the top centre (TC) for the first and fourth piston and to register the angular position of the crankshaft;
- an optic-electronic sensor of the angular position of the distribution shaft was mounted in order to mark the TC of the first piston;
- a microphone was placed in the mounting created on the bonnet of the vehicle;
- sensors of vibrations of engine body acceleration were placed as follows: sensor of axial vibrations was placed in 1/3 of the height of the cylinder liner of the first cylinder in the front of the engine, sensor of perpendicular vibrations was placed in 1/3 of the height of the cylinder liner of the first cylinder in the back of the engine.

The tested object was an internal combustion engine built into the car. The measuring equipment used in testing consisted of:
- a PC computer with data acquisition card NI PXI 4472B;
- two piezoelectric converters (vibration sensors);
- Norsonic signal analyser with a capacitor microphone;
- optoelectronic sensor of angular position of distribution shaft;
- sensor of angular position of crankshaft.

The following data was collected during the tests:
- angular position of crankshaft;
- position of distribution shaft;
- acceleration of the vibrations of the engine body in axial direction;
- acceleration of the engine body in perpendicular direction;
- acoustic pressure.

Signals were registered with the frequency of sampling of 50 kHz.

Tests were conducted for the following rotational speeds of the engine:
- 850 rotations/min (idle run);
- 2400 rotations/min;
- 2850 rotations/min.

Experiments were conducted for an engine powered with petrol and LPG gas.

Examples of registered signals are presented in fig.1, 2 and 3.

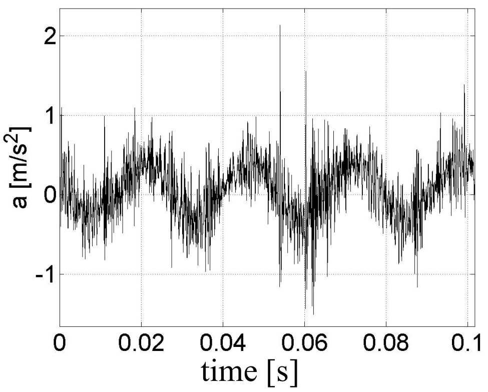

Fig. 1 *Vibrations in perpendicular direction (n=850 rotations/min, petrol, no damage).*

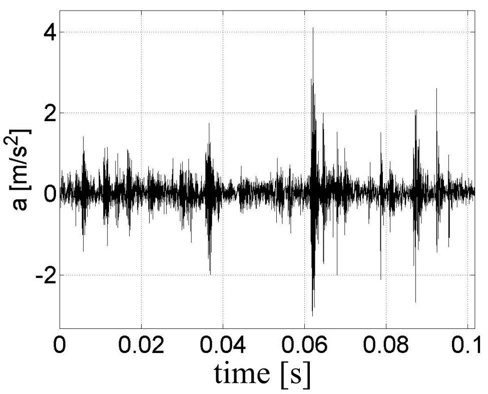

Fig. 2 *Vibrations in axial direction (n=850 rotations/min, petrol, no damage).*

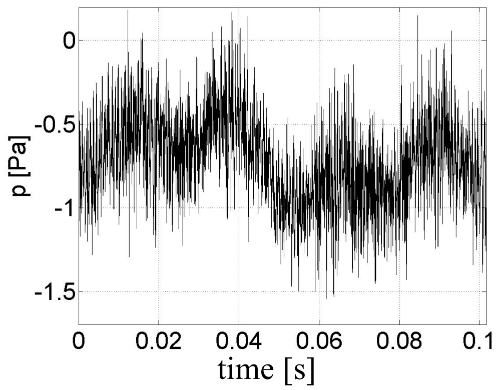

Fig. 3 *Acoustic pressure (n=850 rotations/min, petrol, no damage).*

Registered signals were subjected to processing with the use of software Matlab – Simulink.

3. Neural classifier SVM

Rapid and multi-directional development of diagnostics methodology in the recent years, have resulted in creation of new methods used in the failure localisation systems and for assessing object condition of items [5]. Application of the artificial intelligence in diagnosing equipment condition has become an object of general interest [5,6]. One of the methods belonging to that group are artificial neural networks, which find their application in a growing number of fields. Neural networks are among the sophisticated modelling techniques, capable of mapping particularly complex functions, including a large number of independent variables [7-9,11].

Artificial neural network comprises components linked with each other, known as neurons. Operating principle of individual neurons in artificial neural networks copies the performance of a biological neural cell.

The operating principle of artificial neural networks is based on exacting the knowledge network has been furnished with in the teaching process. Taught artificial neural network uses its knowledge based on associations, as this similarly takes place in a human brain.

Available reference literature describes numerous types of artificial neural networks [7-9,11]. The neural network structures can be divided according to types of problems solved.

The following tasks are performed:
- classifying - division into categories, according to criteria,
- clustering - no-pattern classification,
- approximation - regressive tasks,
- prognosis making - predicting future phenomena based on retrospective data.

In terms of teaching methods the artificial neural networks are divided into self-organizing (taught without a teacher) and taught with the teacher. The principle involving teaching with teacher is based on the fact, that during the teaching process, the network – aside from the input data (symptoms) – is shown its output status. The teaching process, in this case, is based on minimisation of the discrepancy between output value obtained from the network, and the expected value.

According to data flow arrangement, the neural networks can be divided into the unidirectional and feedback (recuperative) types. In unidirectional networks, information flows from its inputs to outputs, whereas in the feedback network, the output status of neurons can be a source of input data delivered to the previous network layers.

One of the artificial neural network types is the SVM (Support Vector Machine) network [7,9,11]. This network is used with the unidirectional networks. Such networks are usually of two-layer structure and are composed of the hidden and output layers.

For this type of network, the following can be assumed as the activating function of *φ(x)* neurons:
- linear function,
- polynomial function,
- radial function,
- sigma function.

For the experiment carried out, the radial function was assumed as the activating function.

The teaching method of the SVM network involves square programming, which maximises the separation margin between classes. Such must be taught by the teacher [7,9,11].

The following strategies fall within the range of teaching algorithms of such networks: "one against all", "one against one" and their combinations.

The issue of classification of patterns which are not linearly separable, consists in determining such optimal hyperplane, which will minimise the probability of classification error occurrence in the teaching set, with possibly widest separation margin.

The teaching process, and consequently the error extent in the SVM network with radial kernel, are controlled by the following coefficients:
- teaching error margin width and ε network testing coefficient,
- C parameter,
- γ values.

The margin width of the e error, determines the admissible deviation, for which the results of a lower deviation are not considered as an error. Complexity of the SVM network is controlled by the C parameter. It determines the priority of considering testing errors, in relation to a determined separation margin.

The gamma parameter for the radial nucleus function is obtained from the following dependency: $\gamma = \frac{1}{\sigma^2}$.

Optimisation of the SVM network can be carried out as follows:
- by optimising all network parameters at the same time (ε, C, γ),
- by assuming a constant level of the error tolerance coefficient while optimising the remaining network parameters (C, γ),
- by assuming the C and γ coefficient and optimising the tolerance coefficient.

In the present paper optimisation of the C and γ coefficients, for the assumed error tolerance coefficient ε, have been assumed.

Input data for artificial neural networks were 22 measurements marked out of registered signals in time domain *x(t)*. On the basis of registered signals of vibration accelerations of engine body in axial and perpendicular direction and of acoustic pressure the following diagnostic amplitude measurements were marked [1,5]:
- maximum value:

$$x_{\max} = \max_{0<t<T}\left(x(t)\right)$$

- minimum value:

$$x_{\min} = \min_{0<t<T}\left(x(t)\right)$$

- peak to peak value:

$$x_{p-p} = \frac{1}{2}\left(\max_{0<t<T}\left(x(t)\right) - \min_{0<t<T}\left(x(t)\right)\right)$$

- signal energy:

$$x_e = \frac{1}{T}\int_0^T x^2(t)dt$$

- quartile 1: q_1
- quartile 2 (median): q_2
- quartile 3: q_3
- effective value:

$$x_{RMS} = \sqrt{\frac{1}{T}\int_0^T x^2(t)dt}$$

- variance:

$$\sigma_{std}^2 = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2$$

- mean value:

$$\bar{x} = \frac{1}{T}\int_0^T x(t)dt$$

- geometric mean:

$$\bar{x}_{geo} = \left(\prod_{i=1}^{N} x_i\right)^{\frac{1}{N}}$$

- harmonic mean:

$$\bar{x}_{har} = \frac{N}{\sum_{i=1}^{N}\frac{1}{x_i}}$$

- quarter deviation:

$$\sigma_{qd} = \frac{1}{2}\left(q_3 - q_1\right)$$

- average deviation:

$$\sigma_{ad} = \frac{1}{N}\sum_{i=1}^{N}\left|x_i - \bar{x}\right|$$

- positional variability coefficient:

$$PVC = 100\left(\frac{\sigma_{qd}}{q_2}\right)$$

- variability coefficient:

$$VC = 100\left(\frac{\sqrt{\sigma_{std}^2}}{\bar{x}}\right)$$

- peak coefficient:

$$PC = \frac{x_{p-p}}{x_{RMS}}$$

- backlash coefficient:

$$BC = \frac{x_{P-P}}{\left(\frac{1}{T}\int_0^T \sqrt{|x(t)|}dt\right)^2}$$

- shape coefficient:

$$SC = \frac{x_{RMS}}{\frac{1}{T}\int_0^T |x(t)|dt}$$

- impulse coefficient:

$$IC = \frac{x_{P-P}}{\frac{1}{T}\int_0^T |x(t)|dt}$$

- asymmetry coefficient:

$$AC = \frac{\frac{1}{T}\int_0^T \left(x(t) - \bar{x}\right)^3 dt}{\left(\sqrt{\frac{1}{T}\int_0^T \left(x(t) - \bar{x}\right)^2 dt}\right)^3}$$

- kurtosis:

$$K = \frac{\frac{1}{T}\int_0^T (x(t)-\bar{x})^4 dt}{\left(\sqrt{\frac{1}{T}\int_0^T (x(t)-\bar{x})^2 dt}\right)^4}$$

where: N – number of samples.

Quartiles, also called percentiles, characterise the measurable value, which divides the ordered set of all values into 25% and 75% - quartile 1; and 75% and 25% – quartile 3. Quartile 2 (median) defines the value above and below which the same number of observations is to be found.

The example of the influence of the occurring defect on the value of the marked measurement is shown in fig. 4, 5 and 6.

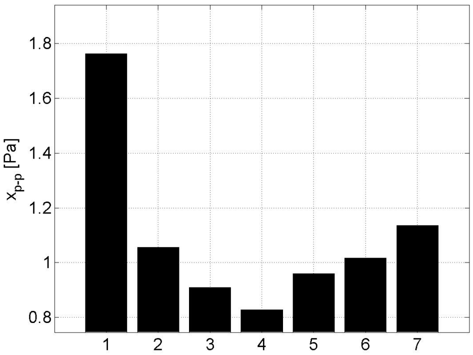

Fig. 4 *Peak to peak value (n=850 rotations/min, petrol, microphone).*

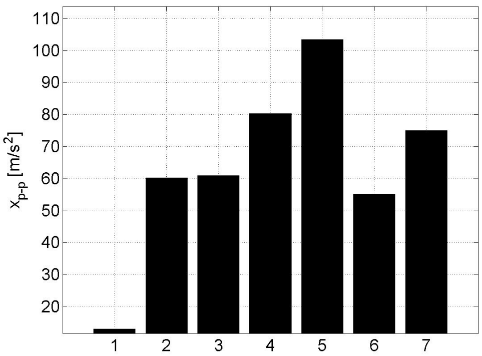

Fig. 5 *Peak to peak value (n=850 rotations/min, petrol, vibrations acceleration – axial direction).*

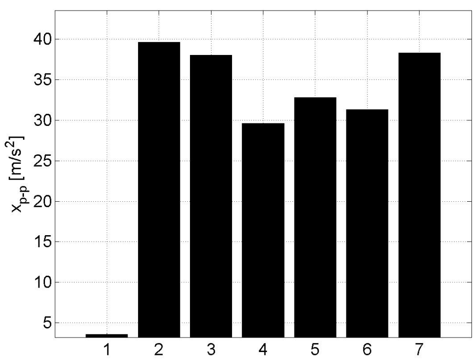

Fig. 6 *Peak to peak value (n=850 rotations/min, petrol, vibrations acceleration – perpendicular direction).*

The neural classifiers SVM used in the experiments have seven output neurons. Each output of the network had a task, which was to show one particular state of the engine (no damage or one of six simulated damages).

4. The results of conducted experiments

In the first experiment, it was decided to construct a neural classifier which would determine one out of seven states of the internal combustion engine and would work independently from the rotational speed of the engine and the type of powering. Teaching data and testing data were the marked measurements from time signals registered by vibration sensors (axial and perpendicular direction) and microphone by four rotational speeds of the engine and two methods of powering (petrol and LPG). Table 1 shows the results of the experiment.

Table 1: *The best achieved results for neural classifiers of SVM type – experiment 1.*

	Microphone	Vibrations in axial direction	Vibrations in perpendicular direction
coefficient C	5	5	-
γ parameter	3	30	-
the lowest test error value [%]	53,7	22,8	-

For data coming from vibration signals registered in perpendicular direction to the axis of the cylinder of the internal combustion engine it was impossible to finish the experiment.

Due to the fact that the gathered results were unsatisfactory, it was decided to try to build two independent neural classifiers working on data registered for one type of fuel (either petrol or gas). It was assumed that the system diagnosing engine condition will be independent from the rotational speed of the engine. That is why the input data were the measurements marked from the signals registered by different rotational speeds of the engine. The results of the experiment are presented in table 2.

Table 2: *The best achieved results for neural classifiers of SVM type – experiment 2.*

	Microphone	Vibrations in axial direction	Vibrations in perpendicular direction
coefficient C	0,05	0,05	-
γ parameter	3000	3000	-
type of power	petrol	petrol	petrol
the lowest test error value [%]	57,0	26,8	-
coefficient C	0,05	0,05	-
γ parameter	3000	3000	-
type of power	LPG	LPG	LPG
the lowest test error value [%]	49,5	23,8	-

Also in this case the satisfactory results were not achieved and the experiments were not completed for classifiers built on the basis of data coming from vibration signals in perpendicular direction to the axis of the cylinder.

The next conducted experiment was performed in order to check, if the construction of a properly working neural classifier identifying the states of the internal combustion engine is possible, when the engine works on one particular rotational speed and is powered by one type of fuel. The achieved results are presented in table 3, 4 and 5.

Table 3: *The best achieved results for neural classifiers of SVM type – experiment 3 (n=850 rotations/min).*

	Microphone	Vibrations in axial direction	Vibrations in perpendicular direction
coefficient C	0,05	0,05	-
γ parameter	30000	3000	-
type of power	petrol	petrol	petrol
the lowest test error value [%]	10,6	1,3	-
coefficient C	0,05	0,05	-
γ parameter	30000	3000	-
type of power	LPG	LPG	LPG
the lowest test error value [%]	3,0	1,7	-

Table 4: *The best achieved results for neural classifiers of SVM type – experiment 3 (n=2400 rotations/min).*

	Microphone	Vibrations in axial direction	Vibrations in perpendicular direction
coefficient C	0,05	0,05	-
γ parameter	30000	3000	-
type of power	petrol	petrol	petrol
the lowest test error value [%]	26,8	5,3	-
coefficient C	0,5	0,05	-
γ parameter	300	3000	-
type of power	LPG	LPG	LPG
the lowest test error value [%]	31,1	6,3	-

Table 5: *The best achieved results for neural classifiers of SVM type – experiment 3 (n=2850 rotations/min).*

	Microphone	Vibrations in axial direction	Vibrations in perpendicular direction
coefficient C	0,05	0,05	0,05
γ parameter	3000	30000	3000
type of power	petrol	petrol	petrol
the lowest test error value [%]	23,1	9,5	25,6
coefficient C	0,05	0,05	-
γ parameter	30000	30000	-
type of power	LPG	LPG	LPG
the lowest test error value [%]	19,0	3,8	-

Empty spaces in the results table mean that it was impossible to finish a planned experiment with given input parameters (engine rotational speed, type of fuel).

The results, achieved during the tests, show that far better results can be achieved for a neural classifier designed for clearly specified point of the internal combustion engine work and not for the diagnosis of the engine condition independently from the parameters of its work.

5. Conclusion

The smallest classification error occurred in case of neural networks of type SVM, which were taught and tested on data coming from vibration signals registered on the engine body in axial direction.

On the basis of the achieved results the best values of coefficients C and γ, which would enable the achievement of the lowest error values of classification for designed neural classifiers type SVM, cannot be marked no matter the input parameters connected with work of internal combustion engine. Achieved results show the necessity of checking the functioning of SVM neural networks by different values of parameters C and γ.

Conducted experiments show the necessity of the use of data achieved as a result of more complex algorithms in the process of neural networks teaching. It is then necessary to conduct more experiments in order to check the analysis of type DWT, WPT, EMD etc. for the initial processing of signals and in order to achieve the models of classes of internal combustion engine damages on their basis.

At the same time, the gathered results show that construction of diagnosing system which consists of a few classifiers designed to work with data coming from particular states of internal combustion engine (set rotational speed and way of powering) is a better idea than construction of one neural classifier which should diagnose particular states of engine without the knowledge of its working parameters.

Acknowledgement

The hereby scientific study was financed with funds of Polish State Committee for Scientific Research in years 2010 – 2013 as a research project.

References

1. CEMPEL C.: *Vibro-accoustic diagnostics of machines*, Panstwowe Wydawnictwo Naukowe, Warsaw 1989.
2. DABROWSKI Z., MADEJ H.: *Masking mechanical damages in the modern control systems of combustion engines*, Journal of KONES, Vol. 13, No 3/2006.
3. HEYWOOD J. B.: *Internal combustion engines fundamentals*, McGraw Hill Inc 1988.
4. ISERMANN R.: *Diagnosis methods for electronic controlled vehicles*, Vehicle System Dynamics, Vol. 36, No. 2-3.
5. KORBICZ J., KOSCIELNY J., KOWALCZUK Z., CHOLEWA W.: *Diagnostics of processes. Models. Artificial intelligence methods. Applications*, Wydawnictwo Naukowo-Techniczne, Warsaw 2002.
6. MADEJ H., CZECH P.: *Discrete wavelet transform and probabilistic neural network in IC engine fault diagnosis*, Eksploatacja i Niezawodnosc – Maintenance And Reliability, No 4(48)/2010.
7. OSOWSKI S.: *Neural networks for information processing*, Oficyna Wydawnicza Politechniki Warszawskiej, Warsaw 2000.
8. TADEUSIEWICZ R.: *Neural networks*, Akademicka Oficyna Wydawnicza, Warszawa 1993.
9. TADEUSIEWICZ R., LULA P.: *Introductin to neural networks*, StatSoft, Krakow 2001.
10. YANG W. X.: *Establishment of the mathematical model for diagnosing the engine valve faults by genetic programming*, Journal of Sound and Vibration, 293 (2006).
11. YU HEN HU, JENQ-NENG HWANG: *Handbook of neural network signal processing*, CRC PRESS, USA, 2002.