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Diagnosing disturbances in the fuel inflow to cylinders with the use of DWT analysis and PNN neural networks

K e y w o r d s

Diagnostics, combustion engines, artificial neural networks, vibration.

S ł o w a k l u c z o w e

Diagnostyka, silniki spalinowe, sztuczne sieci neuronowe, drgania.

S u m m a r y

The article presents an attempt at evaluating the state of engine operation under a simulated shortage of fuel inflow to individual cylinders. The object of research was a four-cylinder 1.2 dm^3 capacity combustion engine. The vibration acceleration signals registered on the engine block ZI were assumed the source of information on the engine condition.

In case of diagnosing combustion engines by vibration methods, the presence of numerous sources of vibration cannot be neglected, which is the reason for reciprocal interference of symptoms of fault. Owing to the necessity of analysing non-stationary and impulse signals, a discrete wavelet transform (DWT) has been applied in this study. Based on the signals' decomposition performed by means of the transform, the value of entropy was determined, which served as a basis in the construction of the states of engine operation intended for teaching neural networks. As research results suggest, there is the possibility of using probabilistic artificial neural networks to assess the process of fuel inflow to cylinders.

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1. Introduction

Diagnostic systems used in modern combustion engines are intended for indicating the location of a component or system which can no longer perform the function assigned by the manufacturer, due to its ordinary wear or damage.

Increasing requirements regarding durability and reliability of combustion engines as well as cost minimisation and an unfavourable effect on the environment make it necessary to acquire information on the condition of the engine during its operation. The 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. Due to this solution, new possibilities present themselves for diagnosing the technical condition of those systems [12].

An important issue in vibroacoustic examination of engines is a correct interpretation of complex measured signals by applying more and more proficient methods of data processing [1, 5, 9, 14, 16]. The main tasks in diagnostics include the separation of a useful vibroacoustic signal and the selection of characteristic damage-sensitive features of the processed signal.

The paper presents an attempt at detecting a lack of fuel inflow to a cylinder by measuring the engine block accelerations and to use them to build patterns for artificial probabilistic neural networks.

2. Method of building models illustrating the lack of fuel inflow to cylinders

One of the methods of acquiring diagnostic information is to measure the vibration generated by the engine. A combustion engine is subject to the action of inner and outer forces. They encompass mainly the following:

- Combustion pressure;
- Movement of the crank-piston system;
- Forces induced by the timing gear system;
- Forces resulting from the work of engine accessories, such as the alternator or the compressor, etc.; and,
- Forces transferred from the vehicle body and the power transmission system.

The vibration signal recorded in any location on the engine block is a weighted sum of its response to all elementary events -- convolutions with pulse functions of transfer from the place of generation to the place of the reception of the diagnostic signal are the weights here [2].

Vibroacoustic signals generated by individual kinematic pairs and combustion engine tooling are most frequently non-stationary, due to the occurrence of nonlinear phenomena provoked, *inter alia*, by the clearance and nonlinearity of the characteristics of elastic components. Frequency characteristics of signals essentially depend on the transmittance of the propagation route of component signals from their source to the measuring point. Vibration measured on a block is of a complex nature due to the overlapping signals that originate from various sources. For these reasons, diagnosing combustion engine faults is a difficult process.

A simultaneous analysis of the time and frequency related properties of signals by means of a wavelet transform is more and more frequently used in diagnosing combustion engines [5, 10, 11, 14, 15, 16, 17].

A wavelet analysis consists in signal decomposition, and its presentation as a linear combination of the base functions is known as *wavelets* [2]. 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 [4]. In the literature, wavelet analysis is commonly presented in two variants: Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT).

The discrete wavelet transform of a signal x(t) is determined as scalar products x(t) and a sequence of a base function $\psi(t)$ [2]:

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

As a result of the multilevel decomposition of a signal, signal approximations are obtained at a given level and a sum of details at subsequent levels [2]:

$$x(t) = a_k + \sum_{l=1}^{k} d_l \tag{2}$$

where: d_l – signal detail, multi-frequency component of the signal,
a_k – signal approximation, low-frequency representation of the signal.

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 [2].

The discrete wavelet transform enables decomposition and selective reconstruction (synthesis) of a signal within the whole range of analysis [1]. It can be compared to signal filtration with a constant, relative bandwidth [4].

Our studies attempted to use a DWT analysis in the process of building fault models in the form of no fuel inflow to a cylinder.

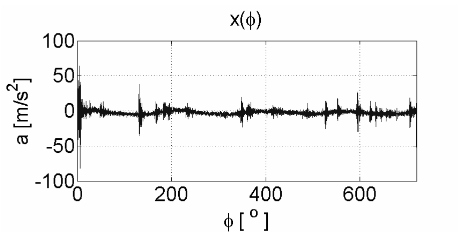
The object of studies comprised 1.2 dm^3 spark ignition engines. During tests, the following parameters were recorded as a function of time: accelerations of the engine block vibration, rotational speed and the location of the crankshaft. The signals were recorded by means of an eight-channel data acquisition card controlled with a programme developed in the Lab View 7.1 environment. The studies were conducted on a chassis test bench. The signals of vibration accelerations were measured on the fourth cylinder in a perpendicular direction, on an idle run, at a constant rotational speed of the engine of 750 r.p.m.

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, listed as follows:

- Fully operational engine,
- Cylinder # 1 off,
- Cylinder # 2 off,
- Cylinder # 3 off,
- Cylinder # 4 off,
- A pair of cylinders # 1 and # 4 off, and
- A pair of cylinders # 2 and # 3 off.

For each state of engine operation, twenty examples of signals were recorded.

In accordance with the DWT definition, the time course of vibration can be decomposed into a prescribed number of decomposition levels. In the conducted experiments, the signals of vibration accelerations underwent decomposition at ten levels. Some examples of time courses of vibration accelerations and their decomposition into low- and high-frequency constituents, performed with use of wavelet filtration for one working cycle of an engine during its correct operation and in the case of switching off the fuel inflow to cylinders 1 and 4, are shown in Figs. 1, 2 and 3.



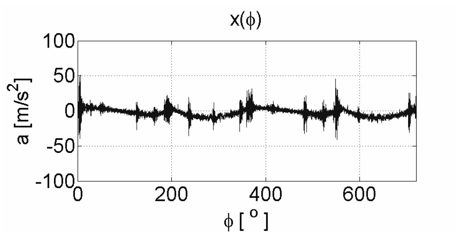


Fig. 1. Examples of recorded courses of vibration accelerations for correct operation of the engine (a) and with fuel inflow to cylinders #1 and #4 switched off
Rys. 1. Przykładowe zarejestrowane przebiegi przyspieszeń drgań dla poprawnej pracy silnika (a) oraz wyłączenia dopływu paliwa do cylindrów nr 1 i 4

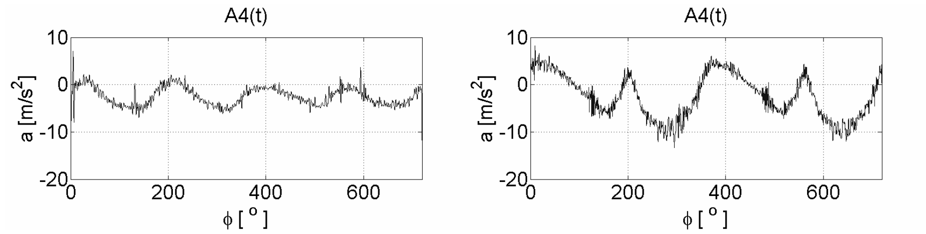


Fig. 2. Examples of the courses of vibration acceleration approximations at 4th decomposition level for correct operation of the engine (a) and with fuel inflow to cylinders #1 and #4 switched off
Rys. 2. Przykładowe przebiegi aproksymacji przyspieszeń drgań na czwartym poziomie dekompozycji dla poprawnej pracy silnika (a) oraz wyłączenia dopływu paliwa do cylindrów nr 1 i 4

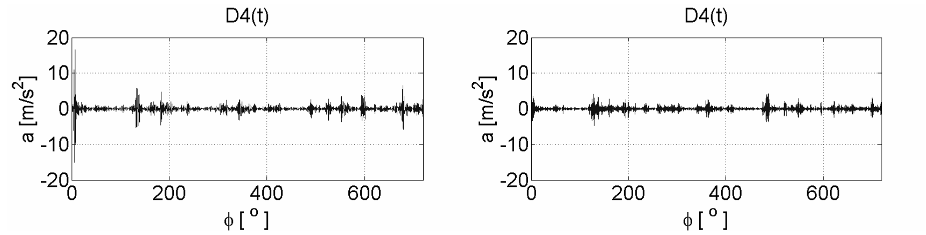


Fig. 3. Examples of the courses of vibration acceleration details at 4th level of decomposition for correct operation of the engine (a) and with fuel inflow to cylinders #1 and #4 switched off
Rys. 3. Przykładowe przebiegi detali przyspieszeń drgań na czwartym poziomie dekompozycji dla poprawnej pracy silnika (a) oraz wyłączenia dopływu paliwa do cylindrów nr 1 i 4

After signal decomposition and reconstruction, at each level separately, a description of the nature of changes of the time amplitude was made by means of the signal entropy values:

$$E = -\sum_i s_i^2(t) \cdot \log\left(s_i^2(t)\right) \tag{3}$$

where: $s_i(t)$ – analysed signal.

Examples of the results obtained for the simulations of different states of engine operation are shown in Fig. 4.

The results obtained indicate the possibility of distinguishing different states of engine operation by using signal approximation entropy calculated at subsequent decomposition levels. However, using signal details instead of approximation does not provide such a possibility.

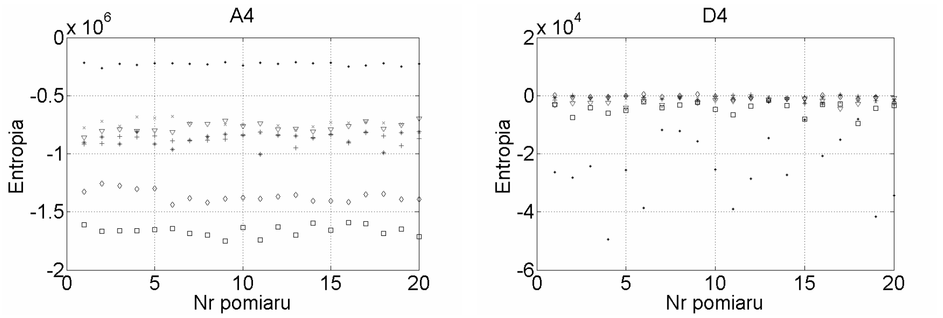


Fig. 4. Entropy of approximation (A4) and details (D4) of vibration acceleration signals for the forth decomposition level; • – efficient engine, × – cylinder #1 switched off, ∇ – cylinder # 2 switched off , + – cylinder # 3 switched off , * – cylinder # 4 switched off , ◇ – cylinders #1 and #4 switched off in a pair, □ – cylinders # 2 and 3 switched off in a pair

Rys. 4. Entropia aproksymacji (A4) i detali (D4) sygnałów przyspieszeń drgań dla czwartego poziomu dekompozycji; • – silnik sprawny, × – wyłączany cylinder nr 1, ∇ – wyłączany cylinder nr 2, + – wyłączany cylinder nr 3, * – wyłączany cylinder nr 4, ◇ – wyłączne parami cylindry nr 1 i 4, □ – wyłączne parami cylindry nr 2 i 3

3. Neuron classifier of the state of engine operation

In the modern literature, there are examples of the broad application of systems using artificial neural networks for solving complicated tasks from various technical, medical, or economic fields [2, 6–9, 14]. The basic feature of the artificial neural networks is the possibility of modelling any nonlinearities while maintaining resistance to interference and the ability to generalise the knowledge acquired in the process of learning, enabling an analysis of new cases of a given phenomenon [9, 14].

In this connection, this study attempted to use the artificial neural networks to classify various states of engine operation, depending on the interference occurring while the fuel inflow to the cylinders is enabled.

The probabilistic neural networks were used in the research (PNN). Neural networks of this type are used as classifiers dividing the data set into a predetermined number of initial categories [4]. Preliminary studies showed that there was no possibility of separating all of the simulated states of the engine operation. In the experiments, the determination of the three states of the engine was assumed to be the aim of the neuron classifier operation. The three states included the following:

- Correct operation of the engine,
- Disengagement of a single cylinder (# 1 or 2, or 3, or 4),
- Disengagement of a pair of cylinders (# 1 and 4, or 2 and 3).

Therefore, 3 outputs were adopted for the research in the network structure.

Probabilistic networks are characterised by a three-layer structure: the input layer, hidden, and output layers [4, 10].

The hidden layer of the network consists of radial neurons, with each of them modelling the Gaussa function centred over one learning formula. Input neurons sum up the values of outputs of the hidden neurons belonging to a class which corresponds to the particular output neuron. The values of the network outputs are proportional to the nuclear estimators of the probability density function for various classes. After the application of normalisation, which ensures the summing to unity, they constitute the estimation of the probability of belonging to the particular classes [10]. Using this type of network, the smoothing coefficient γ should be appropriately chosen [4, 10]. It represents the radial deviation of the Gaussa functions and is a measure of the range of neurons in the hidden layer [10]. Too small a value results in a loss of the property of knowledge generalisation by the network, whereas too high a value makes a correct description of the details impossible [2]. The value of coefficient γ, as in radial networks, is chosen experimentally [2, 10].

In the research, the determined values of the vibration signal approximation entropy were assumed to be the input data for the neural networks. Some variants of the input data sets, varying with the adopted number of decomposition levels, were checked:

- 1–10 (variant I),
- 1– 9 (variant II),
- 1– 8 (variant III),
- 1– 7 (variant IV),
- 1– 6 (variant V),
- 1– 5 (variant VI).

The adopted number of the decomposition levels corresponded to the number of inputs of the neural network.

In the experiments, which aimed at constructing a properly working neuron classifier of the PNN type, the operations of networks for 86 different values of coefficient γ were checked.

The obtained results of the dependence of the influence of coefficient γ on the classification error value are presented in Fig. 5.

The conducted experiments allowed the construction of a faultlessly working neuron classifier. The obtained results indicate an insignificant difference in the level of error of neural networks taught on the data originating from various numbers of decomposition levels. For a majority of model variants, the PNN neuron classifiers were characterised by faultless operation for the values of coefficient γ within the range of 0.004 – 1. When applying γ from a different range of values, a significant increase was observed in the classification error made.

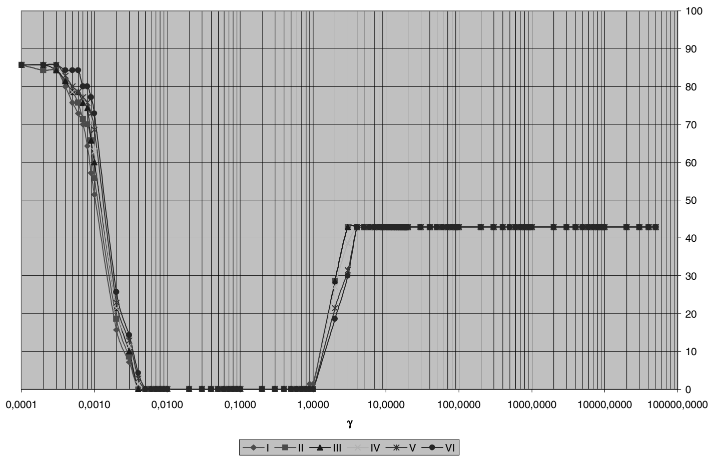


Fig. 5. Influence of the value of coefficient γ on the classification correctness of the PPN neuron network

Rys. 5. Wpływ wartości współczynnika γ na poprawność klasyfikacji sieci neuronowej PNN

4. Conclusion

The studies have proven that it is possible to build a correctly working neuron classifier capable of recognising different conditions of engine work, including those connected with a lack of fuel inflow to the cylinder.

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

The use of a probabilistic neural network with a correctly selected value of coefficient γ enables obtaining a faultless classification.

Hence, a thesis can be posed that it would be possible to increase the effectiveness of the OBD systems, which allow detecting mechanical damage of an engine, masked by electronic control devices of contemporary automotive vehicles, through developing systems which would take advantage of artificial probabilistic neural networks.

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Diagnozowanie zakłóceń w dopływie paliwa do cylindrów z wykorzystaniem analizy DWT i sieci neuronowych PNN

S t r e s z c z e n i e

W artykule przedstawiono próbę oceny stanu pracy silnika w warunkach symulowanego braku dopływu paliwa do poszczególnych cylindrów. Obiektem badań był czterocylindrowy silnik spalinowy o pojemności 1,2 dm^3. W badaniach za źródło informacji o stanie silnika przyjęto sygnały przyspieszeń drgań rejestrowane na kadłubie silnika ZI.

W przypadku diagnozowania silnika spalinowego metodami drganiowymi nie można zapominać o występowaniu wielu źródeł drgań, co jest przyczyną wzajemnego zakłócania symptomów uszkodzeń. Ze względu na konieczność analizy sygnałów niestacjonarnych i impulsowych w niniejszej pracy wykorzystano dyskretną transformatę falkową (DWT). Na podstawie zdekomponowanych za jej pomocą sygnałów wyznaczono wartość entropii, która stanowiła podstawę do budowy wzorców stanów pracy silnika przeznaczonych do uczenia sieci neuronowych.

Z przeprowadzonych badań wynika, że istnieje możliwość wykorzystania probabilistycznych sztucznych sieci neuronowych do oceny procesu dopływu paliwa do cylindrów.