FAULT DETECTION IN ELECTRICAL DRIVE BY MEANS OF ARTIFICIAL NEURAL NETWORKS*

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Summry

The paper deals with problem model-based of fault detection electrical drive by using neural networks. The multilayer perceptron with tapped delay lines has been applied to model the diagnosed process at the nominal operation conditions. In turn, decision about faults has been performed using simple MultiLayer Feedforward Network (MFN). The electrical drive under consideration (AMIRA DR300) works in the closed loop and is controlled by PID controller. This laboratory electrical drive renders it positive to simulate a several faulty scenarios. In this way the proposed fault detection scheme can be tested on a number of faulty conditions.

Keywords: fault detection, neural network, neural classifier, modelling, electrical drive.

DETEKCJA USZKODZEŃ W SILNIKU ELEKTRYCZNYM PRZY POMOCY SZTUCZNYCH SIECI NEURONOWYCH

Streszczenie

Artykuł przedstawia problem detekcji uszkodzeń w silniku elektrycznym przy pomocy sieci neuronowych. Do zamodelowania diagnozowanego obiektu pracującego w warunkach normalnych użyto sieci jednokierunkowych z liniami opóźniającymi. Następnie, jako blok decyzyjny o wystąpieniu uszkodzeń zastosowano zwykłe jednokierunkowe sieci wielowarstwowe. Do przeprowadzenia badań wykorzystano silnik prądu stałego firmy AMIRA (DR300). Silnik pracuje w układzie zamkniętym z regulatorem PID i umożliwia symulację pewnych scenariuszy uszkodzeń. Dzięki temu możliwe jest przetestowanie zaproponowanego schematu detekcji uszkodzeń na przykładzie wadliwych warunków pracy obiektu.

Słowa kluczowe: detekcja uszkodzeń, sieci neuronowe, klasyfikator neuronowy, modelowanie, silnik elektryczny.

INTRODUCTION

Electrical Direct Current (DC) and Alternating Current (AC) engines are very often used in many industrial applications [7]. The changing conditions of operation and intensive exploitation result in systematic wearing off of individual parts of engines. This phenomenon can be interpreted as an incipient fault, which in the final phase changes to an abrupt fault and causes large damages in an engine. It is very important in this case to detect faults at an early stage and apply a special procedure to avoid them so that the worn off elements can be replaced. The faults considered manifest themselves at an early stage by a decreased efficiency, but finally, if the fault is not detected, some parts of the engine can be damaged. Thus, it is important to develop a reliable fault detection algorithm which should detect even small changes in the system behaviour. The traditional methods of monitoring engines require a direct inspection, so the whole process must be stopped for the time of the inspection. Such approaches are usually time-consuming and causes financial loses for the company. Another methods use online identification of engine parameters. Fault detection in this case is done by monitoring the values of the parameters. Unfortunately, these methods require a detailed mathematical model of an engine and the expert who interprets the results should have a deep knowledge about an engine and experience in evaluating its behaviour.

An interesting alternative solution can be obtained using artificial intelligence. Artificial

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neural networks seem to be particularly very attractive when designing fault detection diagnosis schemes. Artificial neural networks can be effectively applied to both the modelling of the plant operating conditions and decision making [1, 2, 3].

1. FAULT DETECTION SCHEME

In order to design fault diagnosis system for the considered-electrical engine, a neural network is used to model the process at normal operation conditions. First, the network has to be trained for this task. Process modelling in closed loop control and is controlled by PID controller. The model is designed applying the multilayer perceptron with tapped delay lines. Two neural models are designed model of tachometer $y^T = f_{NN1}(u)$, where y^T is tachometer measurement and u is control signal, and model of motor drive $y^D = f_{NN2}(u)$, where y^D is motor drive measurement.

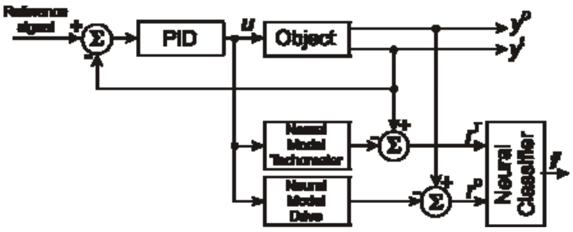

Fig. 1. The FD scheme based on neural network

2. ELECTRICAL ENGINE

The effectiveness of the fault detection scheme has been examined using laboratory stand of the Institute of Control and Computation Engineering of the University of Zielona Góra – *AMIRA (DR300)*. The laboratory stand shown in Fig. 2 can be used to control the rotation speed of a DC engine with a changing load.

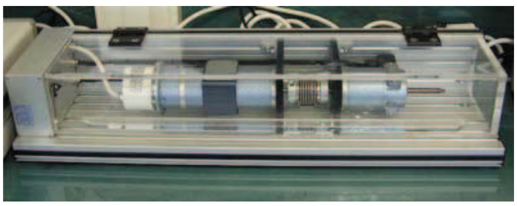

Fig. 2. Laboratory stand with a DC engine

Laboratory object considered consists of five main elements: DC engine M_1, DC engine M_2, two engine-speed indicators, clutch K.

The input signal for the engine M_1 is an armature current. Its value is determined by a cascade control loop. The servo-amplifier of the current controller works in four modes, thus the current direction can be chosen appropriately according to the demanded direction of rotation. The output of the object is the rotational speed of the engine. The rotational speed can be measured using two sensors: a tachometer on optical sensor, which generates impulses that correspond to the rotations of the engine. The shaft of the engine M_1 is connected with the identical engine M_2 by the clutch K. The engine M_2 works in the generator mode and the generated current is controlled by another controller. The basic technical data concerning the laboratory system are shown in Table 1.

Table 1. Laboratory system technical date

Variable	Value
Engine	
rated voltage	24 V
rated current	2 A
rated power	30 W
rated speed	3000 *rpm*
rated moment	0.096 *Nm*
moment of inertia	$17.7 \cdot 10^{-6}$ *Kgm*^{2}
Resistance	3.13 Ω
Tachometer	
output voltage	5 *mV/prm*
moment of interia	$10.6 \cdot 10^{-6}$ *Kgm*^{2}
Clutch	
Moment of inertia	$33 \cdot 10^{-6}$ *Kgm*^{2}

The engine M_1 is controlled using the servo-amplifier, where the control signal has the form of the voltage from range -10V to +10V with amplification 0.4 *A/V*. The engine M_2 is also controlled using the servo-amplifier, where the control signal has the form of the voltage from the range -10V to +10V with the amplification 0.237 *A/V*. The tachometer serves to measure indirectly the rotational speed of the engine M_1. The output range of the tachometer is -10V to +10V [6].

A set of potential faulty scenarios defined for the engine considered. The faults were simulated artificially using the elements of the laboratory system. It was impossible to generate real faults in the laboratory environment. The faults are divided into two groups: tachometer faults and mechanical faults of the engine M_1, which manifest themselves as a decreasing efficiency of the engine. Tachometer faults f^T were simulated by increasing tachometer measure by 5% (fault f_1^T), 10% (fault f_2^T), 15% (fault f_3^T) and decreasing tachometer measure by 5% (fault f_4^T), 10% (fault f_5^T), 15% (fault f_6^T). In order to generate the mechanical faults, the engine M_2 connected with the engine M_1 via the clutch K was used to simulate an additional faulty load. It was assumed that faults can be abrupt. Mechanical faults f^D were simulated by setting load values to 0.5A (fault f_1^D), 1A (fault f_2^D), 1.5A (fault f_3^D), -0.5A (fault f_4^D), -1A (fault f_5^D), -1.5A (fault f_6^D). The effectiveness of the designed fault detection system was tested using data generated during fault simulations. Faulty data were prepared for all designed scenarios. Some results of fault detection are presented in the next section.

3. EXPERIMENTAL RESULTS

3.1. Process Modelling

Due to the complex nature of the fault detection problem, the electrical engine was modeled by the multilayer perceptron with tapped delay lines. The considered neural network belongs to the class $N^2_{1,10,1}$ (2 processing layer, 1 input layer, 1 hidden layer with 10 neurons and 1 linear output unit). Each neuron in hidden layer possesses hyperbolic tangent transfer function. Number of past outputs used for determining the prediction was equal to 3, number of past inputs was equal to 3.

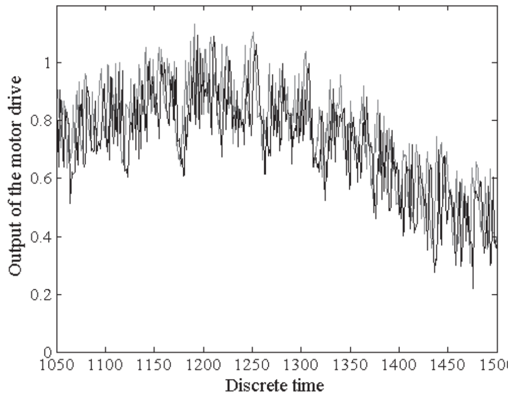

Fig. 3. Output of the motor drive and neural model

In Fig. 3. one can observe that the neural model of the motor drive approximate the modelled object precisely. Moreover, in the Fig. 4. the residual signal for normal condition of the object is presented.

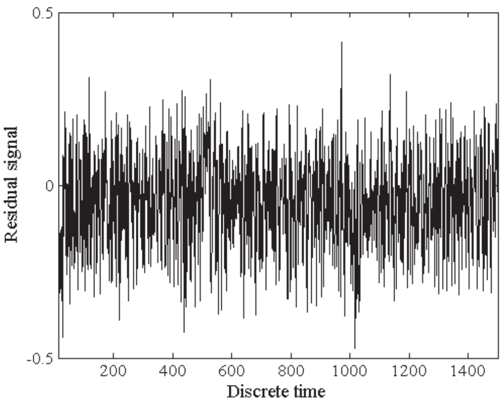

Fig. 4. Residuals for normal conditions

3.2. Tachometer faults

Decision about faults has been performed using simple MultiLayer Feedforward Network (MFN). The neural classifier structure of the neural network was $N^2_{2,5,1}$. Each neuron has sigmoid activation function. The parameters of the network were adjusted by using the well-known Levenberg-Marquardt method. The learning set contains 300 samples for nominal condition, and for each faulty scenario a set of 100 test samples has been generated.

Analysis of the considered working conditions show that it is extremely difficult to differentiate between particular faulty scenarios. This situation is presented in Fig. 5. Even normal operation conditions are not clearly separated from faulty ones.

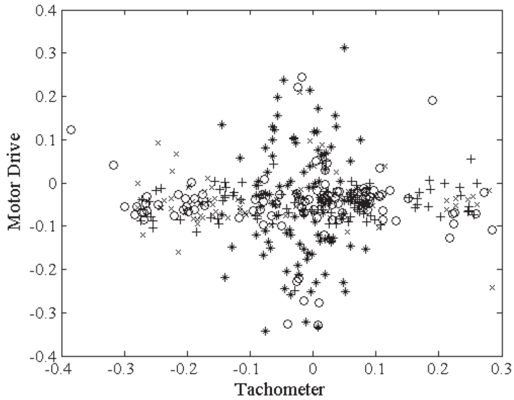

Fig. 5. Distribution of residuals patterns (normal conditions - *, f_1^T - o, f_2^T - x, f_3^T - +

Taking into account that all tachometer faults are hardly distinguishable one from another, let us consider two classes of system behaviour. First class represented by 0 represents normal operation conditions, and second class represented by 1 represents generalized tachometer fault.

The sensitivity of the proposed fault diagnosis system is checked using the so-called false detection rate [4] defined as follows:

$$r_{fd} = \frac{\sum_i t^i_{fd}}{t_{from} - t_{on}} \qquad (1)$$

where t^i_{fd} is the period of ith false fault detection, t_{on} is the benchmark start up time, t_{from} is the period of time from the begin of fault start-up.

The fault detection quality is evaluated using true detection rate [4] defined as follows:

$$r_{td} = \frac{\sum_i t^i_{td}}{t_{hor} - t_{from}} \qquad (2)$$

where t^i_{rd} is the period of ith true fault detection, t_{hor} is the benchmark time horizon.

In the case of tachometers fault patterns related to the nominal condition overlap patterns collected for faulty scenarios, (Fig.5) what results in high false detection rate at the nominal condition $r_{fd} = 0.2225$.

Table 2. True detection rate

f^T	f_1^T	f_2^T	f_3^T	f_4^T	f_5^T	f_6^T
r_{td}	0,83	0,82	0,80	0,87	0,88	0,87

3.3. Mechanical fault of the engine

In this case problem of distinction between nominal and faulty conditions less complicated. One can see in the Fig. 6 that patterns associated with the nominal state are located in the separated area from the faulty space. Thus, the false detection rate at the nominal condition is much better than in the previous case and $r_{fd} = 0.071$.

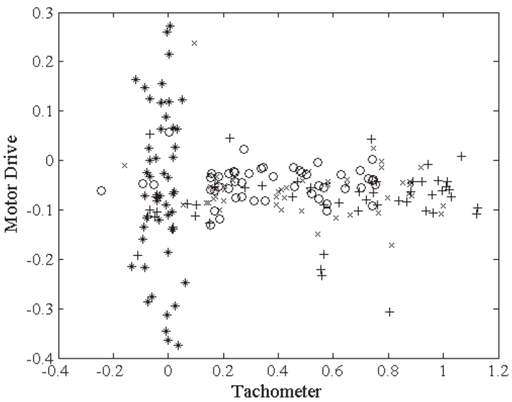

Fig. 6. Distribution of residuals patterns (normal conditions - *, f_1^D - o, f_2^D - x, f_3^D - +

Table 3. True detection rate

f^D	f_1^D	f_2^D	f_3^D	f_4^D	f_5^D	f_6^D
r_{td}	0,93	0,94	0,78	0,91	0,94	0,95

4. SUMMARY

The paper deals with application of neural networks to model-based fault detection systems. On the basis of the experimental results presented in the paper, the multilayer perceptron with tapped delay lines has appeared to be applicable to the system modelling during designing the FD systems. All experimental simulations were carry out with real object, electrical engine.

On the basis of simulation experiments it to turned out that particular faults are not distinguish and an attempt of their isolation by means of simple MultiLayer Feedforward Network ended in failure.

In both cases faults can be isolated as a group of faults.

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