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Sophisticated methods of signal analysis in magnetic testing of wire ropes

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1. Introduction

There are several methods and techniques for assessing the working condition of mechanical structure, such as wire ropes while in service; magnetic testing techniques are in widespread use in these applications. Magnetic testing is a branch of a wide research field called diagnostics. The main aim of magnetic testing is to assess the rope condition basing on the analysis of recorded signals and the interrelations between the physical quantities: rope condition and signals obtained from the tested rope section. Monitoring of time sequences of diagnostic signals makes it possible to prognosticate the rope condition and to draw conclusions as to the causes of rope wearing. However, the signals obtained in that way have nonstationary characteristics, which is their immanent feature. Non-stationary and non-linear characteristics of signals present major difficulties in theoretical considerations, though the spectral analysis of non-stationary signals is not a new problem and there are several techniques of overcoming the difficulties. Non-stationary characteristics of the involved processes have forced researchers to develop new measurement methods and signal processing algorithms.

2. Implementation of the diagnostic process utilising the pattern recognition method

Fault detection methods available in the relevant literature are categorised in three groups:

- estimation methods,

- database methods,
- pattern recognition methods.

The estimation method requires that the mathematical model of fatigue wearing processes be known beforehand. The relationships between model parameters and rope condition parameters are often very complex. Changes of physical parameters, such as material loss are revealed in the wearing process parameters. The relationship between mathematical model parameters and physical quantities ought to be precisely known, which is entirely impossible in magnetic testing. That is why estimation methods cannot be applied in magnetic testing of wire ropes. The pattern recognition is the only method that proves useful in these applications. It is described in more detail in the following Sections.

The measurements signal from the sensor head (for instance GM60Split) may be further analysed in three ways (Fig. 1). In classical fault detection signals are recorded by digital recorders (for example MD 120) and then subjected to qualitative and quantitative analysis, in accordance with the approved standards. Alternatively, signals may be stored on memory cards PCIMCIA and visualised on monitor display. Signals may be also recorded by the A-D (analogue-to-digital) converter in computer memory and then subjected to wavelet analysis, followed by qualitative and quantitative analysis utilising selected bits of information on various fault types. This procedure can be done in an off-line mode. The third approach consists in implementation of wavelet analysis algorithm with the use of fast real-time DSP processors. This solution offers a potential for the design of new-generation recorders.

2.1. Application of wavelets to non-stationary signal analysis

Reliable operation of diagnostic systems requires fast, algorithmic detection of typical faults. As soon as an algorithm is implemented, the diagnostic procedures ought to be activated to assess the degree of rope wearing. Measuring instruments used to date in magnetic detection and utilising signals from induction sensors have a narrowed measuring range, which is their inherent deficiency. The measurement range is limited and some portion of vital information may get lost. Besides, the instruments allow only for a simple analysis of fundamental signal parameters: amplitude, power, energy or the impulse bandwith. One of the reasons lies in design of widely used measuring instruments where the information about the contribution of various fault types to overall rope wearing cannot be separated from the signal. These defects (or their variable weight) may negatively impact on the rope condition and hence the safety of its operation.

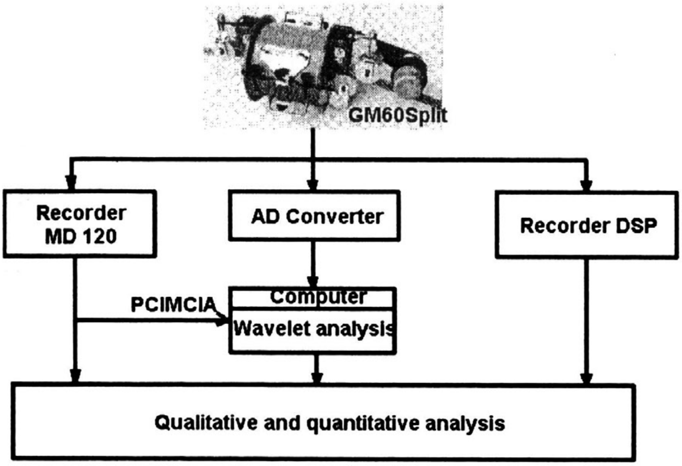

FIGURE 1. Recording of diagnostic signals.

The magnetic detection method is therefore extended and new signal processing algorithms utilising wavelet analyses have been added [2,3]. Implementation of these algorithms on signal processors should allow for real-time solving of most complicated problems. Research has established that when the STFT approach was applied and the signal bandwith was not limited, several faults were detected that could not be identified by induction sensors (so far the measurements signals were often compared with natural noise signals). As the signal component coming from the fault was separated from the rope construction component, the diagnostic process was thus facilitated.

Unlike the pattern recognition method described before, in the present case signals are subject to qualitative detection procedures and all disturbances, such as noise, can be eliminated (Fig. 2). That can be achieved through the application of wavelet analysis. As a result, one gets separate information about various fault types. In the next block the rope wearing due to particular defects is quantified.

The magnetic detection being in widespread use utilises the pattern recognition approach and combines the qualitative and quantitative detection algorithms in one detection block. In classical magnetic detection measurement signals, revealing the condition of the tested structure, cannot give us information on types of wearing and defects, which makes the interpretation of thus obtained defectograms rather difficult and consequently wrong decisions may be taken. Application of wavelet analysis may help to overcome this difficulty.

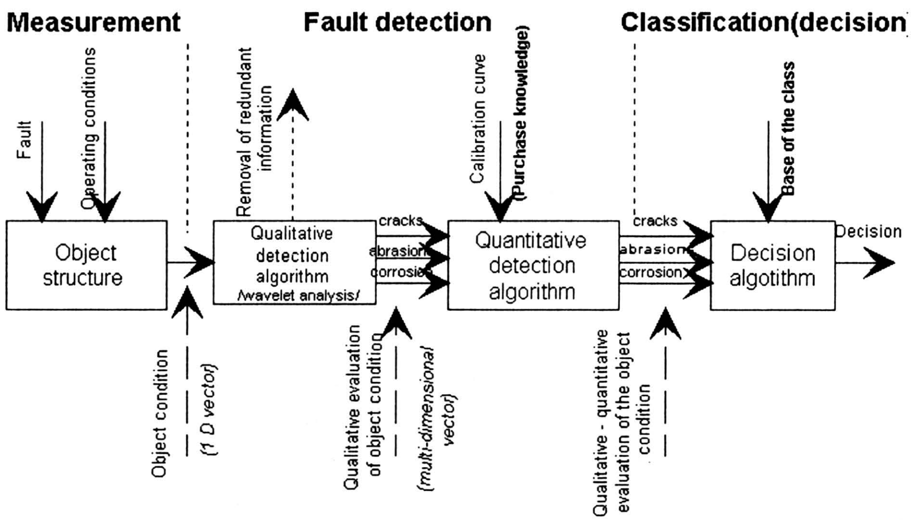

FIGURE 2. Pattern recognition method in testing of wire ropes.

The backgrounds of wavelet analysis.

The classical scalogram can be defined as [4, 9, 10, 11]:

$$S_x^{\mathrm{SCAL}} = \left(\mathrm{CWT}_x(b,a)\right)^2 \tag{2.1}$$

where CWT stands for continuous wavelet transform for the scale factor a and shift b, given by:

$$\mathrm{CWT}_x(b,a) = a^{-1/2} \int_{-\infty}^{+\infty} x(t)\,\Psi^*\left(\frac{t-b}{a}\right) dt. \tag{2.2}$$

This relationship expresses the filtering of the analysed signal $x(t)$ through the analysing signal (wavelet) $\Psi(t)$ scaled in the time domain with the scale factor a.

While calculating the values of the functional (2.2) for the scale factors being integer numbers and subsequent powers of two, the dyadic or non-decimated wavelet transform can be applied.

The values in decimated algorithms are: $a = 2^i$ and $b = k2^j$. Accordingly, the equation defining the continuous transform (2.2) can be rewritten in a discrete form:

$$\mathrm{DWT}_s(j,k) = \sum_{n \in Z} s(n) * \Psi_j^*(n - 2^j k) \tag{2.3}$$

where $\Psi_j^*(n-2k)$ is a discrete counterpart of a continuous analysing function, "$*$" stands for the discrete convolution,

$$\Psi_{a,b}(t) = a^{-1/2}\Psi\left(\frac{t-b}{a}\right) \equiv \Psi_{j,k}(n) = 2^{-j/2}\Psi(2^{-j}n-k). \tag{2.4}$$

The above relationship defines the family of analysing functions for the dyadic case. The inverse transform required for signal synthesis is given by the formula:

$$s(n) = \sum_{j\in N}\sum_{k\in Z} \mathrm{DWT}_s(j,k)\Psi_{j,k}(n). \tag{2.5}$$

The paper compiles the results of model tests performed on twisted and ordinary lay ropes using the discrete transform.

Signs of abrasive wear were modelled on a twisted rope 40 mm in diameter. The signals were comparable with noise caused by the rope. In traditional magnetic testing such defects remain undetected. Abrasions were also made on the specified rope section. Visualisation of signals from modelled ropes and calculations of the degree of rope wear basing on the classical approach proved inadequate. Figure 3 presents a signal obtained from a new rope and

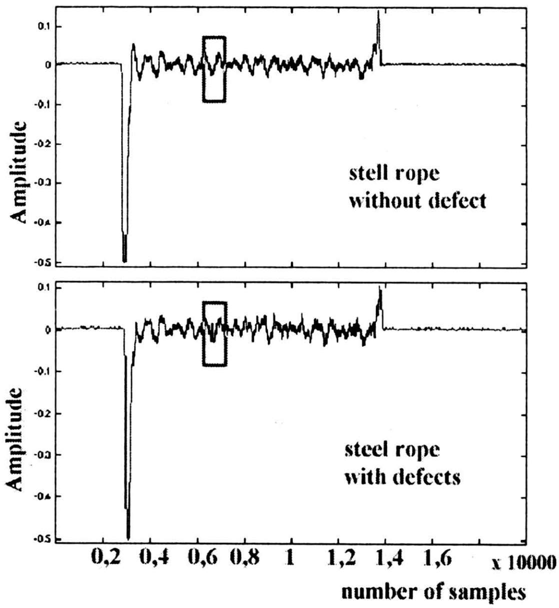

FIGURE 3. Comparing the signals from a new rope and a rope with defects.

from the rope with modelled abrasions. Even experienced practitioners would find it difficult to interpret the fatigue wear symptoms correctly.

This problem was solved with the help of the package MATLAB [5]. The wavelet analysis allowed for signal decomposition. Signals from twisted ropes were analysed using the specially created "mads" wavelet [1, 8] and eight scaling levels ($j = 8$). Figure 4 presents the details (levels of decomposition) of analysed signals. On the 6^{th} level there is an image where the signal from the modelled, step-like fault can be easily pinpointed. The 3^{rd} level represents the abrasive wear.

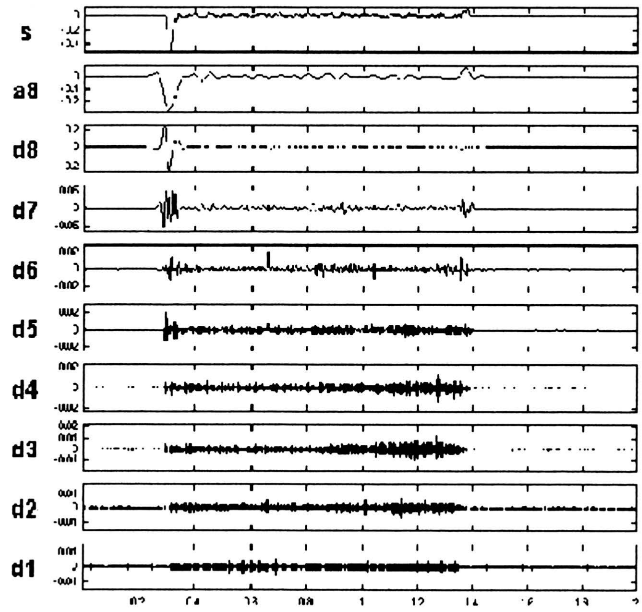

FIGURE 4. Signal decomposition.

Selected details are enlarged and shown in Fig. 5, to illustrate how various types of defects impacts on signal shapes (waveforms). The locations of wire breaks are easily seen on the level 6d, abrasions – on the level d3.

While investigating the influence of the degree of abrasive wear on power spectrum patterns in FFT distributions [7, 8] of selected signal decompositions, it can be assessed in quantitative terms.

A close scrutiny reveals that abrasions give rise to a rapid increase in the amplitude of frequencies responsible for this process of wearing. Selection of the detail representing this process helps in monitoring the changes in the tested ropes.

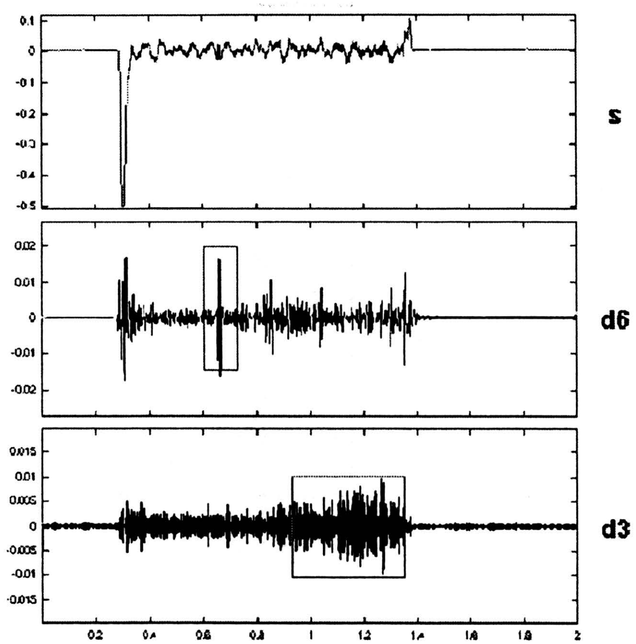

FIGURE 5. Selected details of signal decomposition.

3. Application of artificial intelligence (AI) to fault detection

A major step in magnetic testing of ferromagnetic elements is the application of AI algorithms [4]. The main aim in this approach is to determine the scope of applications of intelligent diagnostic systems in magnetic testing of ferromagnetic elements and to create a neural network which might help to assess the working condition of the tested object (structure). A block diagram of the traditional testing method (see Fig. 6) includes the block for signal recording on a paper chart or on the memory card (PCMCIA) so that the registered data can be transferred to a computer.

The program Browser 120 created for the purpose of the tests allows for signal visualisation and for selection of vital fragments. Calibration characteristics obtained prior to the experiments make it possible to calculate the degree of rope wear. Thanks to the application of neural networks, the diagnostic processes is made faster.

The AI was used to support the pattern recognition method which consists in mapping of the measuring space into the decision-making space and involves measurements, fault detection and decision-making. At the stage of

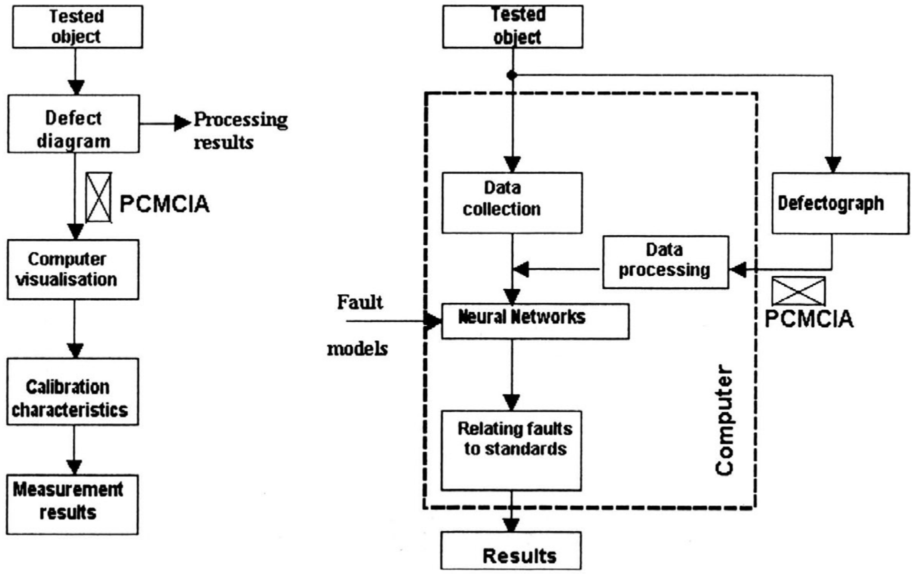

FIGURE 6. Comparison of the traditional approach and the AI methods.

fault detection the signals from standard faults should be introduced to the neural network structure. Comparison of the measurement and standard signals affords a diagnosis, where a fault is localised and its size assessed. At the final stage faults are classified and the required actions are generated, as shown in Fig. 7.

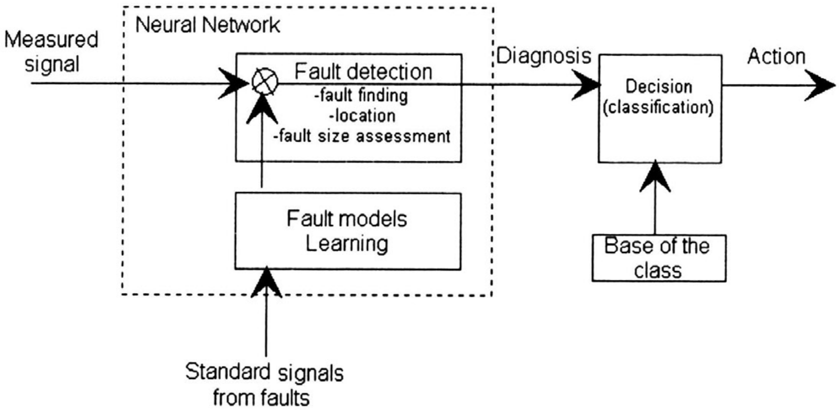

FIGURE 7. Application of pattern recognition method to fault detection (using neural networks).

Preliminary tests reveal that a potential exists for creating a diagnostic system utilising neural networks which would provide reliable information on the condition of the tested object after network pre-adjustment consisting in network learning through introducing several fault standards (patterns).

Modelling the patterns representing all fault types to be found in ropes requires a vast amount of data (i.e. signals from modelled defects). The more signals, the more precise the diagnosis based on neural networks.

In order that the diagnostic system should function properly, the data must be representative for all types of faults, i.e. they should cover the broadest range of variability of input quantities (fault types). In the first part of the study on applications of neural networks in wire rope testing systems, only step-like faults were modelled.

Standard signals were recorded using a computer-integrated wavebook unit. A recorded signals from standard faults is shown in Fig. 8. The signal was registered at the frequency 1 kHz, which corresponds to 2000 data samples.

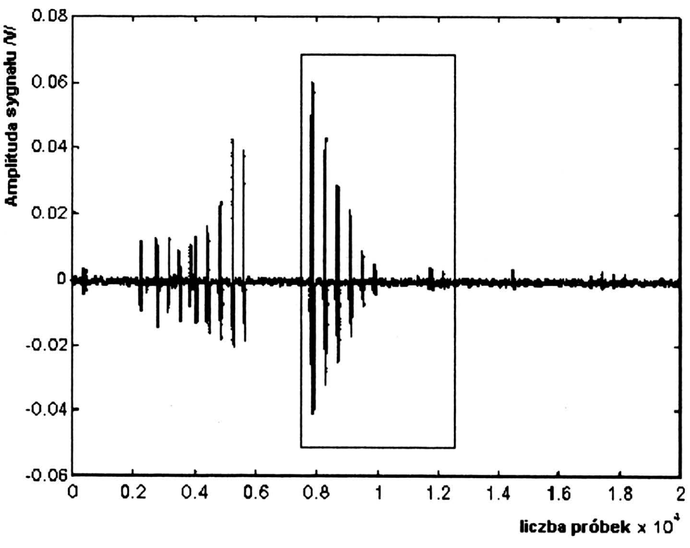

FIGURE 8. A filtered diagnostic signal from standard faults.

As signals from step-like faults are symmetrical, the analysis of half-impulse only was performed. Thus the network learning process is facilitated and the time of network adjustment gets shorter. The standardisation procedure can be fully automatic (Fig. 9). A simple standardising algorithm was applied in segmentation of single impulses [4].

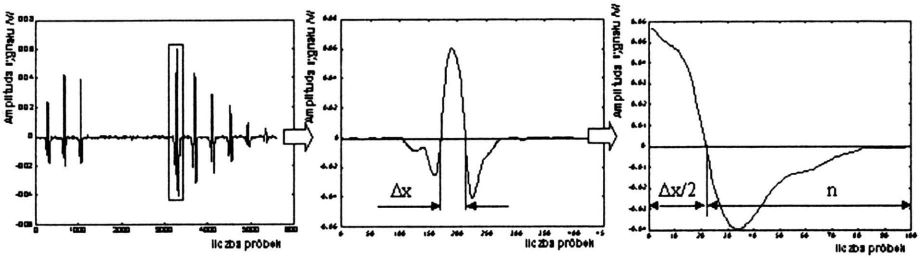

FIGURE 9. Standardisation of diagnostic signals.

This standardisation procedure would yield standard samples with the (signal) waveforms as presented in Fig. 10.

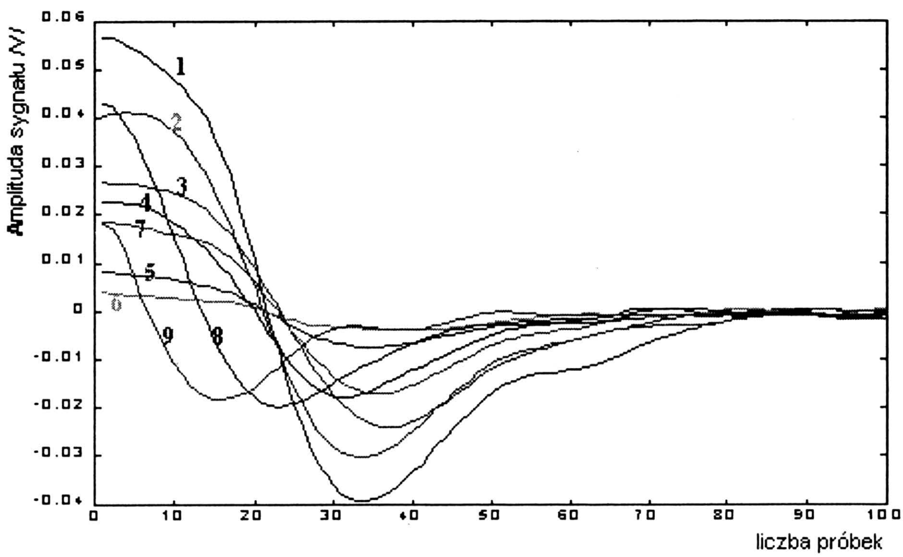

FIGURE 10. Standard signal waveforms after standardisation (1-9 standard signals from modelled faults).

The neural network considered in this study had an input layer, two hidden layers and an output layer (Fig. 11). The number of neurones in the input layer is equal to the number of input signals fed in simultaneously (a number of samples per one standard).

The selection of the optimal number of hidden layers and the number of neurones in layers involves the testing of network behaviour in terms of

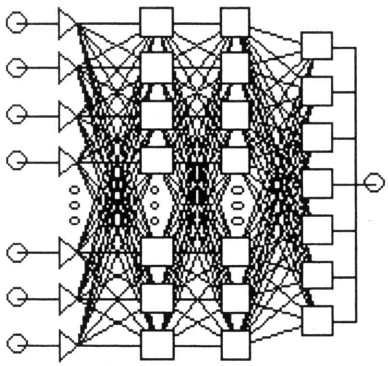

FIGURE 11. Neural network structure.

learning rate and the number of errors for the different values of relevant parameters (the number of hidden layers and neurones).

The function trainbpa [4] (reverse propagation method) proved to be the best learning function for solving the considered problem. It provides for the optimal learning rate, and at the same time correctly relates the real faults to modelled standards.

When the network had been found to be ready, the fault detection procedure was begun (Fig. 12). It was done on the basis of input signals, not correlated with the learning signals.

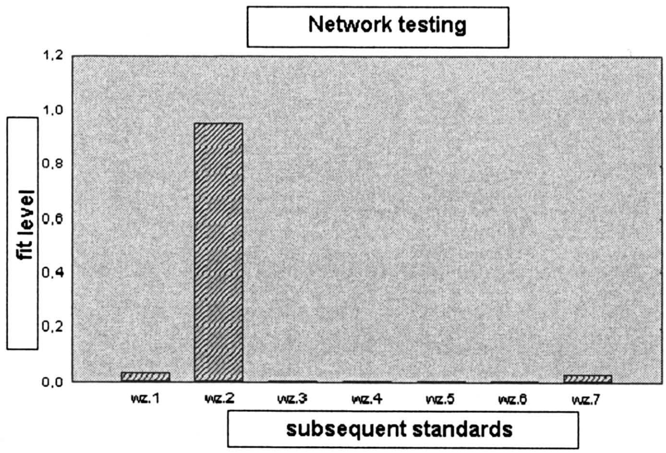

FIGURE 12. Results of fault classification.

The statistical parameters calculated using the program Neural Network [4] relating to the whole sequence of data included the mean error and the matrix of classification results providing the information on correctly and incorrectly classified faults for various fault types. These statistical parameters were obtained independently for the learning, validating and testing sequences. The weighing factors and outputs from the network may be represented as bar graphs (Fig. 12). When an unknown signal resembles the signals introduced as the learning matrix, the output value is close to 1; when no similarity exists the value will be 0.

The results were obtained for one group of step-like faults only. Were other fault types taken into account, the network would have to be extended, which is shown in Fig. 13. Each group of faults have their own network structure and the output values represented as bar graphs are analysed in the classification block. The highest degree of correspondence (the best fit) between the modelled fault and the standard one is the desired result of diagnostic procedure.

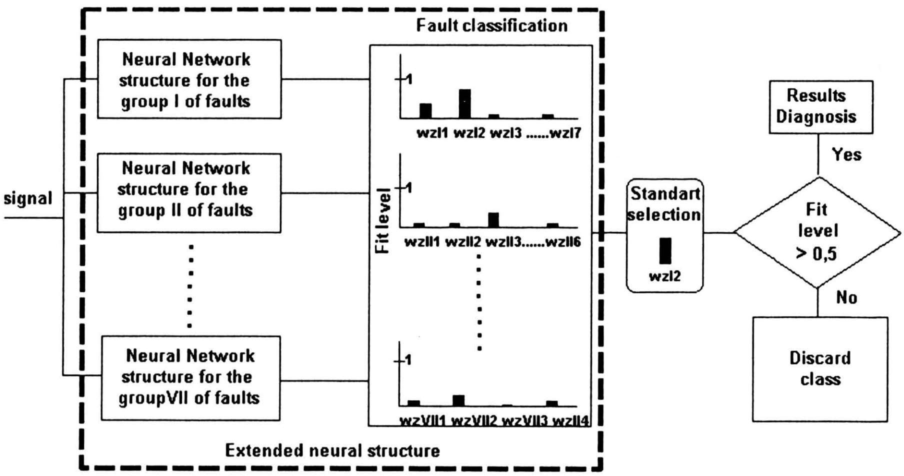

FIGURE 13. Scheme of extended neural network structure.

In extreme, though possible cases, i.e. when the generated signals are not similar to those from modelled faults (the fit level less than 0.5), the faults are immediately categorised for the "discard" group. However, modelling continuous faults still presents a major problem and requires further research.

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