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SOFT COMPUTING TOOLS FOR MACHINE DIAGNOSING

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This work is aimed at creating soft computing tools for machine diagnosing systems. There are some problems with interpretating measured data in these systems. To overcome the problems with a big number of information in a diagnosing system, a neural pre-processor was proposed. A neural network can be used for reducing the size of analysed features. The fault detection and isolation is difficult due to context and broaden relations between measured data and a machine state. Soft computing methods are helpful in solving such problems. Artificial neural networks and fuzzy logic systems were used in these studies. An approximation of the unknown diagnostic relations symptom-state was done by both created tools. The only information about these relations were hidden in measured data that illustrate an expert knowledge formulated in a natural language. Such a form of information is the basis of constructing neural networks and fuzzy systems adequatly. The case study was fault detection of a high power fan. The working correctness of soft computing tools, presented in this work, was examined in the context of results obtained by utilisation of pattern recognition methods. The comparison of their performance speed, noise robustness and early detection of failure was also made.

Key words: soft computing, diagnosing systems

1. Introduction

There are many machines having strategic significance for industry processes duties. Because of economical reasons, these machines require regular maintenance to avoid a failure leading to halt of plant activities. In order to perform an efficient maintenance, many machine diagnosing systems have been developed (Watanabe, 1988; Yamaguchi, 1992). Because of growing complexity of plants, highly accurate diagnosing systems are required. We can also expect a change of the maintenance style from the Time Based Monitoring (performed in a constant time cycle) to the Condition Based Monitoring (performed according to the degradation degree of machine parts). Such machine diagnosing systems are designed to detect an abnormal condition and estimate the cause of failure. Among popular methods there are vibroacoustical methods. When failure occurs, the vibration signature of the machine changes and the fault occurrence can be detected by measuring the machine mechanical vibrations. The machine diagnosing system selects a failure feature from the mechanical vibration data and estimates the degree and cause of the fault. In machine surveillance, the machine fault degree is approximately represented by a vibration magnitude and a root-mean-square value of the vibration data. If the fault degree increases, the vibration magnitude will also increase. Therefore, we can measure the machine fault degree by cyclic monitoring of its vibration magnitude.

In order to judge the normal or fault conditions, we check the absolute level or the trend of the vibration data. The Machine Surveillance Technique uses a simple algorithm for the judgement and high-speed diagnosis.

On the other hand, in the precise diagnosis technique, we use frequency analysis where the vibration data is transformed to a power spectrum by the Fourier Transform, and some features of the fault are selected. For example, faults of rotating machines cause vibration power concentrations in the frequency domain. For example, when an unbalance condition occurs, the power of the rotating frequency (f_0) component increases. When a misalignment condition occurs, the power of the second harmonic of the rotating frequency increases (Cempel, 1992). Figure 1 depicts the power spectrum with marked examples of components corresponding to machine faults.

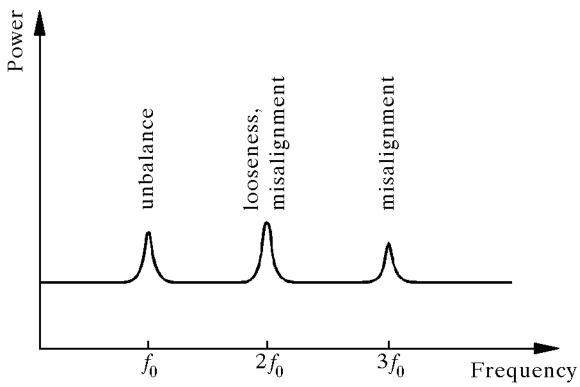

Fig. 1. Selection of the power spectrum components

The selected features are obtained on the basis of kinematic analysis of a rotating machine and relationships between the power spectrum and different machine failures described by the human expert.

This diagnostic process consists of the following stages:

- Data measuring
- Preprocessing of measured data
- Features classification
- Diagnostics and decision making

Some of these stages can be realized by the use of soft computing techniques.

This work aims at creating soft computing tools for fault detection of a high power fan. Artificial neural networks and fuzzy logic systems are used. The correctness of this tools is examined in the context of results obtained by utilisation of pattern recognition methods. The comparison of their performance speed, noise robustness and early detection of failure is also made.

2. Artificial neural networks

Artificial neural networks (ANN) are modern tools efficient in signal processing and numerical routines. Their characteristic features are: ability to approximate an arbitrary mapping, high processing speed due to the parallel connectivity, ability to generalise and possibility of approaching a problem for which the exact mathematical model cannot be specified beforehand. They can also identify context and broaden relations (Duch *et al.*, 2000). Due to these features, the ANN found application in machine fault detection problems (Sorsa *et al.*, 1991).

The most popular neural networks application to diagnostics is building a neural classifier of state that works on the basis of former and present measured data. Supervised, multilayer, nonlinear neural networks are used for feature diagnostics – machine state mapping approximation. Also unsupervised, competitive networks are used (Batko and Gibiec, 2000). In that case, reference sets of diagnostic features corresponding to machine states are hidden in the neural network structure. A method of input signals affiliation to these sets is set up, too.

The first practical application of neural networks to diagnostics was fault diagnosing in a complex chemical plant. The ANN have also been used for fault detection and localisation in tooth gears, combustion engines and in energetic industry.

Another neural approach in diagnostics is machine model building. Such a model can be used for generating output signals of a machine without faults, defining residuals between the model and diagnosed object and identifying feature-condition relationships.

Neural networks are also useful filters for communication interferences, sonar noise or measured signal disturbances elimination. They can estimate the disturbances and can eliminate them from the signal.

Nowadays, vast amounts of data are acquired. Using auto-associative neural networks, one can select input information, reduce size of input signals but save their statistical features.

Neural networks can also realize a prediction task of changes of measured signals. It gives a possibility to estimate the time of state changes of a diagnosed object.

3. Fuzzy logic

A diagnostic process depends on a human expert who determines the strategy to proceed. Such a process is based on broaden heuristic rules not allowed in conventional diagnostic systems. The operator uses linguistic variables such as: low, high, to express his knowledge. They are imprecise but the system works correctly. Because of growing complexity of plants, facilitation of the human expert work is required. One can do it by using automatic procedures in the diagnostic process. The method of Artificial Intelligence (AI) – Fuzzy logic, formulated by Zadeh, is a method for realisation of this concept. It enables one to describe the expert heuristic knowledge via linguistic rules easy and fast. The use of the basic fuzzy logic concept gives an automatic and objective diagnostic system.

The Fuzzy Inference System consists of three modules (Kacprzyk, 2001):

- Fuzzyfication
- Inference
- Defuzzyfication

The first one divides the input and output space into sets corresponding to the defined linguistic variables. Each set has its membership function. The result of this module work is determination of the membership degree to these sets. The second module is a rule knowledge base. The inference mechanism operates on input values – membership degrees and uses fuzzy logic rules. As a result, the membership degrees of output variables are specified. The third module accumulates results of every rule and gives sharp output values.

Such fuzzy systems can realize tasks of diagnosed object modelling (Yager and Filev, 1995), residual generation (Hirota, 1993) as well as pattern recognition (Bezdek and Pal, 1992). An arbitrary mapping approximation, often required in diagnostics, is performed correctly by fuzzy logic systems (Piegat, 1999).

4. Soft computing tools

A high power fan, driven by a 150 kW motor was the object of this research. The fan has 8 blades and operates at speed of 3000 rpm. The bearing housing vibrations were measured.

In the course of numerous experiments, vibration spectra corresponding to four different faults and the normal condition were collected. The following faults were distinguished: unbalance, misalignment, excessive looseness and blade defects. Except for these faults, the normal condition and unrecognised conditions were signalised as well.

4.1. Neural pre-processor of measured data

A diagnosing algorithm using a neural network has the ability to recognise the learned data. However, learning the power spectrum pattern (even after arbitrary selection) requires a lot of time since there are numerous input nodes. In addition, the information included in non-selected spectrum components is lost. To overcome these problems, the neural network can be used for reducing the number of features but saving the information included in the whole power spectrum. The feedforward network in an auto-associative version was used. During the learning process the same power spectrum is supplied to input and output layers and the network with one hidden layer learns to operate as the approximator of synonymous mapping. The first layer passes the original input vector to the hidden layer input. This layer has a smaller size and generates on its output vector of its size. We can recover to the original input vector passing the hidden layer output through the output layer. When the learning process is finished, the compressed representation of the input signal is presented on the hidden layer output. This compressed information is provided to the input of the classification stage of the diagnostic process.

Figure 2 shows a compressing network structure. In this research, the unipolar sigmoid function was used as an activation function of hidden layer neurons and output layer neurons. The parameter learning rule of Widrow-Hoff was used to perform the training process. Due to the use of a multilayer feed-forward neural network with a continuous differentiable activation function, the application of the back-propagation learning algorithm was possible.

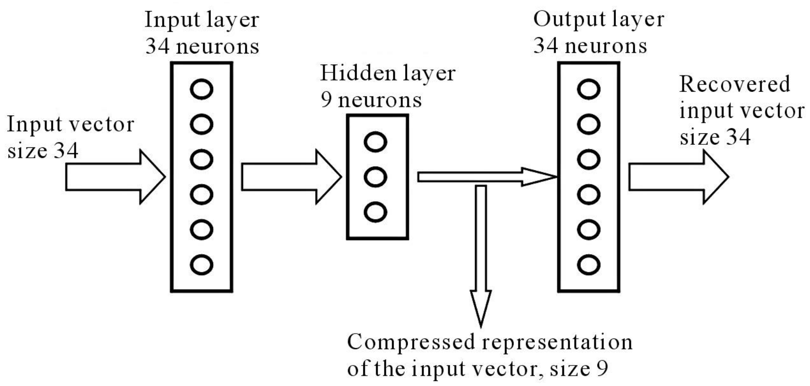

Fig. 2. The structure of a neural network for data compression

In order to increase the learning speed, the adaptive learning rate method was utilised. The learning algorithm was also extended by addition of a momentum term. Equation (4.1) defines the change of weights of the neural network in the k-th iteration of the learning process

$$\varDelta w_{ij}^{(k)} = \eta_1 \frac{df(e)}{de} x_j \delta_i + \eta_2 w_{ij}^{(k-1)} \tag{4.1}$$

where

e_i	–	ith excitation of the neuron, $e_i = \sum_j w_{ij}^{(k-1)} x_j$
$f(e)$	–	activation function
x_j	–	input signal received from the jth neuron
δ_i	–	error of the ith neuron
η_1, η_2	–	learning and momentum rate, respectively
$\varDelta w_{ij}^{(k-1)}$	–	change of the weight of connection between the jth and ith neuron, in the previous learning iteration.

The best speed of the learning process (for the same starting weights values) was achieved for the following parameters: *learning rate* = 0.2; *momentum* *rate* = 0.8. Due to changes in the adaptive momentum rate it was necessary to define its increasing and decreasing rates. We used *increasing momentum rate* = 1.01 and *decreasing momentum rate* = 0.95.

Several neural networks were trained successfully. After testing their co-operation with the classification module described in (Duch *et al.*, 2000), it occurred that the network with nine neurons in the hidden layer was the best one.

4.2. Neural classifiers of machine condition

In the fault diagnostics, the accuracy depends on the suitability of the selected feature and the accuracy of the classifier. The suitability of the selected feature is important to detect the incipient fault, whereas, the performance of the classifier is important to estimate the type of the fault with high certainty. Neural networks proved to be highly effective in performing such tasks. In Fig. 3 the general concept of a neural network used for machine condition assessment is shown.

Two network classes were considered for classification: supervised and unsupervised. In the first case, Back Propagation networks were evaluated to approximate the mapping symptom-state. The second set of the considered networks were Competitive networks. The task of machine condition classification was performed by determining whether the given symptom vector belongs to the subarea of the symptom space corresponding to the given defect type.

The collected data was used for forming a training set for the evaluated neural networks. The selected 11 harmonic components of the spectrum were used as the input vector. The output vector consisted of 5 elements – one for each failure being detected and one for the normal state. The value of a given element is 0 or 1. The machine condition is coded by the value of one for the element associated with this state and the value of zero for all other elements. The training set is formed from pairs: the input vector – the corresponding desired output.

A feed-forward network architecture of three layers was chosen:

The Input layer – the number of neurons equals the size of the input vector, they are connected to each neuron of the hidden layer

The Hidden layer – the number of neurons was determined in the experimental task; neurons from this layer are connected to each neuron of the output layer

The Output layer – the number of neurons equals the size of the output vector.

Figure 3 shows the neural network architecture.

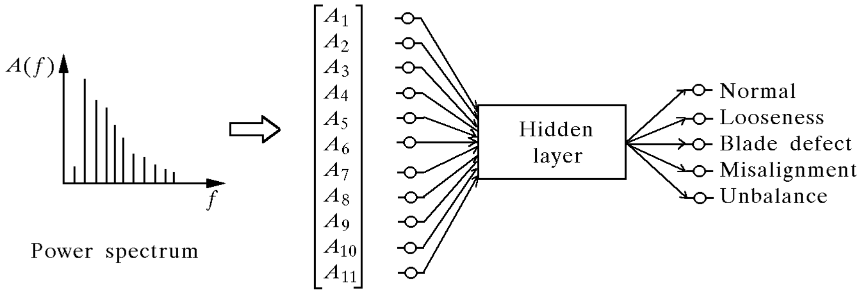

Fig. 3. A scheme of the neural classification

Since competitive networks require unsupervised learning, only the first element of each pair in the training set defined above can be used.

The network architecture of two layers was chosen:

The Input layer – the number of neurons equals size of the input vector, they are connected to each neuron of the output layer

The Output layer – the number of neurons was determined in an experimental task.

The Kohonen training rule was used in the training process. The learning is based on the clustering the input data into groups of similar objects and separating dissimilar ones. In this clustering technique, it is assumed that the number of classes n is known *a priori*. The training set contains the data which represents n clusters, but there is no information indicating which input vector belongs to which cluster. Hence, the Kohonen network classifies the input vector into one of the specified n categories according to the clusters detected in the training set. Then the post processing stage is required in order to interpret the network output.

For solving our problem with rotating machine condition the desired number of classes $n = 5$. Unfortunately, it turned out that the network with 5 outputs does not work correctly even for the training set elements. Some inputs characteristic for the normal machine state were classified as unbalance. Therefore, it was decided to extend the size of the output layer to give the network more clustering freedom. The most accurate results were obtained for 8 neurons in the output layer. The inputs corresponding to the normal machine state were clustered into 4 subclasses.

4.3. Fuzzy logic classifiers of machine condition

As the inputs to the fuzzy logic system representing information about machine state change, the magnitudes of the following spectrum components (up to rotating frequency f_0) were chosen: $f_0/2$, f_0, $2f_0$, $3f_0$, $4f_0$, $5f_0$, $6f_0$, $8f_0$.

To every input a linguistic variable was assigned: very low, low, mid, high, very high. For all the input variables and distinguished fan states a statistical analysis was carried out. The mean value was used for definition of the fuzzy sets placement. Gaussian membership functions were assigned to the sets except for border sets. The variances of Gaussian distributions are equal to the variances of input values counted for each linguistic variable. Z-shaped and S-shaped membership functions were used for sets corresponding to very low and very high variables, respectively. An example of the input variable fuzzyfication is presented in Fig. 4.

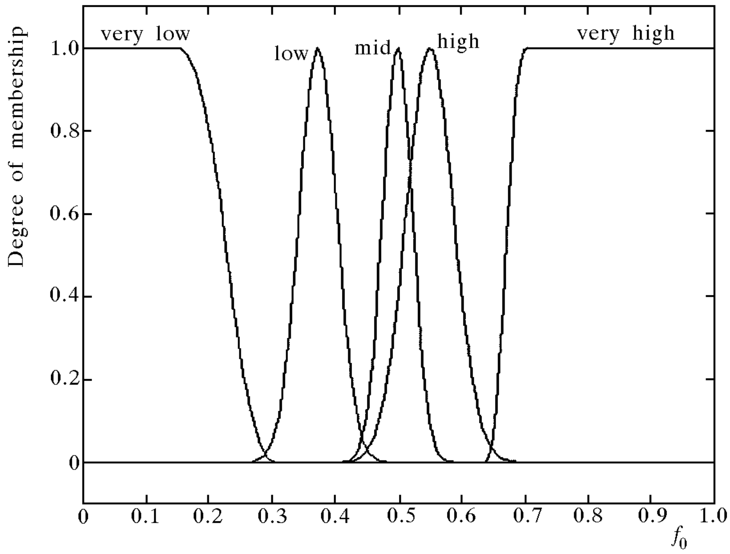

Fig. 4. An example of fuzzyfication

We assumed a fuzzy inference system of the Mamdani type and defined 5 output variables with values from 0 to 1. The variables have labels: high and low. The high level of a variable identifies the machine state corresponding to it. Triangular membership functions were used for fuzzyfication of the output variables.

Next, the rule set describing the strategy of inference in the diagnostic system was defined. In our case, a diagnostic decision table, presented below, was used.

Table 1. Decision table

Variable	Normal state		Blades	Looseness	Misalignment			Unbalance
$f_1/2$	mid	mid	v. mid or high	v. low or mid or high	v. mid	v. mid	high	mid
f_1	v. mid or high	mid	v. low	low	v. low	v. low	v. low	v. mid or high
f_2	mid	v. mid or high	v. low	high	v. high	mid	v. high	low
f_3	mid	mid	low	low	low	low	high	mid
f_4	mid	mid	v. mid	mid	mid	mid	mid	mid
f_5	mid	mid	mid	low	low	mid	v. mid	mid
f_6	mid	mid	mid	low	low	low	mid	mid
f_8	mid	mid	high	low	low	low	mid	mid
output	high	high	high	high	high	high	high	high

Some machine conditions are described by more than one rule. It may result from too many fuzzy sets. But on the other hand it extends the system sensitivity and gives more precise explanations of generated decisions.

For defuzzyfication, the gravity centre and bisector methods were used. An example of fuzzy diagnostic tool performance is presented in Fig. 5. Every row from 1 to 6 represents one inference rule. In the first eight columns titled by input variables names, we present their fuzzy values shading sets used by them. These sets define the antecedents rule. In columns named by the output variables, one can see their fuzzy values which are the result of degree of rules satisfying the calculation. The additional 5-element line presents the results of the aggregation procedure and defuzzyfication. A sharp value of each variable is presented near its name.

In the course of numerous experiments with different input vectors it was observed that the results obtained by the use of both defuzzyfication methods are similar.

4.4. Neural optimisation of fuzzy tool

A fuzzy inference system of the Sugeno type resembles a neural network structure. A neural network learning algorithm can be used for optimisation of

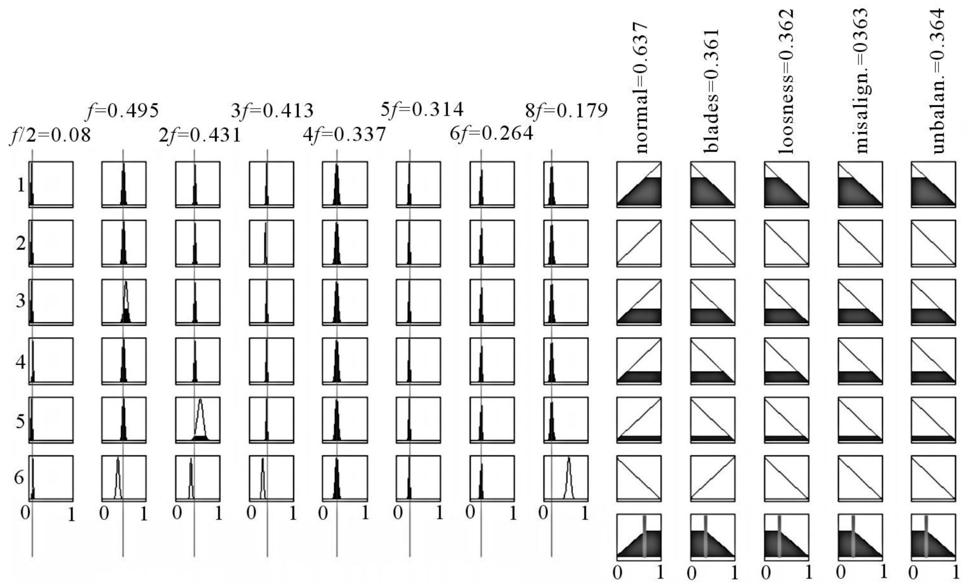

Fig. 5. Fuzzy inference

fuzzy inference system parameters. In this part of the fuzzy inference system they are treated as neural network layers. In this case, the parameters defining fuzzy sets correspond with network weights.

Obviously, some network connections have a constant weight equal one. The correctness of the Sugeno type inference system depends on fuzzy sets location in the space of input variables and on weights of the rules. The parameters describing fuzzy sets location and shape are associated with weights of network connections between the input and the first hidden layer. The weights of connections with the next layer are coefficients of a polynomial defining the degree of fulfilling the rule. Every rule can have its own weight important in yhe aggregation procedure, also corresponding with the network connection weight. Assuming this concept and forming a learning set of the pairs: the input vector-expected fuzzy system output, a backpropagation learning algorithm was used for optimising fuzzy diagnostic system parameters.

A modification of fuzzy sets and corrections of their locations after the neural optimisation improved the system operation – a decrease in the number of not recognised machine states for the testing set was observed.

But still we have the diagnostic system based on rules formulated by a human expert. In recent years, trials of the simultaneous use of both methods, i.e. fuzzy logic and neural networks in hybrid systems have been made. In our case, an expert decides about the number of input variables and their features, i.e. number of fuzzy sets and their initial location in the input space. The task of the neural network is the knowledge base creation, that is generation of a set of rules basing on the learning set. At the initial stage all possible rules are formulated as combinations of all fuzzy sets. The learning algorithm eliminates not used rules setting their weights near zero.

The hybrid diagnostic system created on the basis of this concept contains the knowledge of the human expert and information from archived measurements.

4.5. Unrecognised machine state

It is a known feature of soft computing that it always gives output values, even for irrational inputs. To avoid false classifications of an additional output, signalling of an unrecognised state was added. Usually, the result of state classification via neural networks or fuzzy logic system looks as in Table 2.

Table 2. Examples of diagnostic tool outputs for given machine conditions

Normal condition	Blades defect	Looseness	Misalignment	Unbalance
0.9982	0.0001	0.0053	0.0147	0.0299
0.0003	0.9784	0.0074	0.0015	0.0033
0.0006	0.0047	0.9774	0.0158	0.0014
0.0022	0.0011	0.0229	0.9651	0.0001
0.0047	0.0062	0.0001	0.0002	0.9724

If all elements of the output vector are close to zero and one is close to one, it signals that the machine condition is the state associated with this element. But sometimes it is not clear what the machine state is. Then, the diagnostic tool signals an unrecognized state.

It happens when:

- The maximum value in the output vector is smaller than the desired one
- The difference between the maximum value and the next one is too small
- The maximum value to the sum of other elements ratio does not show a decisive nature (capacity).

These requirements were also used for the analysis of the membership function values in the pattern recognition methods.

5. Pattern recognition

In this group of methods, an object is represented by a vector of measurements. Thus, the objects similarity can be described by the vectors similarity. Such vectors are called the features vectors (Tadeusiewicz, 1991). In our research,the features vector is a vector of selected power spectrum components. The similarity between the features vector representations of two machine states can be described by the use of different distance norms. The Euclidean, Tchebyshev and taxi norms were used. The nonparametric methods, used in the research, are based on the similarity ratio definition and the existing training samples.

5.1. Nearest neighbors

In this method, the former training set was modified. Its elements are pairs of the input vector and the number of the machine state which is characteristic.

In this method, the similarity ratio was defined as follows

$$c^i(\boldsymbol{x}) = \frac{1}{\sigma(\boldsymbol{x}, \boldsymbol{x}^{i,k}) + \varepsilon} \qquad i = 1, 2, ..., L \tag{5.1}$$

where

$\sigma(\boldsymbol{x}, \boldsymbol{x}^{i,k})$ – distance between the vector in question $\boldsymbol{x}$ and training vector $\boldsymbol{x}^{i,k}$

$\boldsymbol{x}^{i,k}$ – ith training vector corresponding to the kth machine condition

ε – small constant necessary for division feasibility.

The similarity ratio has to be computed for all training set vectors.

The biggest value of the similarity ratio describes the most similar training vector to the vector in question. The class number corresponding to it results from classification.

5.2. Nearest class mean

In this method, the input vector is compared with generalized reference. Some training subsets can be used. To increase computing speed a short training set was used. Each machine state is represented by only one features vector. These vectors can be obtained according to the formula

$$\boldsymbol{m}^i = \frac{1}{N_i} \sum_{k=1}^{N_i} \boldsymbol{x}^{i,k} \qquad i = 1, 2, ..., L \tag{5.2}$$

where N_i is the number of training vectors corresponding with the ith machine condition.

The similarity ratio is given by the formula

$$c^i(\boldsymbol{x}) = \frac{1}{\sigma(\boldsymbol{x}, \boldsymbol{M}^i) + \varepsilon} \qquad i = 1, 2, ..., L \tag{5.3}$$

where $\boldsymbol{M}^i$ is the ith training vector from a new training set.

6. Comparative studies

In this research, the proposed soft computing tools and pattern recognition methods for rotating machine condition assessment were verified for test cases.

First, robustness of tools for external disturbances in input data was examined.

The software for simulating gradually raising disturbances in the input data was created. A random noise with the normal distribution was added to the input vectors. The correctness of tools answers depending on such inputs was checked. The obtained results are presented in the following figures.

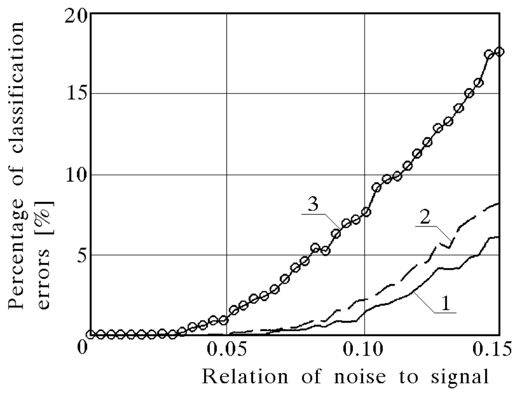

Fig. 6. Robustness for external disturbances of the nearest class mean method with norms: 1 – Euclidean, 2 – Taxi, 3 – Tchebyshev

The presented here simple fuzzy logic classifiers are rather sensitive to external disturbances. All input variables are required for proper reasoning. The inference system consists of rules that fire only if all antecedents are non zero, which means that the values of all input variables have to belong to fuzzy sets used by the rule.

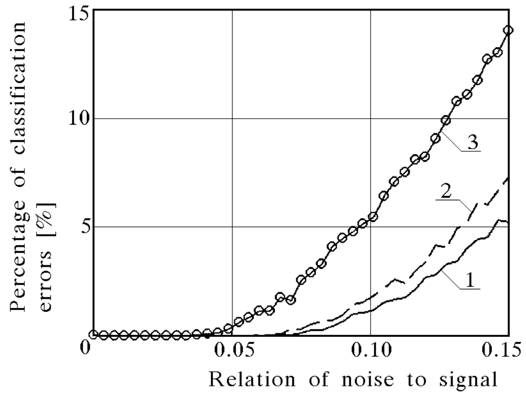

Fig. 7. Robustness for external disturbances of nearest neighbours method with norms: 1 – Euclidean, 2 – Taxi, 3 – Tchebyshev

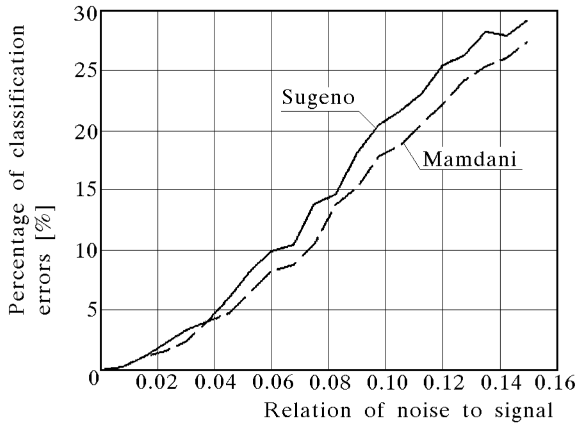

Fig. 8. Robustness for external disturbances of fuzzy logic classifiers

In Fig. 9 the comparison of the best robust testing results for neural networks and pattern recognition methodsis shown.

The results presented above proved that neural networks are more robust than pattern recognition methods for input data disturbances that do not exceed 8% of the original signal. For higher disturbances the pattern recognition methods work better. Considering the tools tested in this work, one can notice that simple fuzzy logic systems are more sensitive to disturbances than others.

In the next step a comparison of operational speeds of all the presented methods was performed. The selected power spectrum components were passed to pattern recognition algorithms as well as to fuzzy logic and neural classifi-

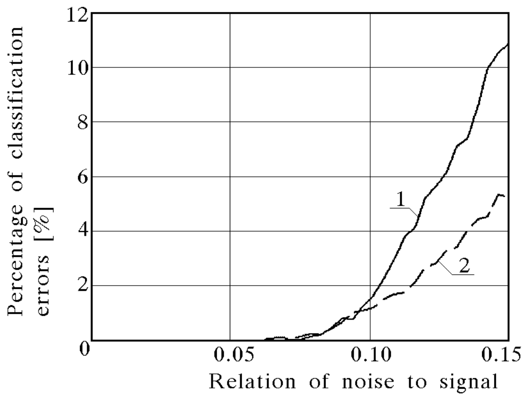

Fig. 9. Robustness comparison of: 1 – the best neural network, 2 – the best pattern recognition method

cation tools while the whole power spectrum to the compression-classification network set. The measured operational speed is the time necessary to compute 1000 iterations of 210-element set of input vectors. In Table 3 the obtained results are presented.

Table 3. Comparison of operational speeds and applicability of all presented methods to early machine fault detection

Algorithm	Operational speed	Degree of power spectrum evolution
Neural classifiers using:		
back propagation network	28 s	33%
compression-classifying neural networks set	31 s	42%
competitive network	24 s	50%
Fuzzy logic classifiers:		
Mamdani	992 s	35%
Sugeno	75 s	37%
Pattern recognition:		
Nearest class mean method with Euclidean norm	144 s	50%
Nearest class mean method with Taxi norm	131 s	50%
Nearest class mean method with Tchebyshev norm	138 s	47%
Nearest neighbour method with Euclidean norm	893 s	39%
Nearest neighbour method with Taxi norm	812 s	35%
Nearest neighbour method with Tchebyshev norm	856 s	65%

The next research tasks included tests of soft computing tools applicability to early machine fault detection. The continuous character of changes in the machine state was assumed. Thus, changes in the power spectrum components are smooth. The created software simulates input vector changes from the normal condition to desired four different failures. The point is how fast the evolution of the input vector should be treated as a possibility of failure occurrence. The 98 intermediates were distinguished between the input vectors characteristic for normal and faulty conditions. The characteristics differ from each other by 1/100 of the Euclidean distance between them. Table 3 shows the obtained results. The column "degree of power spectrum evolution" contains values for which the examined algorithm signaled a change in the machine condition.

7. Conclusions

In this paper, some applications of soft computing to machine diagnostics were presented. The case study of a high power fan and its vibration measurements was analysed.

The use of basic fuzzy logic concepts gives an automatic and objective diagnostic module. Statistical analysis of measured signals is important for determining correct fuzzy sets sizes and locations. Also, the membership function shape should be similar to the distribution function of signal values.

Neural networks proved to be useful filters. Signals after neural filtering and compression are better classified, which gives an opportunity to decrease the size of the classifying neural network.

Learning algorithms of neural networks can be used for optimisation of fuzzy system parameters. In this work, the author considered parts of the fuzzy inference system as neural network layers. In such a case, the parameters defining fuzzy sets correspond to network weights. By the use of training sets and learning algorithms it is possible to optimise the fuzzy diagnostic system.

In the paper, the author tried to take advantage of both these methods working together. A hybrid adaptive neuro-fuzzy diagnostic system was presented. As the input and output the fuzzy sets were used, and a neural network was the knowledge base. The system based on composition of human and artificial knowledge worked with much more precision.

The research presented in this paper proved the usefulness of soft computing tools for automatic rotating machine condition assessment. Simple structures of two network classes: supervised and unsupervised, provide correct solutions to the presented diagnostic problem. Neural networks can also be used as pre-processors compressing input data. Such networks optimise hidden layer sizes in a compression-classification feed forward network set. Also, both types of fuzzy systems make correct the condition classification.

The comparative research showed better neural networks robustness, but only in the presence of low measurement noise and disturbances. Fuzzy logic systems require all input signals from desired value intervals. A rather high computational complexity of pattern recognition methods and neural network parallel processing results in faster performance of the second group of methods. A significant difference between the Sugeno and Mamdani fuzzy systems performance is caused by the defuzzyfication stage in the Mamdani system. In the Sugeno system, the result of inference is a scalar that does not need defuzzyfication. It saves a lot of time and space, which makes the efficiency similar to the performance of neural tools.

The evaluated soft computing tools proved their applicability to early machine fault detection. Detection of condition changes takes place when the evolution degree reaches 30%. It enables early reaction to condition changes of a machine.

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Metody *soft computing* w narzędziach do diagnozowania maszyn

Streszczenie

W pracy omówiono wykorzystanie metod *soft computing* do budowy narzędzi stosowanych w systemach diagnostyki maszyn. W takich systemach istotnym zagadnieniem jest interpretacja mierzonych danych. Aby rozwiązać problemy związane z analizą dużej ilości informacji w systemie diagnostycznym, zaproponowano neuronowy procesor. Sieć neuronową wykorzystano do redukcji rozmiaru analizowanego wektora cech. Detekcja i izolacja uszkodzeń jest zadaniem trudnym z powodu rozmytych i kontekstowych relacji pomiędzy mierzonymi danymi i stanem maszyny. Metody *soft computing* są pomocnym narzędziem do rozwiązywania tego typu problemów. W niniejszej pracy wykorzystano techniki zbiorów rozmytych i sieci neuronowych. Zbudowane z ich wykorzystaniem narzędzia dokonują aproksymacji relacji diagnostycznych symptom-stan. Wiedza na temat tych relacji jest ukryta w zarejestrowanych danych, które ilustrują wiedzę ekspertów pozyskaną w języku naturalnym. Taka forma zgromadzonej wiedzy jest podstawą konstruowania sieci neuronowych i systemów rozmytych. Ich działanie zilustrowano na przykładzie detekcji uszkodzeń wentylatora dużej mocy. Dokładność działania prezentowanych w pracy narzędzi *soft computing* przetestowano w kontekście wyników otrzymywanych za pomocą metod rozpoznawania obrazów. W pracy przedstawiono także porównanie szybkości działania, odporności na zakłócenia i zdolności do wczesnego wykrywania uszkodzeń dla wszystkich wymienionych metod.

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