Computer Assisted Mechanics and Engineering Sciences, **12**: 123–132, 2005.

Non-contact model-based diagnostics of electrical motor involving uncertainty and imprecision of model parameters

Piotr Czop
LABMOD, Leśna 2a, 42-624 Ossy

Lucjan Miękina
University of Mining and Metallurgy,
Department of Mechanical Engineering and Robotics,
Al. Mickiewicza 30, 30-059 Kraków, Poland

(Received March 31, 2005)

System identification of a parametric "black box" model for the purpose of electrical motor diagnostics is discussed in this paper. The measured acoustic pressure signal is used for identification of a model which structure is considered as a transfer function. Poles of denominator are calculated and collected on a complex plane. Fuzzy, two-stage algorithm is used for clustering and classification of poles which are assumed as symptoms of the motor conditions. The statistical uncertainty and fuzzy imprecision of the poles placement is taken into account by the clasterization procedure. The aim of this procedure is a separation of classes regarding a priori information of their number. Classification was performed with the use of the faulty electrical motors.

Keywords: fuzzy classification algorithm, acoustic process control, parametric model

1. Introduction

Considering higher performance and prolonged lifetime of machinery components, special attention is paid to rapid and non-destructive testing of a product under final assembly conditions. Since the electrical motor is a critical component of the product it is important to ensure reliable testing at the stage of manufacturing. Electrical motors and other components assumed to be non reparable within lifetime. Faulty and obsolete product is usually replaced by the new one available on the market.

The linear regressive model can be used for detection of changes of the system properties regarding the monitoring of poles placement. The simplest input-output "black-box" model is ARX structure (AutoRegressive with eXougenous input) [2]. ARX model consists of a discrete transfer function which parameters of a numerator and denominator are identified. Simplification of this model is AR structure, called signal model. This model assumes that signal is generated by a linear system driven with the use of white noise. In other words this is an all-pole linear filter with all of its zeros at the origin in the z-plane [2]. The output of such a filter for white noise input is an autoregressive (AR) stationary process. Regressive models are successfully used to estimate power spectrum of periodic signal characterized by harmonic components [2]. There are a few estimators of model parameters such as Yule–Walker, Burg, covariance, and modified covariance method [2].

A parametric method used at the stage of fault detection provides a few important advantages such as:

- high resolution in the frequency domain,

- possibility of nonstationary process modeling,
- increase of system identification performance in the case of feedback-loop systems and highly noised data.

The fundamental advantage of the parametric approach is a high accuracy during identification of the short signal realizations in comparison to a nonparametric approach [2]. This accuracy is mainly related to the frequency image of parameterized signal. AR model can be also presented in the form of a nonparametric model, e.g. power spectrum, autocorrelation function, and impulse/step time domain response.

The proposed fault classification method is based on the theory of pattern recognition. Parameterized signal model is decomposed with the use of multidimensional space. In the case of direct approach the number of dimensions is equal to the number of model parameters. Reduction of dimensions is possible when poles representation of signal is considered [2]. Each pole has real and imaginary parts. Poles are placed on 2-D complex plane with real and imaginary axes. Arrangement of poles can be also considered from the physical point of view. Frequency and damping ratio are taken into account in this case. In the proposed method poles are instantaneously collected during motor operation. Fuzzy model applied at the fault classification stage consists of the inputs (poles coordinates) and outputs (cluster centers). The fuzzy model is formulated as a set of rules ([4, 2]):

Premise	u is A'
Implication	**IF** u is A' **THEN** y is B'
Conclusion	y is B'

where $A, A' \subseteq X$, and $B, B' \subseteq Y$ are the fuzzy sets [1], u and y are the input and output variables. The fuzzy rule is a fuzzy relation $R = A \to B$. Therefore, conclusion B' can be obtained by taking the composition of fuzzy set A' and the fuzzy relation of $R = A \to B$:

$$B' = A' \circ R = A' \circ (A \to B). \tag{1}$$

The fuzzy rule is represented by the "**IF-THEN**" formula consisting of the condition and consequent. Set of collected fuzzy rules creates the rule-base of fuzzy system. There are the two basic types of fuzzy systems: Mamdani with qualitative consequents and Sugeno (TSK) with function-like consequents. Mamdani multi-input and single-output system has the following form:

$$\textbf{If } \varphi_1 \textbf{ is } A_{i,1} \textbf{ and}, \ldots, \textbf{ and } \varphi_d \textbf{ is } A_{i,d} \textbf{ then } y = B_i, \tag{2}$$

where i is number of rule and d is number of inputs. Sugeno (TSK) multi-input and single-output system has the following form:

$$\textbf{If } \varphi_1 \textbf{ is } A_{i,1} \textbf{ and}, \ldots, \textbf{ and } \varphi_d \textbf{ is } A_{i,d} \textbf{ then } y = f_i(\varphi), \tag{3}$$

where $y = f_i(\varphi)$ is general form of regression. The output of the inference system is the weighted average of all rule output.

2. Test-rig and data acquisition

The measured acoustic pressure level is related with operation of an electrical motor. The data represents the three operation modes (Table 1): idle mode (without load) under the three constant operating speeds, throttling air flow mode under constant operating speed and throttling air flow mode under transient operating speed (start up, coast down). The motor is equipped with the integrated radial fan which is a source of an additional aerodynamic noise. Such a noise is characterized by a broadband spectrum with numerous harmonics. The manufacturer has provided the faulty motors. Particular motors have a one basic malfunction (excessive rotor vibrations, excessive loudness, bearing problem, and excessive looseness).

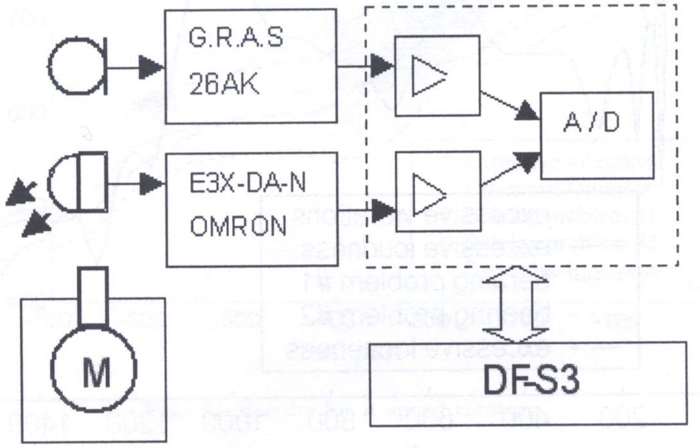

Fig. 1. Scheme of the measurement setup (GRAS 26AK – amplifier, E3X-DA-N – phase marker measurement, DF-S3 computer local bus, M – tested electrical motor)

The measurements (Table 1) were conducted in the anechoic chamber. A phase signal of rotating shaft was simultaneously recorded with an acoustic signal. This signal can be used for a synchronous spectrum analysis [1]. The configuration of laboratory setup is presented in Fig. 1. The investigated motors were mounted in the shaped bearing made of a damping material. Microphone and preamplifier were placed on a stand. The distance was 0.5 m above the investigated motor from the side of the commutator.

Table 1. Matrix of conducted measurements

Malfunction	Idle mode	throttling air flow mode under constant operating speed	throttling air flow under transient operating speed (start up, coast down)
Excessive vibrations	X	X	X
Excessive loudenss	X	X	X
Bearing problem #1	X	X	X
Bearing problem #2	X	–	X
Excessive looseness	X	–	X

The preliminary nonparametric system identification was performed with the use of Blackman–Tuckey algorithm. It can be observed that each malfunction has specific pattern of frequencies (Fig. 2).

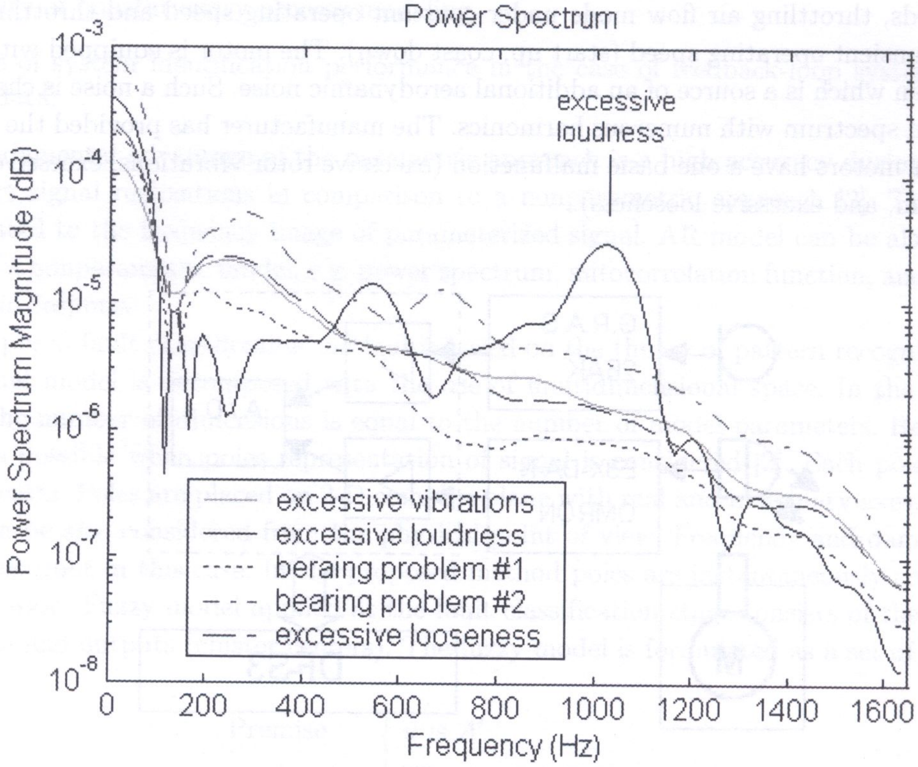

Fig. 2. Result of nonparametric system identification

3. Verification of proposed method

The algorithm of fault detection is based on the periodic identification of AR model parameters. System identification is performed for a buffer of the length 1000 samples. The 4-th order lowpass digital Butterworth filter with the cut-off frequency of 400 Hz was applied before system identification. Parameters of the denominator are formulated in a characteristic equation which is a base for determination of the poles placement. Exemplary detection process was conducted based on the idle mode data. The data block of 30 min was recorded for tested motor including the three uniform changes of speed vs. operation time (Fig. 3). During preliminary tests, the dependence of the spectrum pattern on the rotating speed was noticed.

The second order AR(2) autoregressive model was applied. It was assumed that the poles placement is mainly affected by the nonlinearities corresponding to the particular malfunctions. General

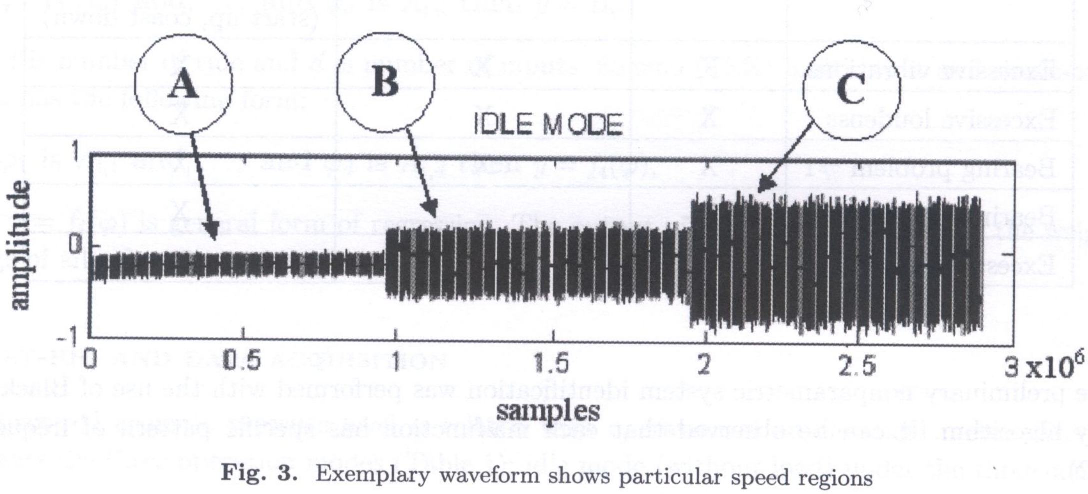

Fig. 3. Exemplary waveform shows particular speed regions

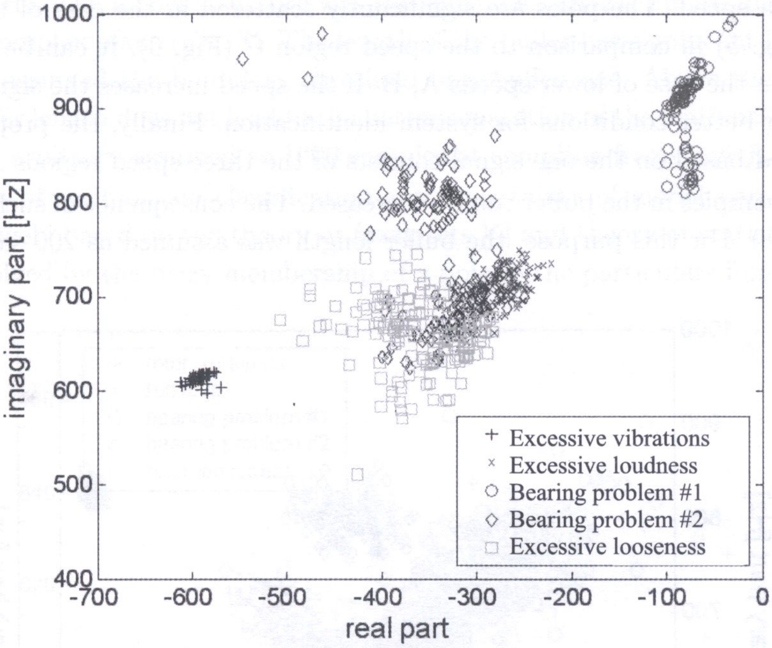

Fig. 4. Results for A speed rotation

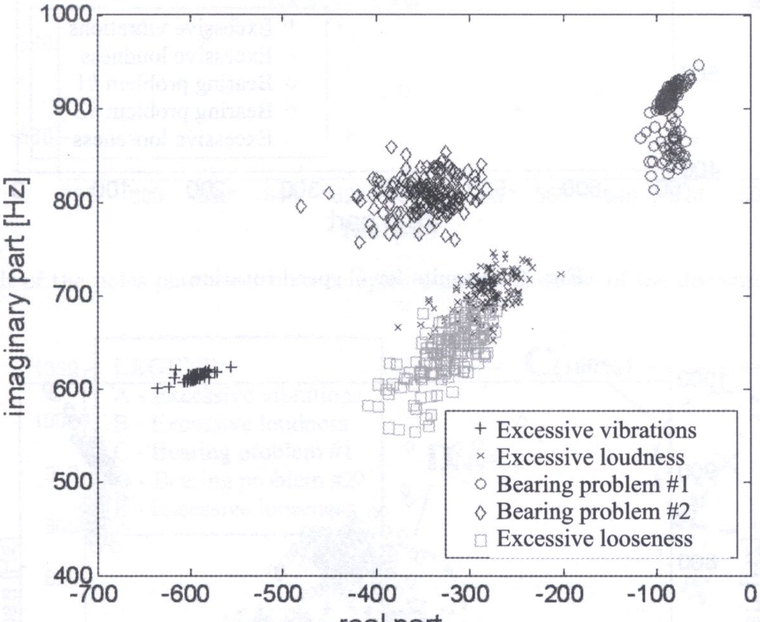

Fig. 5. Results for B speed rotation

interpretation of the poles placement can be considered. For instance, loose component decreases locally stiffness of a mechanical system causing lower natural frequency; rotor rubbing to stationary parts of a motor increases locally stiffness and causing the pole placement towards higher frequencies. Arrangement of poles for the five types of malfunctions (Fig. 6) was plotted. The circular data buffer of the size 1000 samples was used to obtain the poles placement. Finally, 750 poles were placed on the complex plane (Fig. 7).

The method of fault detection was verified with the use of the three different signals related to the particular speed regions (Fig. 3). The results show that the pattern of the poles placement is different for each speed. The poles are significantly scattered in the case of the speed region A (Fig. 4) and B (Fig. 5) in comparison to the speed region C (Fig. 6). It can be caused by the low signal/noise ratio in the case of lower speeds A, B. If the speed increases the signal/noise ratio also increases providing better conditions for system identification. Finally, the proposed classification method was verified based on the one signal consists of the three speed regions A, B, C (Fig. 7).

The number of samples in the buffer can be decreased. The consequence of such a change was also investigated (Fig. 8). For this purpose, the buffer length was assumed as 200 samples at sampling

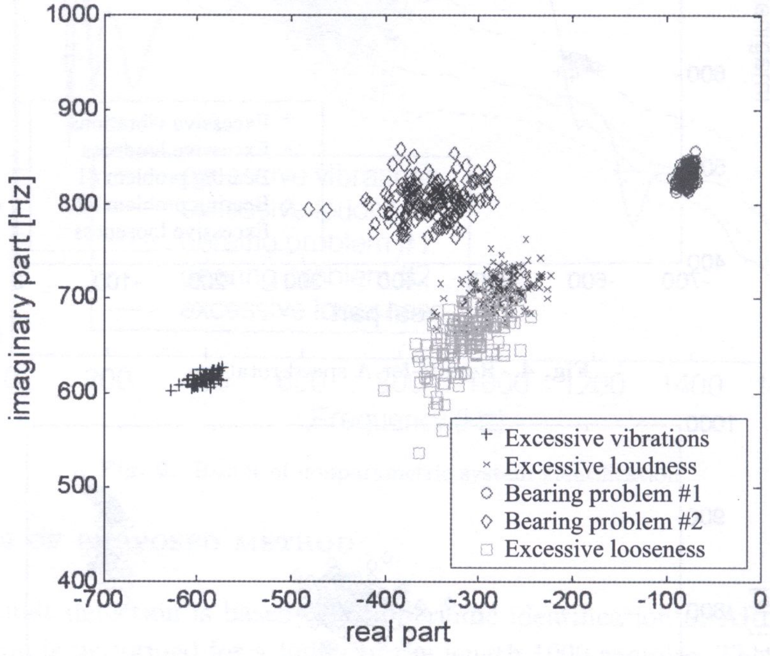

Fig. 6. Results for C speed rotation

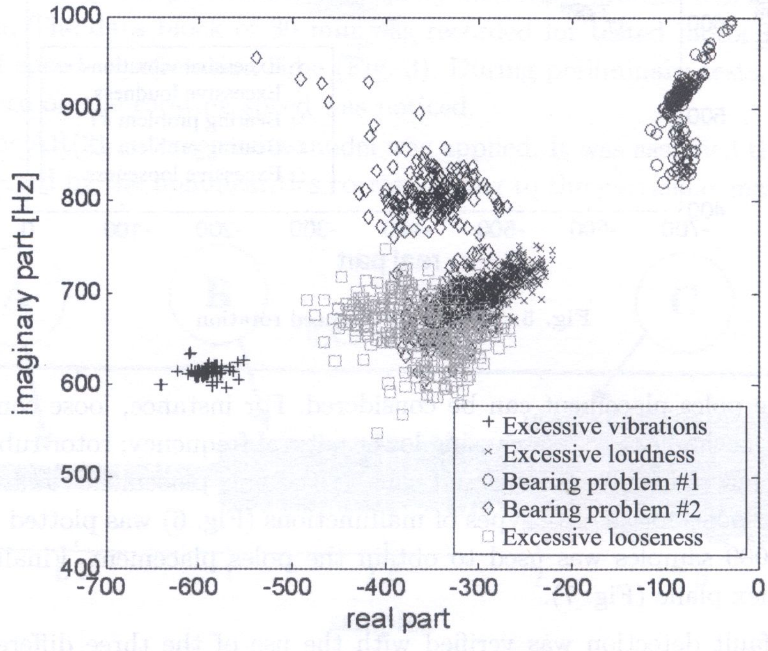

Fig. 7. Result of the poles placement on a complex plane (speeds A, B, C)

frequency $f_s = 3$ kHz. The model structure was the same, i.e. AR(2). The results of fault detection are shown on the complex plane (Fig. 8). The length of the buffer has significant impact on the poles scatter. It can be assumed the boundary threshold of a buffer size. Above the threshold, further increase of the buffer length does not lead to the better separation of the malfunction classes. Finally, the buffer size was arbitrary assumed as 1000 samples at sampling frequency $f_s = 3$ kHz.

The imprecision of malfunction classification and uncertainty of model parameters can be distinguished respectively based on the theory of fuzzy sets [5] and theory of statistical estimation [2]. Imprecision is involved by the fuzzy membership of a pole to the particulars fuzzy sets representing

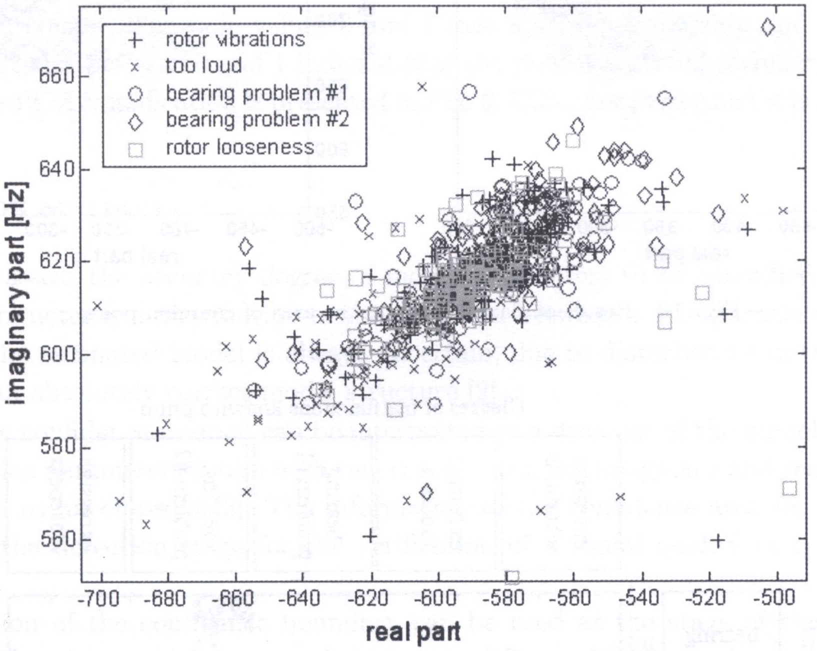

Fig. 8. Result of the poles placement on a complex plane in the case of the decreased buffer length

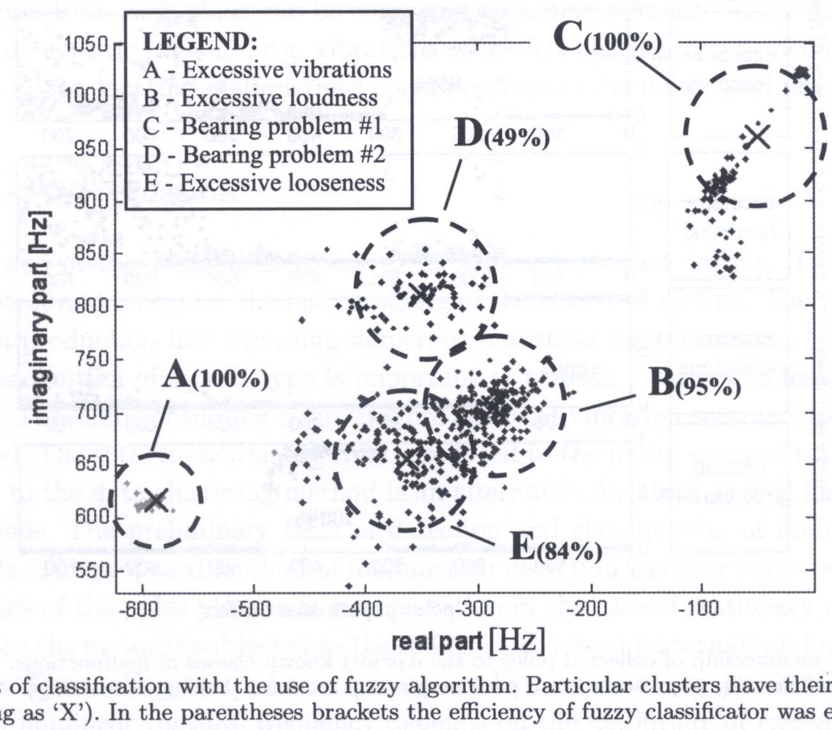

Fig. 9. Result of classification with the use of fuzzy algorithm. Particular clusters have their representatives (denoting as 'X'). In the parentheses brackets the efficiency of fuzzy classificator was estimated

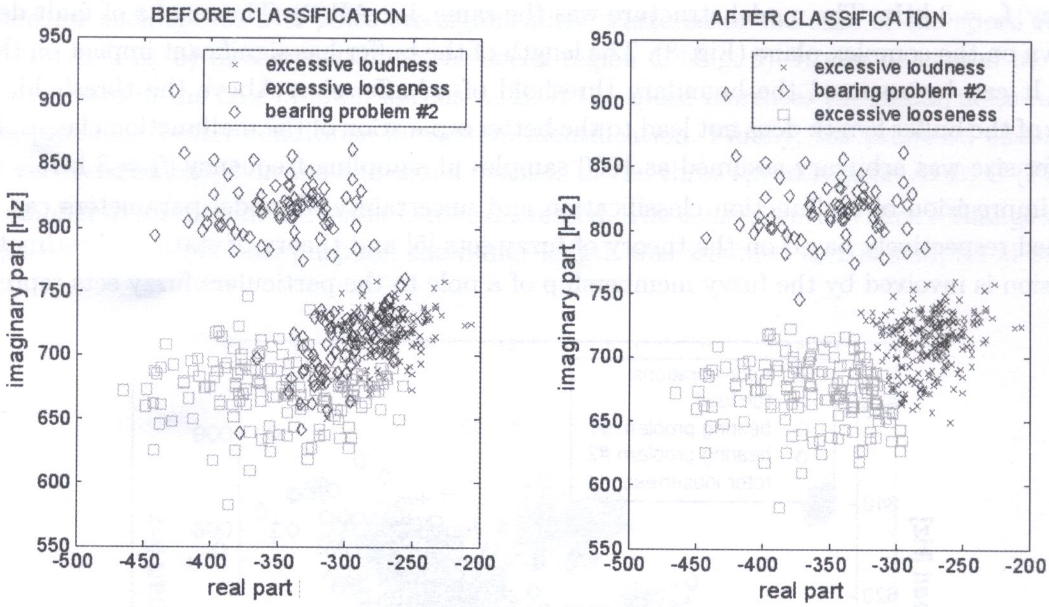

Fig. 10. Result of classification in the area of common poles

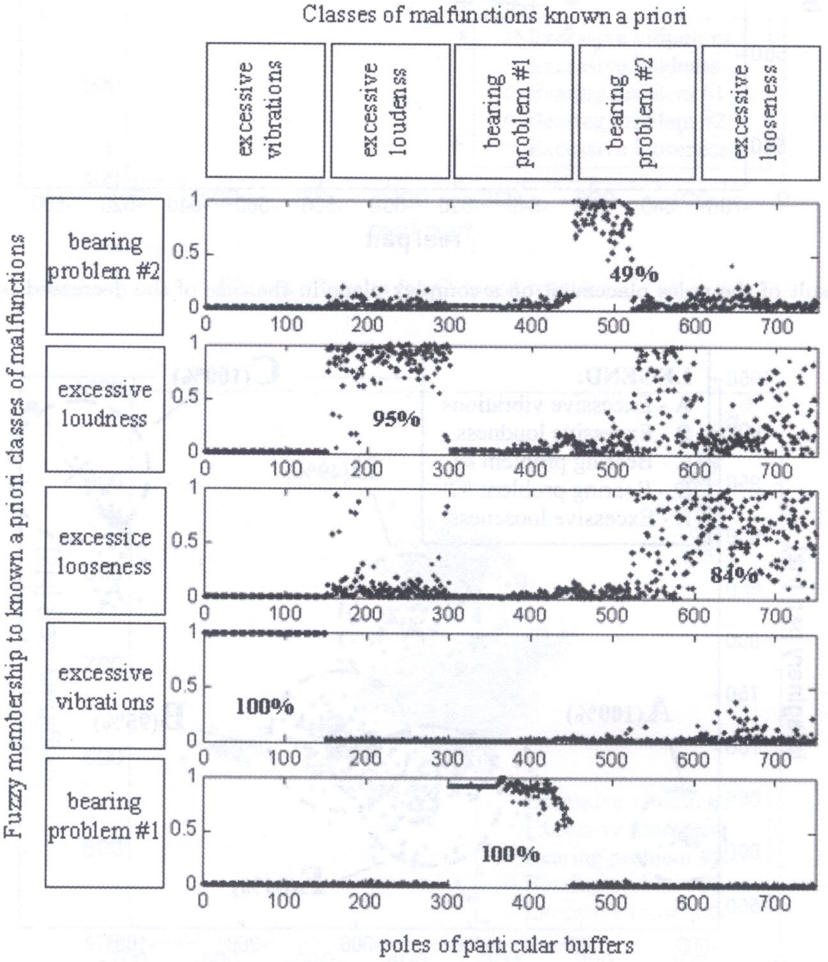

Fig. 11. Fuzzy membership of collected poles to the *apriori* known classes of malfunctions. The efficiency of classifier is presented as a percentage crisp measure {belong/not belong}

the malfunctions. The uncertainty of the model is expressed by confidence ellipsoids determined directly for the model poles [2].

The poles related to the five *a priori* known classes of malfunctions are grouped with the use of the fuzzy cluster algorithm [4]. Cluster analysis is performed on a set of poles. For this purpose is the most suited, fuzzy c-means (FCM) technique, which was originally introduced in 1981 as an improvement on the earlier clustering method [4]. The common region can be noticed for the three clusters (Fig. 10). It is extremely difficult to classify poles located in this region. The fuzzy algorithm provides a compromise solution. Classification was conducted based on a fuzzy membership of each pole coordinate (real, imaginary). The membership function contains the grade of membership of each pole in each cluster. The pole values 0 and 1 indicate no membership and full membership respectively [5] Grades between 0 and 1 indicate that the pole has partial membership in a cluster. An exemplary result of classification is presented in Fig. 9. Classifier performance is shown in Fig. 11.

4. Remarks on method

It is possible to assess the accuracy degree of model parameters to be identified. The confidence interval for a parameter is a distribution of the deviation between a true parameter and estimated parameter [2]. The estimated model is always uncertain, due to disturbances in the observed data and the lack of an absolutely correct model structure [2].

Increase of the confidence interval can be interpreted as a decrease of the model accuracy. In the case of the complex parameters (poles with two coordinates, the imaginary and real) the confidence area is expressed as an ellipsoid [2]. The information of the confidence area for the specific pole can be used at the detection stage for the verification of a signal quality in comparison to the reference one.

The information of the confidence boundary can be used at the stage of classification of the malfunctions. When the signal is measured at the two different locations, the two independent AR models can be identified. In this case poles are observed simultaneously on the two complex planes. The sizes of ellipsoids on each plane can be compared regarding reference historical measurements. Specific sources of acoustic pressure, e.g. vibrations of the left bearing, can be occurred only on one of the planes. It allows locating malfunctions corresponding to the motor geometry.

5. Summary and discussion

The method is one of the possible alternatives for the end product testing. Two-stage test was conducted to detect and recognize the failure modes of the electrical motors. The proposed method can be used in a production line regarding numerous industrial limitations, e.g. low cost and high performance. Recognition of a fault type is important to provide a corrective feedback to the production process. The time-consuming mounting procedure of vibration sensors is not needed in the proposed method. The total measurement time is reduced to the motor operation at given speed(s). Fuzzy approach to the data clustering method is an alternative for classical well known in statistics taxonomy methods. The preliminary tests of detection and classification of faults have provided promising results. The proposed method of malfunction detection has also numerous disadvantages such as difficulties of the poles placement interpretation in the case of stationary motor operation. In such conditions the motor is subjected to the self-excited, forced (external) and natural (internal) vibration modes. The malfunctions of a motor are involved in theory, by parametric (time-varying coefficients) and nonlinear (natural frequency depends on the amplitude of excitation) differential equations. It is not possible to cover system dynamics with the use of linear and time-invariant "black box" model. However, the influence of the nonlinearites corresponding to particular malfunctions is observed through variation of the values of AR model parameters.

It is planned to extend the measurement group of faultless motors and other cases of malfunctions during further research and development. The models of higher degrees will be used and tested during considering investigations.

Acknowledgment

Authors would like to express their gratitude to the KBN, Scientific Research Committee for financing the research work presented in this paper within the framework of a research project No. 8 T07C 019 20.

References

[1] M. Gibiec, L. Miekina. Electrical machines diagnostics with acoustic measurements application. *Internoise 2004, The 33-rd International Congress and Exposition on Noise Control Engineering* August 22–25, Prague, 2004.

[2] L. Ljung. *System Identification – Theory for the User.* Prentice-Hall, 1999.

[3] R.J. Patton, P.M. Frank, R.N. Clark. eds. *Issues of Fault Diagnosis for Dynamic Systems.* Springer-Verlag, London, 2000.

[4] M. Sugeno. *Industrial Applications of Fuzzy Control.* Elsevier Science, Pub. Co., 1985.

[5] L.A. Zadeh. Fuzzy sets. *Information and Control* (8), 338–353, 1965.