Monitoring and Analysis of Manufacturing Processes in Automotive Production

Volume 6

ISBN 978-3-96595-018-4
e-ISSN (PDF) 2629-3161

Bibliographic information published by the Deutsche Nationalbibliothek
The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliographie; detailed bibliographic data are available on the Internet at http://dnb.dnb.de

© 2022 RAM-Verlag
RAM-Verlag
Stüttinghauser Ringstr. 44
D-58515 Lüdenscheid
Germany
RAM-Verlag@t-online.de
https://www.ram-verlag.eu

Editorial Board of the Book Series:

Monitoring and Analysis of Manufacturing Processes in Automotive Production

e-ISSN: 2629-3161

Chairman of the Editorial Board:

Panda, Anton	Technical University of Košice, Faculty of Manufacturing Technology with seat in Prešov, Slovak Pepublic	anton.panda@tuke.sk

Members of the Editorial Board:

Pandová, Iveta	Technical University of Košice, Faculty of Manufacturing Technology with seat in Prešov, Slovak Pepublic	iveta.pandova@tuke.sk
Dyadyura, Kostiantyn	Sumy State University, Sumy, Ukraine	dyadyura@pmtkm.sumdu.edu.ua
Zaborowski, Tadeusz	Institute for Scientific Research and Expertises, Gorzów Wlkp., Poznaň, Poland	tazab@sukurs2.pl
Buketov, Andrey	Kherson State Maritime Academy, Kherson, Ukraine	buketov@tstu.edu.ua
Svetlík, Jozef	Technical University in Kosice, Slovak Republic	jozef.svetlik@tuke.sk
Pilc, Jozef	Žilinská univerzita v Žiline, Slovak Republic	jozef.pilc@fstroj.uniza.sk
Mrkvica, Ivan	Vysoká škola banícka, Strojnícka fakulta, Ostrava, Czech Republic	ivan.mrkvica@vsb.cz
Jančík, Marek	Spinea s.r.o. Prešlv, Slovak Republic	marek.jancik@spinea.sk
Katuščák, Ján	ZVL Auto spol. s r.o., Prešov, Slovak Republic	katuscak@zvlauto.sk
Hajdučková, Valentína	ZVL Auto spol. s r.o., Prešov, Slovak Republic	hajduckova@zvlauto.sk

Yury NIKITIN
Tibor KRENICKÝ
Pavol BOŽEK

Diagnostics of automated technological drives

2022

Yury NIKITIN[1], Tibor KRENICKÝ[2*], Pavol BOŽEK[3]

[1] Kalashnikov Izhevsk State Technical University, Department of Mechatronic Systems, Studencheskaya Ulitsa 7, 426069, Izhevsk, Russia
[2] Technical University of Kosice, Faculty of Manufacturing Technologies with a seat in Presov, Bayerova 1, 080 01, Presov, Slovakia
[3] Slovak University of Technology in Bratislava, Faculty of Materials Science and Technology in Trnava, Institute of Production Technologies, J. Bottu 25, 917 24, Trnava, Slovakia
[*] Corresponding author's email: tibor.krenicky@tuke.sk

ABSTRACT

The monograph deals with the topic of the diagnostics of technological drives. It focuses on the dependence of diagnostic parameters on technical state of technological drives, which is of crucial significance for industrial plants. The main aim is to contribute to knowledge within the topic of diagnostics of mechatronic systems by the analysis of the elements reliability characteristics; using methods, models, and algorithms for diagnostics and by studying examples of model diagnostic systems using AI methods based on neural networks and fuzzy inference systems. The diagnostic models of automated technological systems drives have been also developed.

Keywords: technical diagnostics, engine reliability, vibration analysis, diagnostic model, fuzzy inference system.

Authors:
Yury NIKITIN, Assoc. Prof. PhD.
Department of Mechatronic Systems
Kalashnikov Izhevsk State Technical University
Izhevsk, Russia

Tibor KRENICKÝ, Assoc. Prof. PhD.
Department of Design and Monitoring of Technical Systems
Faculty of Manufacturing Technologies with a seat in Prešov
Technical University of Košice
Prešov, Slovakia

Pavol BOŽEK, Dr.h.c. Prof. PhD.
Faculty of Materials Science and Technology
Institute of Production Technologies
Slovak University of Technology
Bratislava, Slovakia

Reviewers:

Witold BIAŁY, Dr. hab. inz. Prof. PS, Politechnika Slaska, Institute of Industrial Engineering, Zabrze, Poland

Aleksandr Ivanovich KORSHUNOV, Prof., Dr, Udmurt State University, Votkinsk branch, Udmurt federal research centre of the Ural Branch of the Russian Academy of Sciences, Udmurt Republic, Izhevsk, Russia

Dagmar JANÁČOVÁ, Prof. Ing. CSc., Tomas Bata University in Zlin, Faculty of Applied Informatics, Department of Process Control, Zlin, Czech Republic

ISBN: 978-3-96595-018-4

Contents

List of Figures and Tables

Figures

Tables

Acknowledgements

The study was elaborated within the cooperation of the Slovak University of Technology in Bratislava and the Technical University of Kosice, Slovakia, with the Kalashnikov Izhevsk State Technical University, Russia, supported by the grant agency VEGA within projects No. 1/0823/21 and 1/0019/20 and also by KEGA project No. 006STU-4/2021 project. Moreover, this study was supported also by the Slovak Research and Development Agency under contract No. APVV-18-0316.

The original methodology of diagnostics implemented in this monograph is influenced by the long-year scientific work and ideas of Professor Ivan Vasilyevich Abramov that has shaped and inspired the development of the scientific research group mainly at the Kalashnikov Izhevsk State Technical University. The authors proudly acknowledge this legacy.

The authors would also like to thank Dr. Gabriela Chmelíková for her help in translating and editing the text.

Introduction

Most production instrumentation devices of the older generations are kept in the operational condition by reactive maintenance, without detailed monitoring of operating parameters. Thus, due to the fact that production plants still use a significant number of older functional equipment, it is necessary to evaluate their reliability, and keep them in the ready state to perform production tasks.

Key equipment is regularly serviced as part of preventive maintenance, which increases the reliability of the equipment, but at an increased cost of spare parts and related activities. Predictive or rather proactive maintenance uses predictive diagnostics based on monitoring to timely identify emerging fault states and eliminate their causes. Maintenance costs vary significantly, e.g. depending on the age of the plant and its equipment, but in any case, it is an important factor in ensuring the reliability or quality of production, but also the economy and safety of the plant. This monograph is based mainly on the situation in the East European and North Asian region, which is, however, analogous in several other regions.

Several industrial sectors are affected by the current crisis, so a more massive renewal of machinery, which provides an extension of the planned lifetime is often less probable. Many companies are postponing investment in new equipment, so older ones need to be kept in shape even after their planned life. On the other side, the machinery of all generations is often overwhelmed in trying to meet demanding production plans or in the event of replacement of production outages in the event of another equipment failure. A significant proportion of faults occur without warning due to the lack of relevant information due to non-monitoring of the operation. As most failures begin with the neglecting of problems, the early solution of which is simple and can prevent the development of major damage such as loose screws, unbalanced and misaligned machines, problems with lubrication and cleaning (filtration), etc., monitoring and diagnostic systems are therefore effective part of early warning systems, but also fault analysis systems. The automation of production places high demands on the reliability of the technological systems. Technological systems include mechanical, electronic and electromechanical components. Recent techniques and tools for diagnosing these components are steadily developing. In order to increase the efficiency of drive diagnostics, a system approach for complex diagnostics using intelligent sensors and high-performance digital signal processors is required. This creates the prerequisites for the development of intelligent systems that evaluate the technical condition and remaining service life.

Failure of components leads to significant economic losses and can be dangerous to life and health. Efficient and intelligent diagnostic systems with advanced sensor systems are required for the early detection of faults.

The implementation of technical diagnostics tools makes it possible to

- to monitor the current technical condition of drives of automated technological equipment;

- determine terms and content of repair works, control quality of their performance;

- reduce operating costs;

- prolongation of overhaul period and service life;

- to get rid of sudden breakdowns and production stoppages.

Despite the need to introduce diagnostic systems, this issue has not taken the place it deserves in practice.

A "revolution" is currently taking place in machine diagnosis systems, driven by the development of a wide range of intelligent sensors with information transfer over wireless technology, high-performance computing systems and artificial intelligence methods.

Promising mathematical apparatus for creation of systems of automatic diagnosing of machine units are methods of artificial intelligence. They possess the following advantages: fast algorithms of training, possibility of work at presence of hindrances, possibility of work with information from sources of a various physical nature, possibility of the simultaneous decision of several problems.

1. Increase of intensity of research of methods and means of systems of diagnostics is caused by a number of reasons.

2. Increase in the cost of complex automatic production systems leads to the fact that their failure brings large financial losses. The expediency of repair according to the state of the equipment, rather than according to the plan is justified.

3. microminiaturization of microprocessor means, sensors, reduction of their power consumption, development of wireless technologies of information transfer allow to embed them into any objects of diagnostics, up to bearings.

4. The development of a mathematical apparatus based on artificial intelligence methods for recognizing equipment defects makes it possible to increase the accuracy of diagnosis.

5 The use of new programming methods allows to conduct diagnostics in real time, passing in parallel the information about the state of the object to the adaptive control system.

6. Reducing the cost of microprocessor-based tools while increasing their computing power and functionality allows the implementation of complex diagnostic algorithms.

7. The application of the principle of modularity facilitates the design of diagnostics, which should be developed at the stage of designing the diagnostics object.

The monograph is intended for engineers on diagnostics and maintenance of complex technical systems, for research staff, students of higher education programs.

Regarding the production automation, it is particularly the reliability of technological systems that is of high importance. An automated device comprises mechanical as well as electronic components. At present, there are various methods and tools developed for an independent diagnostics of such places. To increase this diagnostics efficiency, a systematic approach to complex diagnostics of mechanical and electronic components via intelligent sensors and powerful processors of digital signal is needed. This is a prerequisite for the development of intelligent systems able to evaluate the technical state and residual operational life.

Automated technological systems comprise electrical drives. A failure of such drives can lead to significant economic losses and be dangerous to human life and health.

For an early detection of the drives´ defects, the efficient intelligent diagnostic systems equipped with an advanced sensor system are needed.

The introduction of technical diagnostic tools allows to:

- monitor the current technical state of an automated technological device drives,

- determine the timing and content of repairs and check the quality of their execution,

- decrease the operational costs,

- prolong the period of general repair as well as the life,

- get rid of sudden failures, and hence the production interruptions.

Despite of this, it is necessary to introduce the diagnostic systems, the issue is not paid enough attention in practice it deserves. The importance of the research in the field is proved by the fact that the issue is comprised in critical technologies on a national level in the following:

- artificial intelligence (systems of decision making based on the access to neural network, fuzzy logic, and fuzzy neural network),

- information and telecommunication systems (systems of information exchange among sensors, and diagnostic and control systems utilising wireless technologies),

- elementary basis of microelectronics (advanced diagnostic methods and equipment, monitoring of technological processes),

- recognition of patterns and analysis of images (mathematical methods for recognition of drives technological state).

At present, there is a ”revolution“ in machine diagnostic systems, which is the result of the development of a wide scope of intelligent sensors able to transfer information via wireless technologies, powerful computer systems, and artificial intelligence methods.

One of the suitable mathematical apparatus for the development of systems for automated diagnostics of the machine nodes is represented by the artificial intelligence methods.

They have the following advantages:

- fast learning algorithms,
- ability to operate in noise,
- ability to operate with information from the sources of various physical characters,
- ability to execute several solutions simultaneously.

The construction of physical and mathematical models of materials´ structural state in different operational conditions and based on collected diagnostic information as well as on the development of diagnostic devices and technologies for the monitoring of materials and structures are an important research task.

The importance of the task is proved also by the fact that the expert committees for automated diagnostic and testing systems have recommended to develop new structures and fields related to the diagnostics of technical systems on the basis of diagnostic systems.

The intense research growth of methods and means of diagnostic systems is caused by several reasons.

1. Increase of costs for complex automated production systems leads to the fact that its failure can cause high financial losses. Regarding the state of the device as well as the plan, the efficiency of repairs execution is not due.

2. Microminiaturisation of microprocessor means, sensors, decrease of its power consumption, and the development of wireless technologies for information transfer has allowed their integration into any diagnostic objects, including the bearings.

3. The development of a mathematical apparatus based on the artificial intelligence methods of the device breakdowns recognition can increase the diagnostics accuracy.

4 The use of new programming methods allows for diagnostics in real time, and at the same time it transfers information about the object state into an adaptive control system.

5. The decrease of costs for microprocessor tools and increase of their calculation capacity and functionality allows for complex diagnostics algorithm implementation.

6. The implementation of the modularity principle eases the construction of diagnostic tools, which should be developed in the stage of the diagnostic object design.

Terms and Definitions

Instancy – is a complex property including no-failure operation and reparability of the object in the operational conditions.

Maintainability – is the object´s property to have the capability to precede the failures, to learn about the causes of its failures, and to eliminate the failures´ possible consequences via imposed maintenance or repair.

No-failure operation – is the object´s ability to execute the required functions in the determined time period and under stated conditions.

Operational life – is the ability of the object to fulfil the required functions up to reaching the limiting state by the determined system of imposed maintenance and repairs.

Quality – of the product is a set of properties expressing the capability to execute the determined functions, and at the same time, the economic parameters of the product, its accessories or spare parts, etc. The availability as well as the prerequisites of the product related services provided by the manufacturer are considered.

Reliability – is a general property of the object saying that the object is able to execute the required functions while retaining the values of the stated operational indicators within given limits and in time according to stated technical conditions. Reliability is one of the most important indicator groups of the product quality.

It comprises the following partial properties:

- no-failure operation,
- operational life,
- maintainability,
- reparability,
- instancy,
- safety.

Reparability – is the object´s capability to learn about the causes of its failures origin and the possibility of the elimination of the failures consequences by the repair.

The resources dealing with the *reliability* issues provide with several definitions of the term. When reading them in detail, we can see there are two tendencies to define the term: either quantitatively or qualitatively. The quantitative definition uses numeric characteristics, and regarding the solution to the tasks in the field of reliability, two mutually exclusive states of the object´s state are considered: the no-failure operation state ”1“and the state of failure idle time ”0“.

1 Basic Characteristics of Elements Reliability

The following prerequisites are to be considered:

- *mutual independence of the individual elements´ failure origin,*
- *exponential probability arrangement of failures and repairs´ origin,*
- *prompt execution of repairs characterised by immediate repair after any element´s failure.*

For further use only the following characteristic quantities and functions are introduced.

Characteristics of element reliability

The basic characteristics of the element or device reliability are as follows: the **probability of no-failure operation R(t)** and **probability of failure F(t)** defined by the relations (1.1) and (1.2). Depending on the failures intensity λ(t), these characteristics can be of different forms.

F_i (t) probability of failure origin of i-th element, where:

$$F_i\,(t) = 1 - \exp(-\lambda.t) \tag{1.1}$$

R_i (t) probability of no-failure operation of i-th element, where:

$$R_i\,(t) = 1 - F_i\,(t) = \exp(-\lambda.t) \tag{1.2}$$

A_i (t) availability of repairable i-th element in time t (providing that in time t = 0 s, it is in regular operation 0, where:

$$\mathrm{A_i}\ (\mathrm{t}) = \frac{\mu_i}{\mu_i + \lambda_i} + \frac{\lambda_i}{\mu_i + \lambda_i} e^{-(\mu_i + \lambda_i)t} \tag{1.3}$$

K_{vi} coefficient of utilising the reparable i-th element, where:

$$K_{vi} = \lim_{t \to \infty} A(t) = \frac{\mu_i}{\mu_i + \lambda_i} + \frac{T_i}{T_i + \theta_i} \tag{1.4}$$

K_{pi} coefficient of idle time of the i-th reparable element, where:

$$K_{pi} = 1 - K_{vi} = \frac{\lambda_i}{\mu_i + \lambda_i} + \frac{\theta_i}{T_i + \theta_i} \tag{1.5}$$

- T_i [h] - mean time between two subsequent failures of the i-th element,
- λ_i [h^{-1}] - mean value of the failures´ intesity of the i-th element,
- θ_i [h] - mean time of the i-th element repair duration,
- μ_i [h^{-1}] - mean value of the repairs´ intensity of the i-th element.

Relations (1.1) and (1.2) represent the exponential division of failures.

Characteristics of the systems reliability

The result reliability characteristics of the production systems, which consists of individual components (machine tools, robots, manipulators, transport components, rack folders, etc.) has to be determined from the system structure, where the sequence (succession, dependence) is defined by the relations of the material flow. In specific cases, it is necessary to consider also such issues as the possibility to repair an individual production cell component during the surrounding machines operation, etc.

In these cases, it is essential to pre-analyse the individual components/cells of the production system by using their description coming from the representation of stationary Markov processes, composition, and solution via Kolmogorov differential equations.

For the basic reliability structures, i.e. serial and parallel structures, for the coefficients of the system organised within these structures, it is possible to derive simple relations.

Serial structure

In this production structure, the system comprises only the essential inevitable number of elements to execute its function. In this case, for the no-failure operation of the system, all the elements have to be in the no-failure operation state as the functional failure of any element can cause the failure of the whole system.

The intensity of failures $\lambda(t)$ is determined by the ratio of the probability density $f(t)$ to the probability of no-failure operation $R(t)$ in given operation time, and it is one of the most important characteristics in the theory of reliability. It will be as follows:

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{f(t)}{1-F(t)} = \frac{-\frac{dR(t)}{dt}}{1-F(t)} = -\frac{\dot{R}(t)}{R(t)} \qquad (1.6)$$

The intensity of failures $\lambda(t)$ in time t (since being introduced into operation) numerically expresses the probability of the amount of failures falling on the time period Δt (time unit) in the following time $t + \Delta t$ of the operation if the monitored element or system is in time t in the no-failure operation. The value $\lambda(t)$ of technical devices is ca within the range of (0.01 - 0.0001) h^{-1}. The probability that on the monitored element, whose intensity of failures in the time t of its active operation is $\lambda = 0.001$, occurs within the subsequent one hour of operation, is one thousandth.

A typical change course of the failures′ intensity by the more complex systems is illustrated in Fig.1.1. The course of the tube curve can be different for various devices of various structures and is also dependent on the operational conditions, in which the device operates as well as on the maintenance quality, however, its form for the specific system is usually considered for normal (defined) operational conditions.

In normal life, the intensity of failures for the systems with a complex structure and high number of elements (components) is close to *the constant value*.

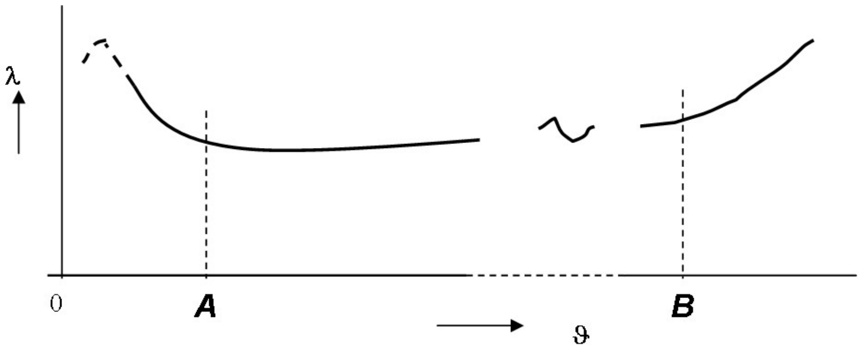

Fig. 1.1 – Tube curve of the course of system failures in its "life" *where the time period* $\vartheta \in (0, A)$ is called "running-in period"

$\vartheta \in (A, B) \equiv t$ "period of normal (active) life"

$\vartheta > B$ "period of end-of-life"

Here it is useful to note that also the producers of complex (especially production and transport machines and devices) design and produce the products, so that after their normal operational life end the intensity of failures of the majority of functional elements increases, and thus evokes the necessity to reject the device from the operation, which sometimes has a positive impact and frequently is of a safety importance as well.

The mean time between the failures T_s is:

$$T_s = \frac{1}{\lambda_s} \tag{1.7}$$

The mean time of the system repair is:

$$\mathbf{C}\,\theta_s = \sum p_i \theta_i \tag{1.8}$$

Where $p_i = \frac{\lambda_i}{\lambda_s}$ is the probability of the failures occurrence by the i-th element of the system.

The probability of the no-failure operation of the system R_s (t) is:

$$R_S(t) = \prod_{i=1}^{n} R_i(t) \tag{1.9}$$

The probability of the system failure occurrence F_s (t) is:

$$F_S(t) = 1 - \prod_{i=1}^{n} R_i(t) \tag{1.10}$$

The system availability (of repairable elements) is:

$$A_S(t) = \prod_{i=1}^{n} A_i(t) \tag{1.11}$$

The coefficient of the system utilisation:

$$K_{vs} = \prod_{i=1}^{n} K_{vi} \tag{1.12}$$

The coefficient of the system idle time:

$$K_{ps} = 1 - \prod_{i=1}^{n} K_{vi} \tag{1.13}$$

The coefficient of the system susceptibility to the change of the coefficient of sensitivity of the i-th element:

$$\xi_{s,i} = \frac{\partial K_{vs}}{\partial K_{vi}} \tag{1.14}$$

An absolute change of the coefficient of the system utilisation of using only the i-th element ΔK_{vi} will be:

$$\Delta K_{vs,i} = \xi_{s,i} \Delta K_{vi} \tag{1.15}$$

The percentage change of the coefficient of the system utilisation by the absolute change of the utilisation coefficient of only the i-th element will be:

$$\delta K_{vs,i}[\%] = \xi_{s,i} \frac{\Delta K_{vi}}{K_{vs}}.100 \tag{1.16}$$

The percentage change of the coefficient of the system utilisation by the change of the utilisation coefficient of the i-th element o p_i [%] will be:

$$\delta K_{vs,i}[\%] = \xi_{s,i}.p_i K_{vi} \tag{1.17}$$

Note: Relations (14), (15), (16), and (17) are applicable for a random reliability structure, nevertheless, it is essential to determine $\xi_{s,i}$ correctly.

Parallel structure

The structure is characterised by the fact that the system failure occurs only when the failure of all elements occurs simultaneously.

The probability of the no-failure operation of the structure consisting of ”n“ elements is:

$$R_S(t) = 1 - \prod_{i=1}^{n} [1 - R_i(t)] \tag{1.18}$$

where, $R_i(t)$ is the probability of the failure of the i-th element.

The probability of the failure occurrence:

$$F_S(t) = \prod_{i=1}^{n} (1 - R_i(t)) = \prod_{i=1}^{n} F_i(t) \tag{1.19}$$

where $F_i(t)$ is the probability of the failure of the i-th element.

The system availability (of reparable elements):

$$A_S(t) = 1 - \prod_{i=1}^{n} (1 - A_i(t)) \tag{1.20}$$

where $A_i(t)$ is the availability of the i-th element.

The coefficient of the system utilisation will be:

$$K_{vs}(t) = 1 - \prod_{i=1}^{n} (1 - K_{vi}) \tag{1.21}$$

Where $K_{vi}(t)$ are the coefficients of utilisation of individual elements.

The coefficient of the system idle time will be:

$$K_{ps}(t) = \prod_{i=1}^{n} (1 - K_{vi}) \tag{1.22}$$

Example 1

Let us consider a device (e.g. a machine tool) in the period with the constant intensity of failures $\lambda_0 = 0{,}08 h^{-1}$ and intensity of maintenance $\mu_0 = 2\ h^{-1}$.

It is necessary to determine:

- mean time between the failures T_0 and mean time of maintenance θ_0 of a device,
- coefficient of utilisation K_V and idle time K_P of a device,
- probability of machine activity in time t = 8 h if it was in operation in time t = 0 s,
- interval availability of the device for the activity time period of eight hours (the time of the working shift).

Solution:

a. according to the relation 1.7 $\quad T_0 = \frac{1}{\lambda_0} = \frac{1}{0.08} = 12.5\ h$

according to the relation 1.8.

b. according to the relation 1.12

$$K_V = \frac{\mu_0}{\mu_0 + \lambda_0} = \frac{2}{2 + 0.08} = 0.96154 = 96.2\%$$

according to the relation 1.13.

c.

$$A(t) = \frac{\mu_0}{\mu_0 + \lambda_0} + \frac{\lambda_0}{\mu_0 + \lambda_0}.e^{-(\mu_0+\lambda_0)\cdot t}$$

$$A(8) = \frac{2}{2+0.08} + \frac{0,08}{2+0.08}.e^{-(2+0.08)\cdot 8} = 0.962$$

d.

$$E(t) = \frac{\mu_0}{\mu_0 + \lambda_0} + \frac{\lambda_0}{T(\mu_0 + \lambda_0)^2}.\left(1 - e^{-(\mu_0+\lambda_0)T}\right)$$

$$E(8) = 0.96154 + \frac{0,08}{8\cdot(2.08)^2}(1 - e^{-8\cdot 2.08}) = 0.964$$

From the aforementioned example it follows that the probability of a sufficiently long time period of use (after the running-in time) the device will be 96.2% of the operation time, and in 3.8% of the whole time the failure will be removed (the repair will be executed). The probability that the device will operate in time $t = 8\ h$ from the start is 0.962, and the probability that the device will operate without a failure for the time period of 8 hours (i.e. during the working shift) is 0.964.

Serial and parallel structures

a) Serial structure (basic arrangement)

The system with the serial structure is formed by the elements arranged consecutively, i.e. that the output of the precedent element is the input of the consecutive element as well, etc. The structure is illustrated in Fig. 1.2. The elements of the structure are designated by the capital letter E.

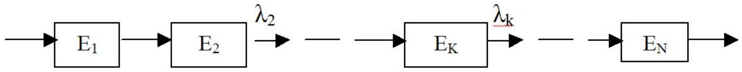

Fig. 1.2 – Serial structure of the system

The transition between neighbouring process states (or system elements) is expressed by the intensity λ.

The failure in the serial system structure always occurs when the failure of its any element occurs. If we consider the independence of the failures occurrence of the system individual elements, then the probability of the no-failure system operation in time of its use will be:

$$R_S(t) = \prod_1^n R_s(t) \tag{1.23}$$

and:

$$\lambda_s = \sum_1^n \lambda_k \tag{1.24}$$

and the probability of the failure occurrence:

$$F_s(t) = 1 - R_S(t) \tag{1.25}$$

The relation (1.24) shows that the intensity of system failures indicating the number of failures occurred in the time unit increases with the growing number of system elements. The intensity of system failures is given by the addition of the intensity of system failures.

In technical practice, each state, in which the system is not able to carry out completely all the requirements of its activity, is considered to be a failure. If we consider the availability of any element of the serial structure as an independent phenomenon (ideal state), then the result system availability will be given by the multiplication of the individual phenomena, and it will be:

$$A_s(t) = \pi_1^n A_k(t) = \pi_1^n \left\{ \frac{\mu_k}{\mu_k + \lambda_k} + \frac{\lambda_k}{\mu_k + \lambda_k}^{\left[-(\mu_k + \lambda_k).t\right]} \right\} \tag{1.26}$$

Since the determination of the system availability by the analysis of its functional structure is sometimes quite demanding (particularly by the systems with high number of elements), we use another process of solving the calculation. We will consider the system as a whole with mean values of failure and reparability characteristics, which will be executed as follows.

The mean time of no-failure system operation Ts will be determined by the results from monitoring the system operation, as the ratio of the overall real time of no-failure operation $T = \sum_1^k T_k$ to the number of failures K, which have occurred during the monitored time interval:

$$T_s = \frac{1}{k} \sum_1^k T_k$$

and *the mean value of the failure's intensity* (by the exponential arrangement):

$$\lambda_s = \frac{1}{T_s} = \frac{k}{\sum_1^k T_k} \tag{1.27}$$

If we assume that after each failure an immediate system repair is carried out, then the mean time of the repairs can be determined from the monitoring in the same time period as

$$\Theta_s = \frac{1}{k}\sum_1^k \Theta_k$$

the mean value of the repairs intensity:

$$\mu_s = \frac{1}{\Theta_s} = \frac{k}{\sum_1^k \Theta_k} \tag{1.28}$$

The relation for predicting the operational system availability in the period of its subsequent activity, providing that in time t = 0 s it was functional, then it will be:

$$A_s(t) = \frac{\mu_s}{\mu_s + \lambda_s} + \frac{\lambda_s}{\mu_s + \lambda_0}^{\left[-(\mu_s + \lambda_s).t\right]} \tag{1.29}$$

The same procedure is used for the determination of other availability characteristics such as:

interval system availability in time **τ = T**

$$E_s(t) = \frac{\mu_s}{\mu_s + \lambda_s} + \frac{\lambda_s}{T(\mu_s + \lambda_0)^2}\left\{^{1-\left[-(\mu_s + \lambda_s)T\right]}\right\} \tag{1.30}$$

coefficient of system utilisation:

$$K_{vs} = \frac{\mu_s}{\mu_s + \lambda_s} = \frac{T_s}{T_s + \Theta_s} \tag{1.31}$$

coefficient of the system idle period:

$$K_{ps} = \frac{\lambda_s}{\mu_s + \lambda_s} = \frac{\Theta_s}{\Theta_s + \Theta_s} \tag{1.32}$$

To consider the system characteristics with the basic arrangement (serial structure), it is important that the failure rate as well as the system availability is negatively influenced by the structure element mostly susceptible to failures, which has to be repaired for the longest time period (in general). Therefore, from the point of the availability of the serial structure system, it is suitable and optimal to use the elements with approximately the same intensity of failures and repairs. At the same time, it follows that in the structure with imperfect functional elements (having no others), it is not suitable to use the elements with extremely good parameters (i.e. expensive) simultaneously. With the use of derived relations for specific systems, it is possible to analyse the influence of the change of the failures and repairs intensity on the utilisation coefficients, or on idle period, and the consequences.

b) Parallel structure (back-up arrangement)

To increase the probability of executing the operation by the system, we frequently require, so that by the initiating the system input, it is possible to complete the required activity even if only one way from the input to output is functional. The system is then formed of parallel branches. Such a parallel structure is then able to execute the given requirement. The structure scheme is shown in Fig. 1.3.

The probability that the system will be functional (input → output) will be given by the probability that the failure of all its elements does not occur at the same time. Since the failures of individual system elements are independent phenomena, and the failure and no-failure operation are opposite phenomena, the probability of the no-failure system operation will be

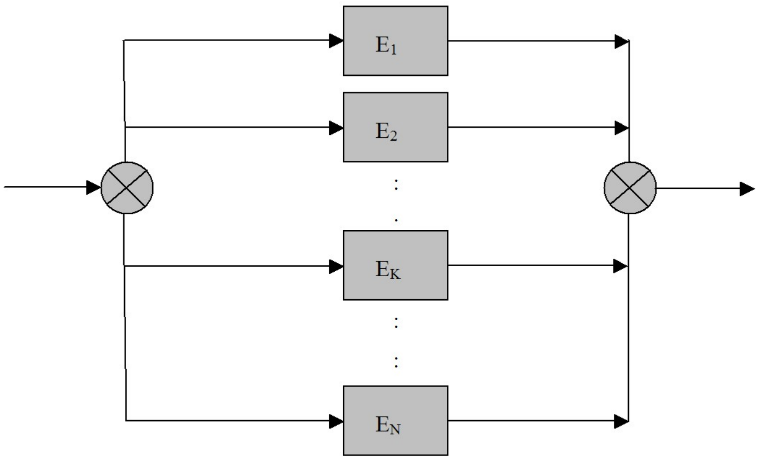

Fig. 1.3 – Parallel system structure

(opposite phenomenon to the failure) in compliance with the use of De Morgan laws given by the multiplication of the phenomena opposite to the probability of the occurred failure of any element, hence:

$$1-R_S(t)=\prod_{1}^{N}[1-R_K(t)] \tag{1.33}$$

wherefrom for *the probability of the no-failure operation of the parallel system* $R_S(t)$ it follows:

$$R_S(t)=1-\prod_{1}^{N}[1-R_K(t)] \tag{1.34}$$

Since the expression after the multiplication symbol on the equation´s (34) right side is always lower than 1, with the increasing number in the structure it converges $R_S(t)$ quickly to the value of 1, which means the probability of the no-failure operation is close to the certainty. The structure availability is not disturbed by the repair of one or more elements, and therefore, by the use of the back-up arrangement it is theoretically possible to achieve 100% availability of the system.

2 Analysis of Existing Methods, Algorithms and Devices for the Diagnostics of Technological System Drives

2.1 Analysis of diagnostic methods of technological system drives

The theoretical fundamentals of the diagnostics of individual elements of technological systems are described by numerous authors (Barkov et al. 2000; Klyuev et al. 2007; Yavlensky 1983). In the work (Skhirtladze 2008), the principles of the diagnostics of technological systems and the parametric diagnostics of technological systems are considered. The approaches of estimating the residual operational life of technological objects based on the model of the system of differential equations are analysed in (Kluyev et al. 2007).

According to the sources, the testing and functional diagnostics are distinguished. The diagnostic methods are classified according to the type of physical processes occurring in the object: mechanical, electric, vibrational, acoustic, ultrasonic, beat impulses, thermal, magnetic, photometric, etc.

The diagnostic methods are classified according to these signs (Skhirtladze 2008):

- stage of information content,
- types of diagnostic information,
- level of technical means utilisation,
- stage of operation,
- depth of diagnostics.

As for the stage of information content, the following diagnostic methods are distinguished (Skhirtladze 2008):

- method of time interval used for the analysis of idle periods, determination of reliability indicators, monitoring of control system activity and acquisition of cyclograms,
- method of reference modules based on the comparison of experimental data or calculated values, and quality indicators,
- method of reference dependences based on the comparison of measured diagnostic parameters with reference diagnostic parameters,
- spectral method based on the measuring the components of complex vibrational and acoustic signals,
- correlation method used for the detection of deviations in the character of relation between the diagnostic parameters (cross correlation) or by the change of diagnostic parameters in the course of time (autocorrelation).

The methods based on the mathematical models describing the operational processes as well as on the spectral analysis of measured parameters, e.g. vibrations, noise, and electric current are also considered as methods for solving the issues of technical diagnostics (Bartelmus 2003; Bencsik et al. 2013; Blatnicky et al. 2020; Božek et al. 2021, 2021; Dalla Vedova 2018; Dietel et al. 2012; Gutierrez et al. 2016; Hannius et al. 2006; Krenicky 2011; Matveev et al. 2020; Mayer et al. 2008; Murcinkova and Krenicky 2013; Repko et al. 2020; Saga et al. 2014, 2020).

Nowadays, the methods of vibration diagnostics of drives designed and developed by the experts from Vibroacoustic Systems and Technologies Company, are commonly used overall the technical world and they replace the diagnostic methods more demanding in terms of its use via the parameters of voltage, current, and electromagnetic field. Via the vibration they detect almost all drives´ failures with the exception of electric insulation failure, which is possible to be detected only after the moment the electric current flows through the damaged area.

The growing complexity of the diagnostic methods of actuators as well as the equipment always leads to the increase of the number of measurement points, which causes also the growth of costs for diagnostic systems. Economically optimal stationary diagnostic system will be the one with the combination of monitoring and diagnostic functions. Therefore, for monitoring and diagnostics, it is possible to select a limited number of control points in units, which are not the strongest vibration (noise) sources in the unit, however, they determine their operational life to a large extent. Most frequently, they are the points on the cover of the roller bearings. In case of high-speed drives, in which the bearings are the main source of vibration, two or three control points on the cover located beyond the bearing systems can be used.

The diagnostic and predictive methods for periodical measurements of vibrations (noise) use the vibrations and noise as diagnostic parameters. The friction forces and high-frequency vibrations caused by them in usable bearings are random processes with the constant performance during the measurement. If defects on the roller bearings occur, a periodical force change of these processes appears, i.e. an amplitude modulation of friction and high-frequency vibrations appear.

The majority of defects developed in the units begins to influence the vibrations and the noise many months before the beginning of emergency situation. Only several production defects and the defects resulting from breaking the operational regulations for drives represent an exception. They can occur in any stage of the machine operational life cycle and they can grow to dangerous values in a short time period. Assuming that such defects are missing, it is not necessary to monitor the drives with short measurement intervals, and therefore, it is possible to develop portable diagnostic systems for drives with the measurement intervals lasting several weeks or even months.

The diagnostic and predictive methods for the periodical vibration (noise) measurements are also based on various combinations of aforementioned information technologies and are usually designed to be used by authorised experts. The best results can be reached via the methods based on the combination of the spectral information technologies.

The considered group of diagnostic methods requires deep knowledge of the defect development processes and their influence on the parameters of vibration and noise in all types of diagnosed propulsions. Since these methods are based on the comparative results analysis of vibrations and noise measurements carried out at different times, they represent also demanding requirements on the vibroacoustic measurements quality. These measurements can be executed only by an expert with wide experience, which limits the possibility and effectiveness of the diagnostics. The provision of the identity of the operational regime of the diagnosed propulsions, without which it is not possible to detect the changes in their state is particularly difficult.

The development of diagnostic methods for the periodical measurements of vibrations and noise, which automate the diagnostics and prognosis, are similarly demanding as the development of methods requiring the operator´s decisions. The most difficult issue is the selection of the measurements of undoubted reliability, especially if they differ from the previous measurements. The complexity of this selection can be doubled by the fact that the cause of the differences can be represented not only by the defects occurrence, or the change of the machine operational regimes but frequent service defects, when selecting the sensor location or by the quality of its assembly. Furthermore, it is practically impossible to keep the same operational regime in terms of load, revolution speed, and the surrounding temperature during the measurements executed in the long-time intervals lasting for several weeks or months.

Despite the difficulties, in many countries the work is carried out to develop the methods for automated machine diagnostics via periodical vibration measurements. Currently, there are multiple diagnostic systems, in which they are used quite efficiently.

The most favourite and the most complex ones are the methods of diagnostics and prediction of single use vibration (noise) measurements. They are built on the basis of a different combination of considered information technologies and as such they can be more or less used only by qualified experts. The diagnostics of the machines or even of the individual elements if they are the oscillations source, are the characteristic sign of these methods. The highest efficiency is achieved, when the experts utilise the abilities of spectrum information technology at maximum.

Any diagnostic method utilising the individual measurements requires so that the expert has deep knowledge in the development of defects characteristics and their influence on vibrations (noise) of the object being diagnosed. For each machine type, it is necessary to know all efficient diagnostic elements and their reliability limits in advance, while taking their construction properties into consideration as well. The issues can be solved only by the experts specialised in specific machine types, or by the methods specialised on the diagnostics of a specific unit type.

Recently, much attention is paid to specialised methods, which can be used for an automated diagnostics of machines or their parts. First, they are the ways of diagnosing the roller bearings according to the vibration cover spectrum, which are excited by the friction forces in the set being diagnosed. The first and the most completed system of the automated diagnostics of roller bearings using these methods was developed by the Vibroacoustic Systems and Technologies Company experts in 1991.

At present, the automated systems for diagnosing the gears, particularly the gearboxes are being developed, and they are based on the measurements of individual vibrations. There are also prerequisites for the development of such diagnostic systems for the blade wheels of pumps or turbines. All of them are based on the information technologies abilities and completed by the spectrum information technology. It is expected that in the nearest future the experts will develop the diagnostic systems for the electric machines running on alternating current utilising the single vibrations measurements.

Deep diagnostic methods based on single vibrations (noise) measurements are based on the individual vibration (noise) measurements do not allow solutions to diagnostics issues as well as long-term prediction of all unit types, i.e. the machines as a whole. The exception is represented by the most dangerous components, especially the roller bearings, for which, as aforementioned, the systems based on the methods of deep diagnostics and prediction of single use vibration measurements to evaluate their state are developed and efficiently used. The subject to utilise these methods can also be the monitoring systems, in which it is possible to develop the system for found changes identification. These identification systems determine many controversial changes, thus decreasing the frequency of false alarms of the monitoring systems.

The classification of slowly changing and fast changing measured parameters led to the development of independent directions in the functional diagnostics.

The diagnostics based on statistical models developed by a common set of statistic data connecting in reliabilistic sense states (diagnoses) with measurable parameters stated during the experiment. Such models are used for slowly changing parameters when there do not exist any other physical processes models.

The diagnostics is based on deterministic models, which represent the system of algebraic-differential equations describing low-frequency (several tens of Hz) operating processes. Currently, the equations describing the physical processes with centralised parameters are the most required ones. These equations can be used to describe the processes in the low-frequency area, i.e. the processes with slowly changing parameters. The numeric methods for fast computer-aided solution to these equations are well developed and implemented.

The diagnostics based on the methods of random processes can perform: correlation and spectrum analysis, provision of high-frequency processes analysis (up to several tens of thousands of Hz). In this case, the range of controlled frequencies is limited by the frequency of parameters registration.

It is necessary to note that to describe the processes in the high-frequency area – fast changing parameters – it is most natural to use the mathematical models of physical processes with distributed parameters. Due to the issues related to numerical solution to equations involved in such models, however, in practice the machine of random processes theory is currently used for technical systems analysis.

The regulation procedure usually involves the recording of the measured values of operational parameters, and transfer of such parameters, e.g. from time domain to a frequency one, determination of their deviations (shifts from some predetermined thresholds (tolerances) corresponding to normal operation of the monitoring object. The measured values of parameters, their calculated values and deviations from acceptable values can be considered as diagnostic signs of the object´s technical state.

The statistical methods for the recognition of the object´s technical state are used mainly in the cases, when the mathematical model of physical processes is unknown, or it has been impossible to acquire it due to specific circumstances. For example, when the physical processes are not adequately described by known equations of mathematical physics or the dimension (number of commonly used machines equations) of the model exceeds the possibilities of existing computer technology. At the same time, the methods of statistical recognition require a significant amount of data and priorities, i.e. the data gained from prior experiments. The statistical methods do not have to be acceptable, particularly in case of expensive experiments, therefore, here we limit their use.

To eliminate the demanding theoretical and experimental work for the determination of strict functional dependence of each signal parameter on state parameter, the associative diagnostic method is used. In this case, the object´s state is not compared, but the diagnostic signals are corresponding.

In numerous works (Abramov et al. 2014, 2014, 2015, 2017; Blanke et al. 2003; Costa 2016; Ding 2008; Gulyashinov et al. 2005; Isermann 2006, 2011; Janda et al. 2011; Muller et al. 2007; Nikitin et al. 2010, 2010, 2011, 2011, 2016, 2020; Nurieva and Nikitin 2012; Rafajdus et al. 2012; Rothe and Soffker 2015; Sinopaljnikov 2005; Soffker et al. 2007; Stepanov et al. 2014, 2014, 2021; Trefilov and Nikitin 2019; Turygin et al. 2016, 2018; Vekteris and Cereska 2006; Vrban et al. 1983, 1985, 1988; Zhang et al. 2012, 2012; Zhirabok et al. 2016, 2017; Zykina and Nikitin 2008, 2009), the fundamentals and methods enabling development of automated technical diagnostics systems based on the artificial intelligence (AI) are considered.

Currently, the development of systems for deep diagnostics and prediction of nodes state is one of perspective fields of technical diagnostics. For the diagnostics of technological systems, the following diagnostic methods are proposed: by vibrations, by temperature, and by electric current. Mechanical elements can be diagnosed by vibrations and by temperature, e.g. vibro-acoustic diagnostics is ”in-place“ diagnostics and the vibro-acoustic signal carries a lot of information about the mechanical unit´s technical state, the increased temperature ”speaks“ about significant defects. Electromechanical vibrations and electric current are the next ones, electric current carries the information on the defects of electrical and mechanical elements as a result of the relation between the starting torque and the current in the electric motor. In such case, it is necessary to consider the load and speed of the elements´ rotation, which influence the change of diagnostic parameters.

In the last decade, several efficient methods to detect the main defects of machines and devices by the vibrations in the state of their origin were developed. They are based mainly on the analysis of high-frequency vibrations, by whose excitation not big vibration forces are needed and they occur only in the area of its activity, and in the course of their spread they are quickly damped. The diagnostic operators in many countries have used such methods to transit from the monitoring of vibrations to the deep diagnostics. In parallel, the methods of diagnostic algorithms have been developed and they have provided many manufacturers of diagnostic systems with the possibility to replace the expert software by typical diagnostic tasks.

The share of such tasks is very high and exceeds 90% of all tasks solved via vibration signals analysis. The pioneering automated diagnostic systems for vibrations were developed in the years 1991-1992 and since that are continuously updated.

For the diagnostics of the mechanical subsystem, the vibration diagnostics is used, then the methods based on measuring the thermal radiation, oil film resistance, and on the particles analysis in oil.

For the diagnostics of electromechanical, electric, and electronic subsystems the diagnostic methods based on measuring the electrical parameters: current, resistance, and digital signals analysis are used.

For the diagnostics of electric drives via the wattmeter method, the windings of the electromotor's stator operates as a sensor. This is due to the induction motor´s construction properties: the presence of mild air gap between the rotor and the stator, which is 0.2-0.3 mm. The presence of this gap causes that its small changes caused by the fluctuation of the shaft´s mechanical load result in significant changes in the current and voltage and have impact on the motor performance. At the same time, the forces, which origin not only by the drive but at the load as well, also influence the motor performance.

As diagnostic parameters are defined as follows: power consumed by the electric motor, efficiency, and current in the motor windings.

The use of wattmeter method for the diagnostics of electric drive allows a good description of its technical state. In the diagnostics process the temporal changes of electric parameters and spectrums of these signals are analysed. The analysis of temporal signal changes and changes of spectrum density of recorded signal provides us with the possibility to solve the diagnostic issue, particularly to evaluate the technical state of the device.

The diagnostics of technical systems failures via the deterministic methods to recognise the defects is efficient in the presence of mathematical model. In the majority of cases the models can be analysed only by numerical methods, which limits their use in real time when solving the issues and the technical system control. Almost all real processes of technical systems operation are of non-linear behaviour, and they are characterised by special situations occurrence. In these cases, the experts are called, i.e. a person interferes into the diagnostics and control of the technical system. If the deterministic knowledge is not at a disposal, or the mathematical modelling requires much time for calculation, or does not provide required accuracy, other methods could be used, which is a quite frequent activity nowadays. The methods then model the operator´s knowledge via heuristic knowledge and strategies of logical interferences, e.g. it is done in expert systems based on fuzzy logic with their implementation on the basis of hardware, or software-algorithm emulation of neural networks.

At present, the fuzzy-logic based methods or methods based on fuzzy sets, expert systems and neural networks are perspective in diagnostics. Fuzzy-logic based methods can significantly simplify the description of controlled and diagnosed objects, and what is more, they are also simpler for hardware implementation. The expert systems allow deciding on the control object state if the state evaluation or problem solution of the control object is a demanding formalised task. Neural networks are used to identify the control object, defects recognition, and prediction of technological system state. The advantages of the classifier based on neural networks, when compared to traditional methods, are the factors as follows: independence on noise, self-learning, possibility of parallel processing.

Neural networks have proved to be a good diagnostic tool for drives. For example, the neural network can be trained to recognise the sound, which is emitted by the disk during the regular operation from the sound, which is an advance signal of a failure.

One of the most important advantages of neural networks is their ability to represent non-linear transformations. Neural networks are able to create a very precise approximation for non-linear functions of random duration.

Neural networks are an alternative proposal of evaluating devices. The neural networks have an important property: they investigate the system dynamics in the training process consisting of several training cycles, while the training data come either from the previous cycle, or they consist of real signals. After each cycle the neural network learns more about the object´s dynamics. The ability to automatedly study the dynamics of non-linear systems behaviour if the neural network architecture comprises at least three layers, is the most important property of neural networks.

Trained neural network based on monitoring the surrounding conditions via radiation, can predict the defects occurrence in semi-conductor devices and evaluate the level of their ability to survive, i.e. immediately eliminate the technical object (robot) from the zone exposed to dangerous radiation and repair it.

The tasks that can be solved by neural networks is determined by the fact how the network operates and how it is trained. Neural networks proved to be very useful as a means of control mechanisms.

During the operation, the neural networks take over the input variables and provides the values of output variables. The network can be used in the situation, when you have certain known information, and you want to obtain some unknown information from it. It has several advantages: it is obvious that the neural networks derive their force: 1) from the parallelism of information processing and 2) from the ability to learn, i.e. make generalisations. These properties provide the neural networks with the possibility to solve complex (large) issues, which are currently considered to be unsolvable.

1) Solution to problems with unknown patterns.

2) Resistance to noise by input data.

3) Accommodation to environmental changes. Neural networks can accommodate environmental changes. Particularly, the neural networks trained to operate in specific area can be easily retrained so that they can operate in the conditions of subtle environmental parameters variations.

4) Potential ultra-fast performance. Neural networks have potentially ultra-high speed due to the use of mass parallelism of information processing.

5) Resistance to failures by hardware implementation of neural network. Neural networks are potentially resistant to failures, i.e. that under unfavourable conditions their performance slightly decreases.

Genetic algorithms of various forms are used in solving many scientific and technical issues. They are used to develop further calculation structures, e.g. automats or classification networks. In machine learning, the genetic algorithms are used in designing the neural networks or control robots.

Advantages of genetic algorithms:

1) Looking for an optimal value if the value is a complex function depending on certain input parameters.

2) Ability to manipulate many parameters simultaneously.

3) Solve issues of functional diagnostics and structural diagnostics.

4) Simple and transparent performance.

5) They can be used for a wide range of tasks. This ability of genetic algorithms can be used in the finishing part of the diagnostics. The genetic algorithms cannot be used: a) in case if it is necessary to find a precise global optimum, b) the time of the evaluation function is too long, c) it is essential

to find all solutions not just one of them, d) configuration is not simple (coding solution).

The subject of fuzzy-logic (FL) is represented by the model construction of approximate person consideration and its use in computer systems. The advantages are as follows:

1) Fuzzy method allows drastically lower the number of calculations, which results in increased fuzzy systems speed.

2) FL allows to store and process inaccurate information.

3) FL allows to quickly execute the tasks analysis and achieve highly accurate results.

4) FL has the ability to create control systems for objects, whose functional algorithms are difficult to formalise.

These are only few advantages of fuzzy logic. In the diagnostic process there are many possibilities, where FL is simply irreplaceable. Its disadvantages are as follows: absence of standard methodology for fuzzy systems design; impossibility of mathematical analysis of fuzzy systems by existing methods; use of fuzzy approach in comparison to reliabilistic data does not result in increased calculations accuracy. Therefore, for the diagnostics of technological systems drives, it is suitable to use the following diagnostic methods: via vibrations, temperature, and electric current, supported by artificial intelligence.

2.2 Analysis of algorithms and software products for the diagnostics of technological system drives

The overview of existing diagnostic algorithms and software products shows that there are no universal diagnostic algorithms for technological system drives.

Neural networks are perspective mathematical tools for developing automated diagnostic systems for technological system drives.

Neural networks have the following advantages:

- fast learning algorithms,
- ability to operate when significant disturbance is present,
- ability to operate with different information,
- ability to solve several issues simultaneously (parallelism of information processing),
- reliable operation.

The main advantage of the neural network approach is represented by the ability to identify the patterns in data, generalise them, i.e. acquire knowledge from data. The statistical methods for the recognition of drives´ state are used, when it is not possible to obtain a mathematical model of physical processes, e.g. if the physical processes are not adequately described by known equations of mathematical physics or the model dimension exceeds the capacity of existing computer technology. At the same time, the statistical methods require a significant amount of data a priori, i.e. data gained from experiments. Therefore, for expensive experiments, these statistical methods for state recognition do not have to be acceptable.

The diagnostics of drive failures by the means of deterministic methods of recognizing the state is efficient in the presence of the mathematical model of its operation is present. In the majority of cases, the models can be analysed only by numerical methods, which limits their use for solving the issues and technical system control in real time. Almost all real processes of technical systems operation are of non-linear behaviour.

According to the mathematical apparatus, the diagnostic algorithms are divided into three groups:

1) algorithms, by which it comes to the comparison of the measured diagnostic parameter and the threshold value;

2) algorithms utilising the processing of measured diagnostic parameter via Fourier transform, Haar transform, and others (cepstrum, wavelet);

3) algorithms using the methods of ”soft computing“ based on artificial neural networks, theory of fuzzy sets, and genetic algorithms.

Regarding the operational regime, the diagnostic algorithms are divided into two groups:

1) working in real time (online);

2) not working in real time (off-line).

The diagnostic algorithm establishes the composition and the procedure of the diagnostics of technological system drives.

If one decides to design a rational diagnostic algorithm, he has to:

- present an automated technological system in the form of a system reflecting the individual functional elements and their mutual relations;
- determine the list of all possible failures and describe formally the system operation;
- prepare the mathematical description of the defective system;

- develop a rational diagnostic algorithm.

The building of diagnostic algorithms can be significantly simplified if within the failures list specification, the location, where the typical failure might occur, is stated. Frequently, it is necessary to find the location of the failure origin and its reason.

The diagnostic algorithm often provides the following consecutiveness: first, the main properties of the area determined and measured, whether it operates in the given regime, or if there are excessive deviations technological system. Further on, the cause of these deviations is found and via specific test (check-ups) the failure is determined.

In the first stage the functional diagnostics is carried out and subsequently, the testing diagnostics is done to learn about the failure.

By monitoring the operational capability (applicability), the diagnostic system has to objectively determine, whether the element or module has the required operational capability, or whether it is defective. The monitoring of the correct operation lies in the determination, how the module operates in current time and whether its operational parameters correspond to working technical state.

Nowadays, the methods of artificial intelligence as a mathematical apparatus for diagnostics are used, e.g. expert systems, artificial neural networks, fuzzy logic methods, and genetic algorithms.

Neural networks represent a non-linear model without the knowledge of its structure, and they provide the results in a short time period.

The inputs of neural networks are as follows: current flow force, voltage, performance, temperature, vibrations and the consistency of the area location, movement parameters, power parameters, and time intervals.

The main issue in using the neural network is represented by the selection of the best input functions and neural network parameters, which makes it compact and then the defects classification is precise.

Interference mechanism of an expert system carries out the classification of the object state via the database comprising the history of the device state, which would describe the trends in characteristic failure types. Knowing the diagnostic parameter susceptibility is a decisive moment, since it allows the expert system to conclude that the failure is accepted or ignored on the basis of the threshold value.

The key decision in the current state diagnostics is the selection of an efficient classification system. They can be divided into two main groups: models are based on knowledge and data.

We need a diagnostic tool able to dynamically acquire knowledge, which does not require the presence of functional failures for correct diagnostics and is usable for various devices typology, at least for the machines of the same series.

The acquisition of data that reflect the overall ”defect area“ is frequently quite difficult, whereas it is easier to define the ”area of the operational value“. Modern approaches are based on neural networks, in addition, they are trained on data acquired from normally operating devices and are able to find the failures on the basis of data lying beyond the area determined during the training.

Neural networks provide us with an efficient determination of the mechatronic system failure cause and type, operate with noisy data, eliminate the need of intermediary electronic filters from the interference, or filtration by mathematical methods as well as they can adjust to the specific case.

Intelligent diagnostic systems are built as self-learning, self-tuning systems with flexible decision procedures as the systems based on knowledge and creating new knowledge in the operation process.

The tasks of the intelligent diagnostic system are as follows: evaluation of the technical state, analysis of functioning area, etc.

The class of intelligent diagnostic systems fulfils the following principles:

- presence of the interaction of the diagnostic system with real outer world by information communication channels. From here, the intelligent diagnostic systems derive their knowledge and influence them. This principle implementation allows organising the communication channel for knowledge acquisition and organisation of suitable behaviour;
- cardinal system openness to increase the intelligence and improve their behaviour (openness of the system is secured by the presence of self- accommodation, self-organisation, and self-learning). The knowledge system of the intelligent diagnostic system consists of two parts: incoming knowledge and verified knowledge. This principle allows organising the knowledge acquisition and complementation;
- the presence of prognostic mechanisms for changes in the area of operation and own system behaviour in the dynamically changing outer world. In compliance with the principle, the intelligent diagnostic system is not completely intelligent if it is not able to predict the changes in the outer world and own behaviour;
- the system has a structure of a building, which is in compliance with IPDI principle (increased decision with intelligence): the higher the control accuracy, the lower the system intelligence. This is the way

how to build complex diagnostic systems in case that the knowledge inaccuracy about the controlled object model or its behaviour can be compensated by the increased intelligence of the developed system;

- maintaining the operation in case of interrupted connection or loss of controlled activities from higher hierarchy levels.

For example, an intelligent diagnostic system for CNC machine tools is based on an information system for the analysis of the technological system operation according to qualitative parameters of forming via artificial neural networks, which represent the basis for knowing the system and optimisation of control activities (parameters of cutting regimes) via a genetic algorithm. The system comprises the following functional blocks:

- information system to analyse the technological system operation according to qualitative parameters of forming via artificial neural networks. It is implemented as a program for the quality parameters determination;
- the systems of control optimisation are based on a genetic algorithm;
- it is an expert system. Genetic algorithms do not guarantee the discovery of a global solution at a shortest possible time, however, they are good to find ”a sufficiently good“ solution and ”sufficiently fast“.

The analysis of domestic and foreign publications showed, there are many successful applications of neural networks for the machine nodes diagnostics. The analysis results are illustrated in Table 2.1.

Table 2.1
Use of neural networks for machine nodes diagnostics (in table captions the number of resources describing the successful solution of diagnostics by this network)

Type of neural networks	**Diagnosed objects**						
	Pumps	Bearings	Gear drives	Gearboxes	Rotor systems	Ventilators	Motors
BPFF	1	1	–	–	–	–	–
FFNN	1	–	–	–	–	–	1
RNN	1	–	–	–	–	–	1
RBF	–	1	–	–	1	–	–
BP	2	1	1	1	1	–	–
MLP	–	2	2	1	2	1	1
SOM Kohonen	–	–	–	–	–	–	1
LVQ	–	1	1	–	1	–	–

BPFF (Back Propagation for Feed Forward Networks) – networks with direct distribution with the back forward algorithm;

FFNN (Feed Forward Neural Networks) – neural networks with direct distribution;

RNN (Recurrent Neural Networks);

RBF (Radial Basis Function Networks) – networks with radial basic functions;

BP (Back Propagation) – networks with a back propagation algorithm;

MLP (Multi Layer Perceptrons);

SOM (Self Organised Maps);

LVQ (Learning Vector Quantization).

Based on the diagnostic algorithms, the software is developed. The most important software functions are as follows:

- presence of the database allowing store information on the controlled device for a sufficiently long time period,
- possibility to build paths and "insert" them into a portable device. Atlant Software enables to build the paths and transfer the insertion into devices produced by other companies (Bruel & Kjaer, SKF, Diamekh, Orgtekhdiagnostika, etc.),
- presence of the function to evaluate the current technical state and residual operational life of the device. The most efficient way to solve the issue is to compare the vibrations levels to standard values. Since the SK3 value of vibrations speed from 10 to 1,000 Hz is standardised in all standards, in practice no other methods are used to evaluate the technical state of a standard equipment.
- presence of adaptive functions describing the change of vibration parameters in the course of time. These functions are sometimes assigned as a "self-regulating model of wear", which connects the vibrations level with the technical state of a device. Each monitored unit is unique and has own characteristics of work, wear, bond of the vibration state with the residual source value. Therefore, the software has to have a mathematical apparatus, which adjusts the theoretical "model of wear" to real operational parameters of the device. Without this function, the calculations of the residual operational life and repairs timing can have an unacceptable big defect.
- presence of the built-in expert vibrodiagnostic system. This system results complement the calculation of repairs timing. In an ideal case, the diagnostic system should "determine" the optimal time for the repair together with the list of defects, which have to be removed.

- presence of the system or only elements of the parametric diagnostics of the device state. It is obvious that between the vibration state of the device and the operational regimes, there is a coherence. The change of device operational parameters changes the general and spectrum image of vibration processes; therefore, it is probable that for the same unit different conclusions can be obtained, however, in different operational regimes.
- planning of repairs timing, this is one of the most important diagnostic system functions as the main costs for the device maintenance origin during the repairs.
- evaluation of repairs quality. By this function, the quality of repair services is evaluated, which is particularly important in the transfer to service of independent suppliers' stores.
- existence of regulation documents, which allow the companies transfer from the existing system to the system according to the technical state.

The basis of all maintenance systems operation according to their technical state are the algorithms working with SK3 value of vibrations speed, for which there are standard parameters complemented by diagnostic conclusions on defects occurrence. The automated system for the defects diagnostics can be based on various operational principles – according to the SK3 size, vibration signals spectrum, envelope spectrum of the vibration signals, etc., however, it still complements the information on the optimal timing of the device repairs.

All the aforementioned items are present in Aurora system manufactured by Vibro-Center Company. It is necessary to note that all algorithms in the system operate with SK3 value including the built-in diagnostic system. It is important, so that the program applicable to ”Corsair +“ specialised device in compliance with the company marketing policy is free of charge.

The remaining diagnostic systems do not comprise more than five points of the abovementioned list, not all of them have the most important function – planning of repairs timing. This is true for all software products including Atlant Software by Vibro-Center Company. In the positive plan we can comparably record the software of research developers from VAST and PROM-SERVICE Companies, which did a lot of work in the field of evaluating the technical state of devices and designing the models for repairs planning.

The diagnostic programs Aurora and Atlant implement a modern approach to vibration diagnostics as they represent specialise diagnostic programs.

In practice, Aurora allows transfer from the repair of rotational devices through the PPR system to maintenance and repairs according to the technical state. The implementation of Aurora system does not require a special training for the maintenance personnel, and if correctly implemented, brings the highest possible economic effect.

Atlant allows to diagnose the device defects on the basis of vibration signals spectrum. The program implements all necessary time and frequency conversions of vibration signals. The built-in expert system and language for writing the diagnostic rules significantly extends the scope of the program.

Complex as a part of ”Corsair +“ and two expert programs with external simplicity and low costs has in its functional completeness no analogues.

Atlant Software comprises:

- expert system for the diagnostics and solving the issues of rotational devices,

- system for the diagnostics of roller bearings according to the spectrum of the vibration signal cover,
- language for writing the diagnostic rules ”Pallas“, by which the user can formalise and utilise their success in the automated diagnostics.

The analysis of the current state of algorithms and software products of automated diagnostic systems has revealed the tendency to design the diagnostic programs based on the artificial intelligence methods built on modular basis.

2.3 Analysis of diagnostic devices for technological system drives

The diagnostics of technological drives is subject to several problems.

First, it is connected with the inaccuracy of accepted information and limited number of diagnostic parameters in the course of the system getting older or with non-authorised access.

Secondly, with the lack of control system points, especially in conditions of several defects.

Thirdly, lack of early monitoring and prediction of the environmental behaviour influencing the process of the system in real time.

Fourthly, for the in-built technological diagnostic systems in the control systems the factor of time is very important, i.e. the speed of decision taking.

Fifthly, any diagnostic system complication leads to unwanted steps from the customer in terms of the financial investments into their development and subsequent production.

The most numerous are the vibration diagnostic devices. The vibrodiagnostics is performed by a wide range of companies, some to mention which are providing original tools and solutions worldwide or locally, such as Brüel & Kjær (Denmark), SKF (Sweden), Bently Nevada (USA), CMMS (Czechia), Technicka Diagnostika (Slovakia), Polytec (Germany), PromService (Russia, Dmitrovgrad), RMS (Germany), Svantek (Poland) etc.:

- National Instruments (USA) offers a wide scale of devices and software tools, which can be used as components of vibration monitoring and diagnostic systems,
- OKTAVA + (Russia, Moscow), supply hardware and software for the vibrodiagnostic method,
- companies VAST (Russia, St. Petersburg), ViKont (Russia, Moscow), DIAMETH 2000 (Russia, Moscow), INCOTES (Russia, N. Novgorod) and Spectral engineering (Russia, Moscow) are also active within the issues of vibrations monitoring, vibrations diagnostics.

One of the newly development trends is represented by a two-channel data collector VIK-3-2 analyser made by ViKont Company (Russia, Moscow) having a sufficient performance, small dimensions and weight, which is suitable especially for the field work. Company VAST (Russia, St. Petersburg) introduces a dual channel analyser able to record the amplitude envelopes of the vibration signal. INCOTES Company (Russia, N. Novgorod) offers a 3-channel device titled DATA COLLECTOR CM-3001 for simultaneous (true, multiplex) vibrations measurements in one point in three directions as well as an expert system titled ARMID-EXPERT.

A vibration data analyser STD-3300 with an advanced software is introduced by Technekon Company (Russia, Moscow). For less experienced users there is a portable vibration collector at their disposal, which provides the fast measurement of vibrations level in the standard frequency range and monitor the spectral image. PromService (Russia, Dmitrovgrad) carries out research and development in the field of continuous vibrations monitoring and diagnostics, with comparable software as it is adjusted to various users and data analysers.

Spectrum Engineering Company (Russia, Moscow) supplies OneProd System to 01dB-MET-RAVIB Company (France). It includes not only a dual channel collector analyse of vibration parameters with in-built means for distant measurement of temperature and rotations speed of parts as well as powerful means of stationary monitoring and diagnostics (e.g. small 32-channel system of parallel broadband collection of diagnostic information). OKTAVA + Company (Russia, Moscow) offers a wide range of advanced measurement devices and systems (including laser ones).

The technological system necessarily interacts with the exterior. Therefore, it comes to the change of the diagnostic parameters values due to external conditions influence. The prediction of this effect is an inevitable part of integrated diagnostic systems.

The performance and quality of the diagnostic system are evaluated regarding the editing speed of information about the defect location, type and cause by the monitoring of the technological system and environment.

First, the diagnostic system has to have a high speed.

Secondly, looking for the defect location can be eased by the correct detection connected with the deep detection coefficient.

Thirdly, the system for the failure detection should have the methodology of correct recognition and classification of defect symptoms of any multiplicity. The defects recognition and their classification determine the type and the cause.

In the technological systems diagnostics, there are frequent defects, by which the relation between the symptom and the cause of the defect is unclear. Simple double-digit assertions such as ”correct – 1“, ”incorrect – 0“ are insufficient as the clear rules of the issues solution in the system are based on mutual correspondence of the defect symptoms and defect cause, i.e. they are strictly defined by the rules. Modern diagnostic systems have to able to recognise dangerous operational conditions, causes, and types of the defect occurred. Besides, the information on the residual operational life evaluation of the whole technological system or its component is needed.

Therefore, the output parameters of the diagnostic system should determine the defect cause and type on one hand, and the diagnosed object state as well as its compliance with the operational and functional purpose on the other hand.

The complexity of technological systems is quite high, and the user cannot sometimes completely and precisely comprehend all processes occurring in the course of system operation. Further step is then a partial or complete transfer of expert analytical functions from the human to the machine, i.e. a complete automation of the whole diagnostic cycle becomes necessary. One of the most popular implementation tools is again represented by the use of human decision models – neural network algorithms.

The possibility of transfer execution has appeared only recently as a result of computer technology development; however, the theoretical research is still carried out. The same algorithm of fast discrete Fourier transform has been developed in the mid of the last century, although its wide utilisation has started quite recently.

Regarding the amount of the diagnostic preparate required by the operator, the systems can be classified into three groups.

The first group is represented by professional diagnostic systems, in which the operator independently selects the information technologies and measuring tools. In using the system, it is the knowledge and experience of an experienced operator that determine the depth and reliability of the diagnostics and prognosis.

The second group are the expert diagnostic systems including the expert programs comprising the responds to typical operator´s requirements, assistance to operator in decision taking in specific situations. The systems can be used by those operators, who have a special training but do not have expert knowledge or experience.

The third group – automated diagnostic systems composed according to methods, which automate the diagnostics, develop the measurement program and do not require any special training. The service training to operate such diagnostic systems does not exceed two or three days. For the first time, the methods and automated diagnostic systems appeared in the early 90s in Russia, in Vibroacoustic Systems and Technologies OJSC. At present, the automate diagnostic systems are widely used and the range of the machines and devices to be diagnosed have been widened as well.

The simplest tools are the measuring tools with general vibration (noise) level and the device for the measurement of top vibration signal factor, i.e. a shock pulse recorder. The tools were affordably priced in all stages of the measuring tools development; therefore, the practical diagnostics was also focused on them. Nowadays, the fast computer technology development and lower prices allow complex utilisation of all of them, even of the use of the most complex information technologies in practice. Currently, the analysers of digital signal are compared in terms of costs with the simplest analogue devices, which replace them in the diagnostic problem's solution.

The most commonly used measuring tools implemented on the computer technology basis are represented by shape analysers, spectrum analysers. The shape analyser functions are to measure the amplitudes and phases of individual signal components and compare the shape analysis of individual signal parts, whose start and end are determined by the shaft rotation angle. Such analysers are widely used for the diagnostics of piston machines and rotors in their balancing process. Spectral analyser is usually used for the monitoring of all machines and device types. The spectrum analyser is determined to study the random processes, whose performance periodically changes in the course of time.

The mostly available way of signal measurement and analysis can be carried out by a personal computer with the devices for vibration and noise conversion into a digital form and their insertion to RAM computer memory.

Such a measuring tool allows using any of the considered information technologies or their combinations. Improved or upgraded professional sound cards can be used as the aforementioned devices. The means for signals measurement and analysis do not differ in small dimensions and can be used in laboratory or testing conditions. For the measurement of vibrations outside, it is possible to use the measurement and analysis means constructed according to the same rules, although on the basis of portable computers. There are also sound cards or the cards with analogue input devices. Then, for their measurement and analysis, it is sufficient to have such a card and an input device, including the vibration (noise) sensor, supply of its performance, and the device for the input card sensor modification. Such devices are made by many other world producers.

Digital analysers are produced for the specific group of technologies on the principle of signal processing and only some of them are designed to use all known technologies. Generally, in all analyser types, the narrow band signal spectral analysis is used, and very rarely the spectral analysis of the belt signal envelope is used, which is needed for the IT via envelope methods. Such analyser is quite complex and is produced only by few producers, including the aforementioned Russian companies.

The analysis of main trends in the computer technology development has shown that in the upcoming years we can anticipate a wide distribution of small devices with various purposes, in which there is one in-built microcomputer with excellent calculation abilities and a standard operation system. Obviously, the technology for vibroacoustic signals measurement and analysis will be developed, which leads to the prices decrease. Another perspective is represented by the use of common information technologies in the field of technical diagnostics, which could result in higher production and lower prices of analytical tools.

The increase of the microcomputers performance induces the development of further technological tools for the machine and devices diagnostics. It is the combination of functional and testing diagnostic abilities in one device.

For this purpose, it is necessary to provide the possibilities – a multi-channel signal analysis including the correlation, cross spectrum, and others, as well as implement the functions test signals generation and external supplies of these signals into the software.

Technical means for the signals measurement and analysis in stationary systems for machine monitoring and diagnostics do not functionally differ from the means used in portable systems. The differences are present only in the technological implementation connected with the need of repeated measurements in the same control points with such a short time interval, which can ensure the in-time machine turn-off, although ”avalanche“ problems could occur.

The number of units for signal measurement and analysis in the stationary systems is usually determined by the number of control points and maximum allowed interval among the measurements. The number of sensors per block can be in the range from one to several tens. The measurement unit functions include the vibrations and noise analysis as well as other physical quantities according to the program defined by the diagnostic centre. The program algorithms automatedly change in dependence on the diagnostic results of the controlled object state. Sometimes the measuring unit´s function also includes the comparison of measurements and analysis with threshold values determining thus the allowable change boundaries of the diagnostic parameters. If the allowable time of periodical measurements is sufficient enough, the system can use the unit, to which the sensors are connected via the electronic signals switch devices. The measuring unit can be combined in the cover together with the diagnostic centre. The diagnostic centre is represented either by the only connected computer or a group of computers operating in parallel or with separated functions.

The anticipation of the stationary monitoring systems development is also connected with the development of microcomputer abilities, which can result in separated functions of the measuring units and the diagnostic centre. The measuring unit can overtake the monitoring functions and refer to the diagnostic centre only in case of defects occurrence, so that they can be identified. In such a case, one diagnostic centre can work with a high number of measuring units and thus monitor the equipment state of the whole company.

The production of specific diagnostic centres for testing the powerful semiconductor devices is quite complex, they are produced only in rather small amounts (as there are only a few potential customers), and in addition, they are expensive.

The analysis of main trends in the field of IT development shows that in the upcoming years we can expect a wide distribution of small devices for various purposes, in which there will be an in-built microcomputer with excellent calculation abilities and a standard operational system. This trend will be seen also in the field of measuring technology of vibroacoustic signals, which will lead then to further price decrease. The other perspective is the use of common information technologies in the field of technology diagnostics, which can lead to increased production and further depreciation of the analytical tools.

The increased microcomputers performance induces the development of other branch of the technical tools for the machines and devices diagnostics – the combination of functional and testing diagnostic abilities in one device.

For this purpose, it is necessary to provide the possibilities of a multiple channel signal analysis including the correlation, cross spectrum and others, as well as introducing the functions of generating the testing signals, and control of external signal sources into the software.

The analysis of diagnostic devices for technological systems drives has shown that the development of small diagnostic devices is perspective. They are based on microcontrollers or processor for digital signals processing with excellent calculation abilities and standard operation system for fast diagnostics and connected with the deep diagnostics server, can calculate diagnostic trends, parameters, or the residual operational life of the technological systems drives.

For the diagnostics of critical technological systems drives, or accidents resulting in causalities, technological disasters, or significant economic losses, it is to use the continuous diagnostic systems.

2.4 Classification of diagnostic systems for automated technological drives

Technological diagnostic systems are classified according to their functional purpose, number of diagnostic signs, degree of diagnosed object cover, the interaction character of the diagnostic devices and the diagnosed object, used means, degree of automation, form of used signals and device, and diagnostic methods.

The classification of the diagnostic systems is proposed takes into consideration the costs of the accidents (destruction) consequences and the degradation speed of the diagnosed object. The feasibility of the diagnostic systems use is depicted in Table 2.2.

The slow degradation rate of the diagnosed object is determined by slow processes causing damage in the course of months or years. For example, such processes include the wear of the drive parts, released strain, leakage of metal (dimension damage), and corrosion.

The average degradation speed of the diagnosed object is determined by the processes causing damage in minutes or hours, e.g. thermal processes or changes of forces.

The high speed or sudden failure of the diagnosed object is determined by fast processes, which can cause the damage in seconds, or even in fraction of a second. Such processes include e.g. oscillations, or periodical change of forces.

Kotv – coefficient characterising the device type and production properties is from 0 to 1, the relative value of production losses related to its emergency exchange.

Kdegr – the coefficient characterising the degradation speed of the diagnosed object is from 0 to 1.

Table 2.2
Feasibility of system diagnostics

	Slow degradation speed of the diagnosed object	**Average degradation speed of the diagnosed object**	**High degradation speed or sudden failure of the diagnosed object**
Nonrelevant costs of accidents consequences (destruction)	Portable diagnostic devices Kotv = 0, Kdegr =0	Non-portable diagnostic devices Kotv=0.3, Kdegr =0.5	Stationary diagnostic devices Kotv=0.5, Kdegr =1
Average costs of accidents consequences (destruction)	Portable diagnostic devices Kotv=0.5, Kdegr =0	Statioanry diagnostic devices Kotv=0.7, Kdegr =0.5	Continuous diagnostic devices Kotv=1, Kdegr =1
High costs of accidents consequences (destruction)	Statioanry diagnostic devices Kotv=1, Kdegr =0	Continuous diagnostic devices Kotv=1, Kdegr =0.5	Continuous diagnostic devices Kotv=1, Kdegr =1

For example:

Kotv = 0 for additional, doubled, periodically used device,

Kotv = 0.5 is responsible for the main part of the device,

Kotv = 1 for one, especially unique device,

Kegr = 0 for slow degradation speed of the diagnosed object,

Kdegr = 0.5 for average degradation speed of the diagnosed object,

Kegr = 1 for the high degradation speed of the diagnosed object.

The results of the accident (destruction) are the main factor determining the suitability of the use, the form and contents of the diagnostic system. The other factor is the accessibility of the equipment. Table 2.3 shows the suitability of the diagnostic systems use and types of devices maintenance in dependence on the device type.

Table 2.3
Suitability of using diagnostic systems and maintenance types

	Feasibility of systems diagnostics	**Types of maintenance and repairs**
Additional, doubled, regularly used equipment	By using portable diagnostic devices no regular diagnostics is needed	Repairs after an accident, planned preventive repairs
Corresponding basic equipment	Portable diagnostic devices, stationary diagnostic systems	Maintenance and repairs according to technical state
Unique, very critical equipment	Continuously diagnosed systems	Maintenance and repairs according to technical state, continuous protection

The proposed classification of the diagnostic systems in dependence on the accidents consequences and degradation processes speed in the diagnosed object (portable devices, stationary systems, and continuous diagnostic systems) allow rational organising of the technological drives diagnostics (Krenicky and Jacko 2011; Krenicky and Fabian 2013; Mascenik and Pavlenko 2018, 2019; Panda et al. 2016, 2018, 2019, 2021; Prislupcak et al. 2014; Saga 2014; Straka and Panda 2018).

3 Development of Diagnostic Models of Technological Drives

The analysis of known diagnostic systems has shown there is no general approach to the construction of the diagnostic systems for AI-based technological drives. The diagnostic system construction for the technological drives is usually based on the mathematical model of the diagnosed object. Such models are very complex even for simple sets such as the bearing is. Besides, in such a model there is no mechanism for defects or failures detection and their impact on the target functions of the technological systems drives is not considered.

Logical-linguistic model for the diagnostics and prediction of the residual operational life of technological drives and for the calculation of diagnostic intervals on the fuzzy logic basis is represented by a system of equations:

$$\begin{cases} x(t) = F(x(t_0), t), \\ D(t) = G(x(t_i), t), \\ Z(t) = H(x(t), D(t), t), \\ R(t) = W(x(t), D(t), Z(t), t), \\ \Delta t = V(x(t), D(t), R(t), t), \end{cases} \tag{3.1}$$

where $x(t) = F(x(t_0), K, t)$ - equation of diagnostic parameters,

x (t) - vector of diagnostic parameters;

t - time of technological drive work ;

$D(t) = G(x(t_i), t)$ - equation for calculation of vector diagnostics of diagnostic parameters trend

ti - is the file of measurement moments of diagnostic parameters;

$Z(t) = H(x(t), D(t), t)$ - equation for technical state evaluation;

$R(t) = W(x(t), D(t), Z(t), t)$ - equation for residual operational life calculation in t time;

$\Delta t = V(x(t), D(t), R(t), t)$ - equation for diagnostics intervals calculation.

The diagnostic and prediction model of technological systems drives was implemented into MatLab software product within the Fuzzy Logic Toolbox package.

3.1 Development of fuzzy inference system for the evaluation of drives technical state

Fuzzy inference system for the technical state evaluation is implemented on the basis of fuzzy knowledge such as Mamdani, with three input variables x, D, and t. The scheme of the fuzzy inference system is illustrated in Fig. 3.1.

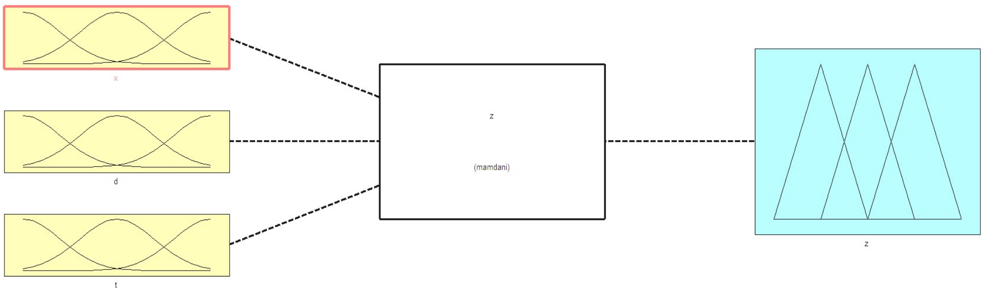

Fig. 3.1 – Scheme of the fuzzy inference system for technical state evaluation with three input variables x, D, and t

As the basic function of the term M linguistic variable a Gaussian function was selected since it is quite simple, differentiable, and is defined only by two parameters, which allows decreasing the algorithm´s calculation complexity. As the basic functions of expression L and H of the linguistic variable are selected from the function.

Selected Mamdani fuzzy inference, such as t-norm selected maximum defuzzification method is executed according to the importance as it provides very good accuracy and fuzzy setting of the knowledge basic speed. The weight coefficients of the rules, the coordinates of the maxima of the membership functions of the term M of the linguistic variable are used as adjustable parameters. The example of the known variables x, D and t functions is shown in Figs. 3.2–3.4.

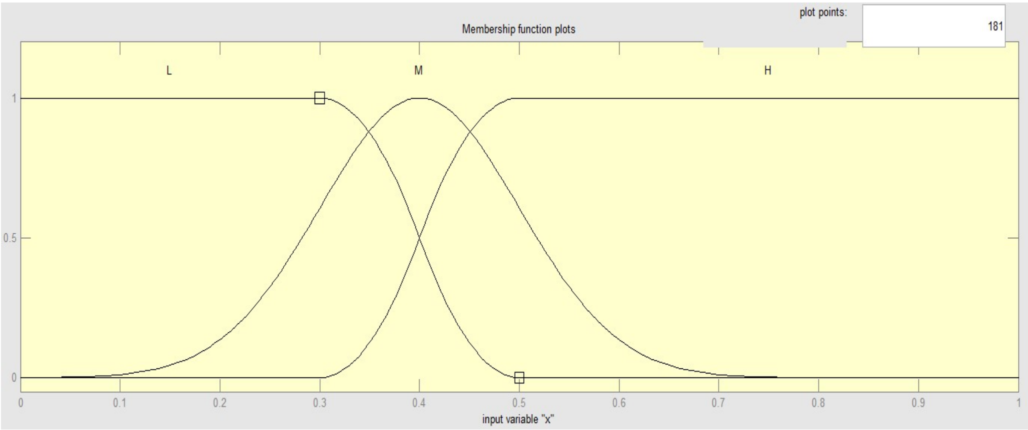

Fig. 3.2 - Example of expressions L, M, and H of x input variable

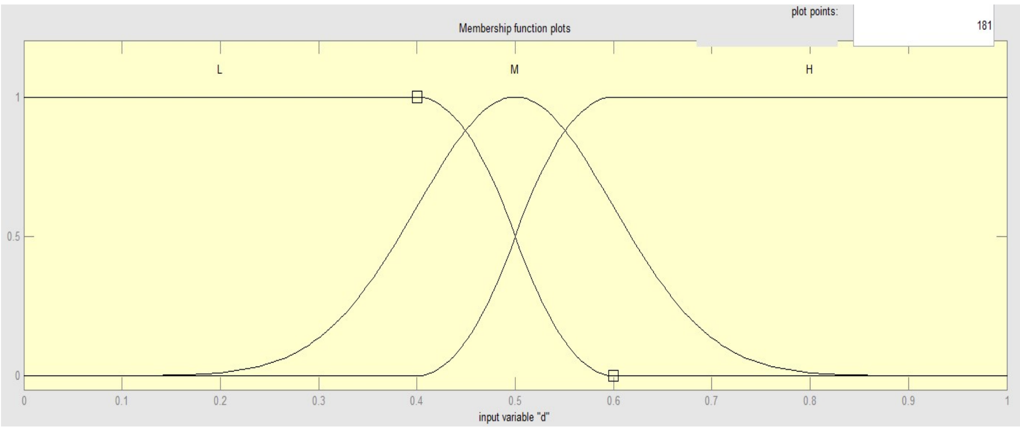

Fig. 3.3 - Example of expressions L, M, and H of D input variable

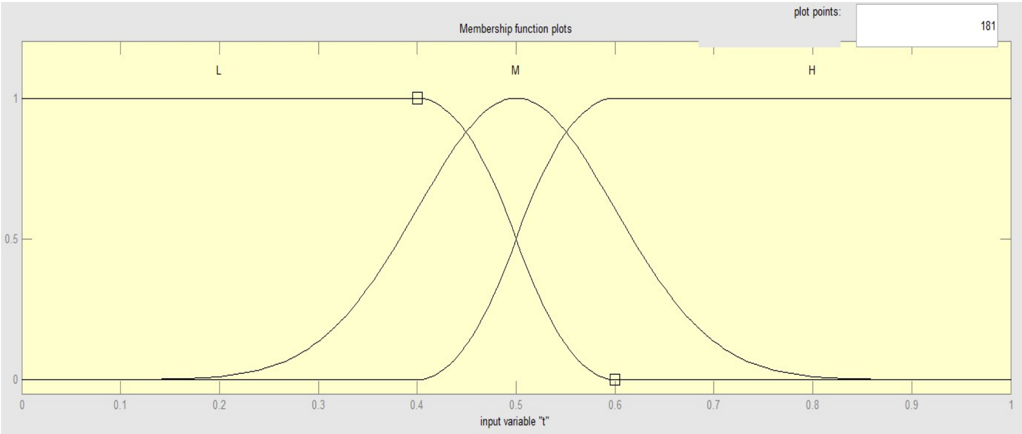

Fig. 3.4 – Example of expressions L, M, and H of t input variable

The example of the known output variable function *y* is shown in Fig. 3.5.

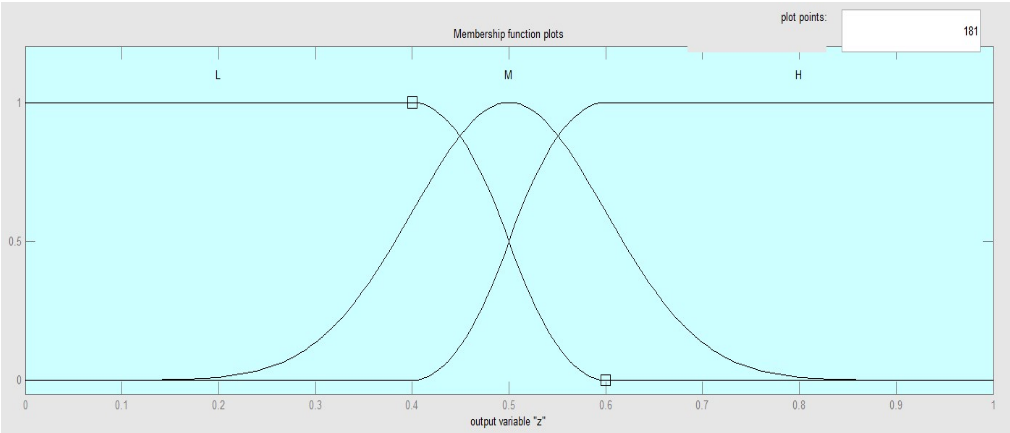

Fig. 3.5 – Example of expressions L, M, and H of Z output variable

By using three linguistic variables with three terms and by combining the logical operations AND and OR, seven rules reflecting the technical state dependence on the diagnostic parameters values, diagnostic parameters trends and elaborated source were obtained. They are illustrated in Fig. 3.6.

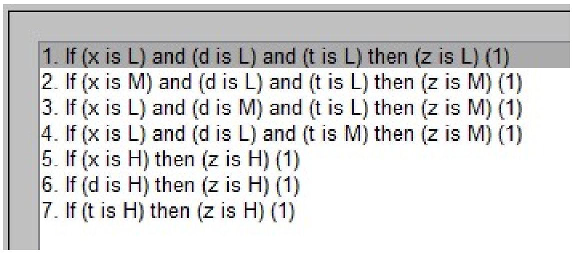

Fig. 3.6 - System fuzzy inference rules of the technical state evaluation by combining AND and OR logical operations

The surface of the fuzzy inference system response for the technical state evaluation is shown in Fig. 3.7.

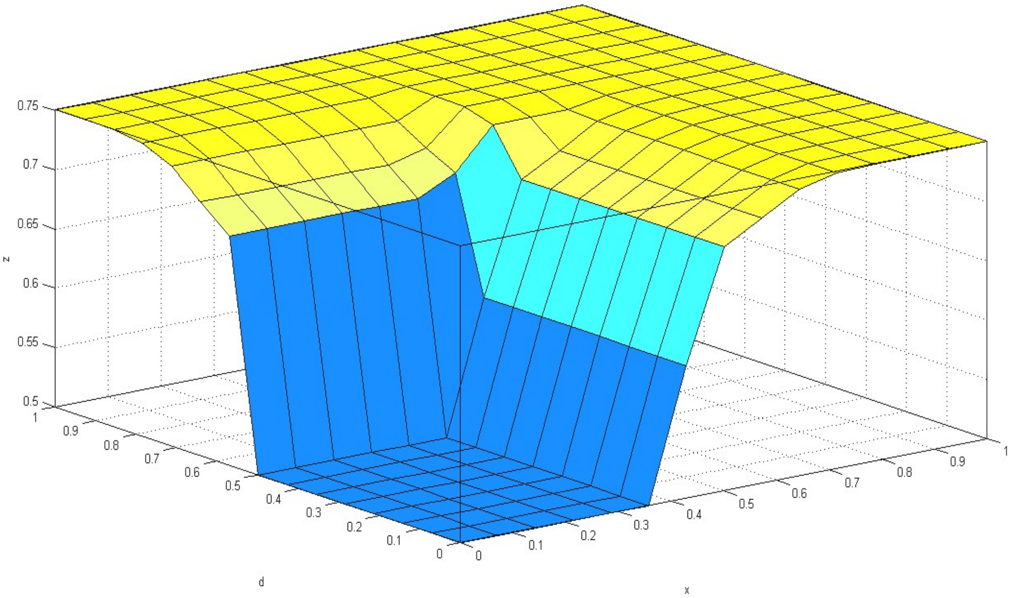

Fig. 3.7 - Surface of fuzzy inference system response for the technical state evaluation by combining AND and OR logical operations

3.2 Development of the fuzzy inference system for the estimation of the residual operational life of drives

Fuzzy derivation system for the estimation of the residual source is implemented on the fuzzy knowledge-base of Mamdami type with the input variables x, D, Z, and t. the scheme of the fuzzy inference system is shown in Fig. 3.8.

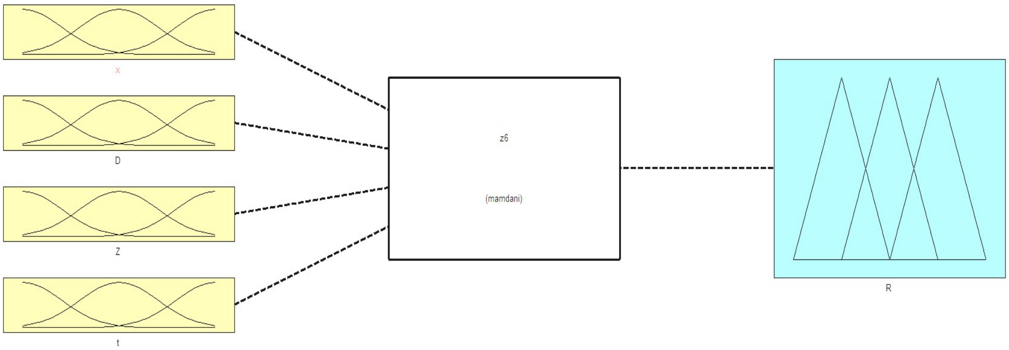

Fig. 3.8 - System diagram of fuzzy derivation estimation of the residual operational life with input variables x, D, Z, and t

The terms L, M, and H of input variables x, D, and t are the same as in the fuzzy inference system for the technical state evaluation. The example of expressions L, M, and H of Z input variable is illustrated in Fig. 3.9. The example of expressions L, M, and H of R output variable is shown in Fig. 3.10. Fig. 3.11 depicts the rules for the residual source output.

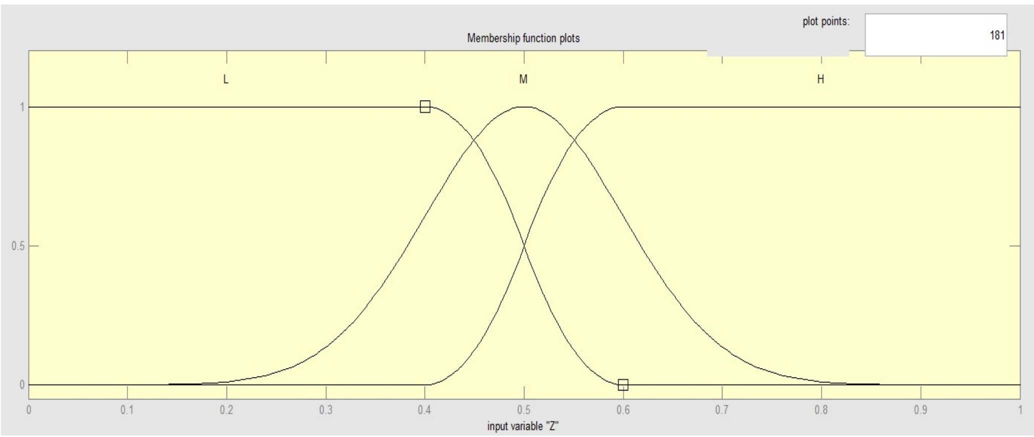

Fig. 3.9 – Example of expressions L, M, and H of Z input variable

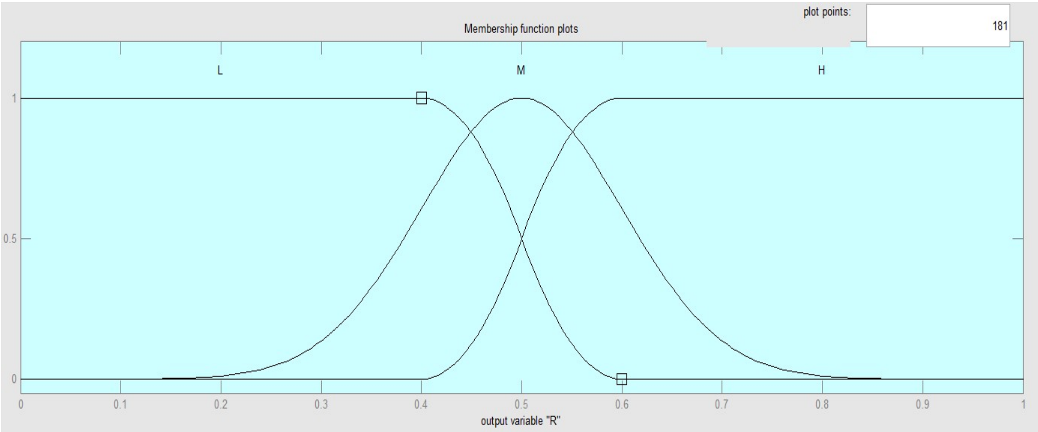

Fig 3.10 – Example of expressions L, M, and H of R output variable

1. If (x is L) and (D is L) and (Z is L) and (t is L) then (R is H) (1)
2. If (x is L) and (D is L) and (Z is L) and (t is M) then (R is M) (1)
3. If (x is L) and (D is L) and (Z is M) and (t is L) then (R is M) (1)
4. If (x is L) and (D is M) and (Z is L) and (t is L) then (R is M) (1)
5. If (x is M) and (D is L) and (Z is L) and (t is L) then (R is M) (1)
6. If (x is H) then (R is L) (1)
7. If (D is H) then (R is L) (1)
8. If (Z is H) then (R is L) (1)
9. If (t is H) then (R is L) (1)

Fig. 3.11 - System fuzzy inference rules of the residual operational life estimation by combining AND and OR logical operations

Fig. 3.12 shows the surface of the fuzzy derivation system response for the estimation of the residual operational life.

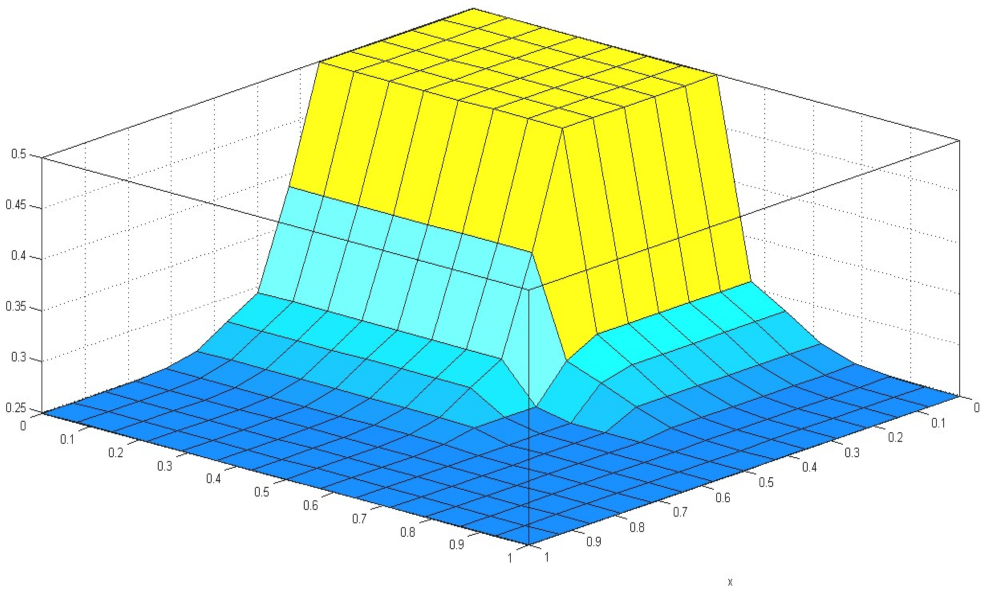

Fig. 3.12 - Surface of fuzzy derivation system response for the estimation of the residual operational life by combining AND and OR logical operations

3.3 Development of the fuzzy inference system for the calculation of drives diagnostics intervals

Fuzzy inference system for the diagnostic intervals calculation is implemented on the fuzzy knowledge basis, such as Mamdani with input variables x, D, Z, and t. The scheme of the fuzzy inference system is illustrated in Fig. 3.13.

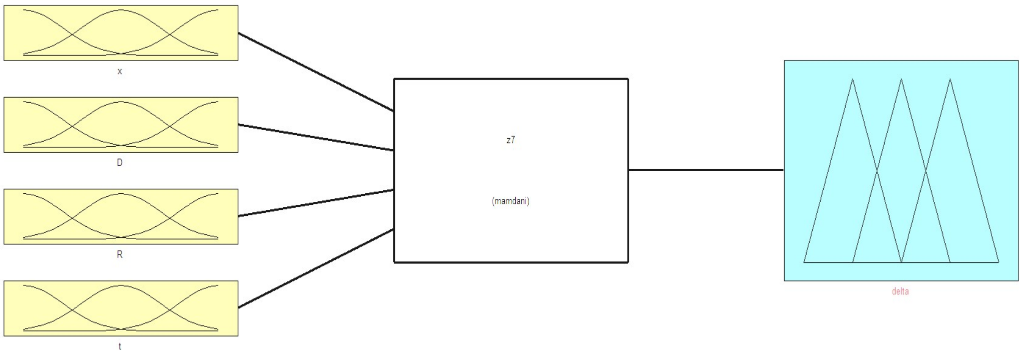

Fig. 3.13 – Scheme of fuzzy inference system for the calculation of diagnostic intervals with input variables x, D, R, and t

The terms L, M, and H of input variables x, D, and t are the same as in the fuzzy inference system for the evaluation of the technical state and the residual operational life. The example of expressions L, M, and H of R input variable is illustrated in Fig. 3.14. The example of expressions L, M, and H of delta output variable is shown in Fig. 3.15. Fig. 3.16 depicts the inference rules for the diagnostic interval's evaluation.

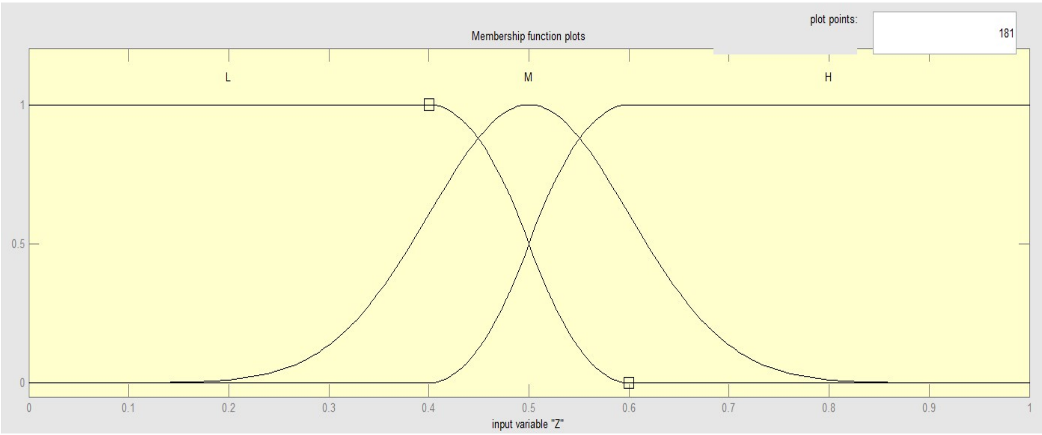

Fig. 3.14 – Example of expression L, M, and H of R input variable

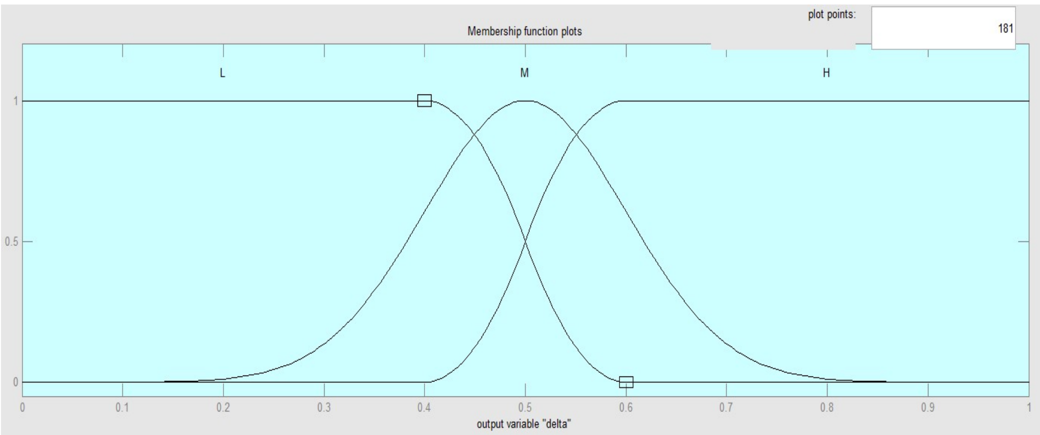

Fig. 3.15 – Example of expressions L, M, and H of delta output variable

1. If (x is H) then (delta is L) (1)
2. If (D is H) then (delta is L) (1)
3. If (t is H) then (delta is L) (1)
4. If (R is L) then (delta is L) (1)
5. If (x is M) and (D is M) and (R is M) and (t is M) then (delta is M) (1)
6. If (x is L) and (D is L) and (R is H) and (t is L) then (delta is H) (1)

Fig. 3.16 – Fuzzy inference system rules for the diagnostic intervals evaluation by combining AND and OR logical operations

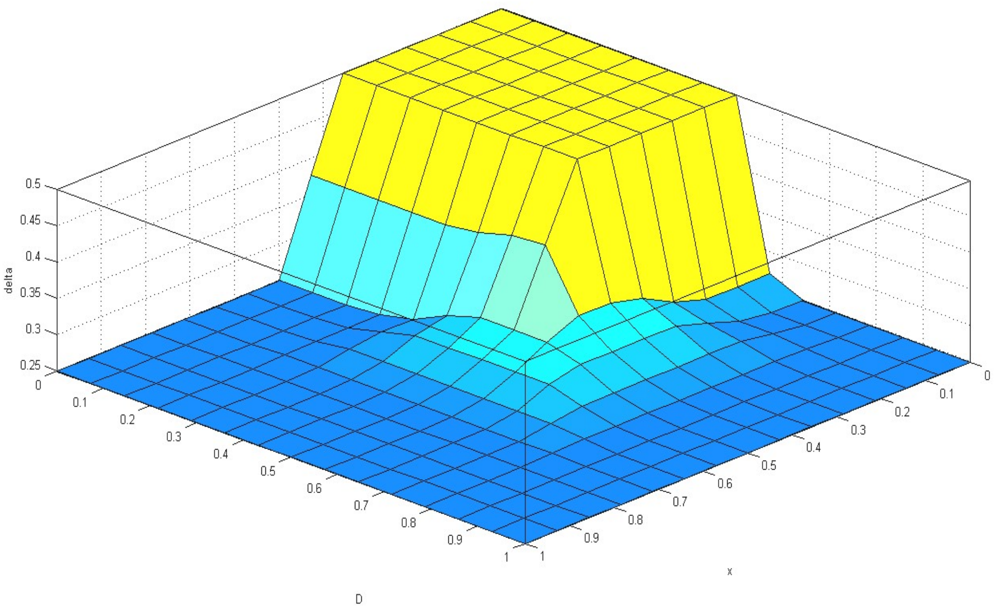

Fig. 3.17 – Surface of fuzzy inference system response for the diagnostic intervals evaluation by combining AND and OR logical operations

Generally obtained models for the diagnostics and prediction of the residual operational life of technological systems drives and for the calculation of diagnostic intervals based on fuzzy logic are tuned to each of the objects. The development of the fuzzy rules (knowledge) basis Mamdani is in the setting of variable functions and rules weigh and is executed according to the method of least squares, the fastest descent (Fig. 3.17). The logical-linguistic model serves as the basis for diagnostic algorithms development.

4 Identification of the Technical State Diagnostic Parameters of Technological Drives

4.1 Analysis of technological equipment of the production line for chipboards in "Uvadrev-Holding" Company

The technological equipment of the production line for chipboards in Uvadrev-Holding Company is represented by the automated production line BISON WERKE from Germany, which was introduced in the 90s. In 2008 the complete exchange of production devices was carried out.

The technological production process of chipboards starts with the manufacturing of the chipboard basics comprising three levels of chips of various fractions. The boards come together with the specific amount of jointing material from the moulding machines to the conveyor belt arranged consecutively. Once the basics is built, the upper layer is moistened by water spraying and it enters the two-storeys press in its upper level. The following layer enters the lower press level and pressing is executed according to the given program so that the required veneer width is obtained. After pressing, they come out of the heating to the cooler with fans, where the hot boards are cooled by one device cycle. Further, the ready board is conveyed to the moulding machine, where on its exit the correct width is controlled by sensors. The latest operations are the weighing of the ready plate and its grinding by several grinders. The ready plate is then classified and stocked. For each operation a specific device is used, which is driven by electric drives and consists of various units and parts. The block scheme of the production line is illustrated in Fig. 4.1. The technological production process of chipboards is controlled by ”Trace Mode 6“ SCADA system. On the lower control level, there are programmable logic regulators – Omron. As the feedback sensors the series of induction sensors, optical sensors, coders, laser sensors, and weight and temperature sensors are used. The frequency control is used to control the electric induction motors.

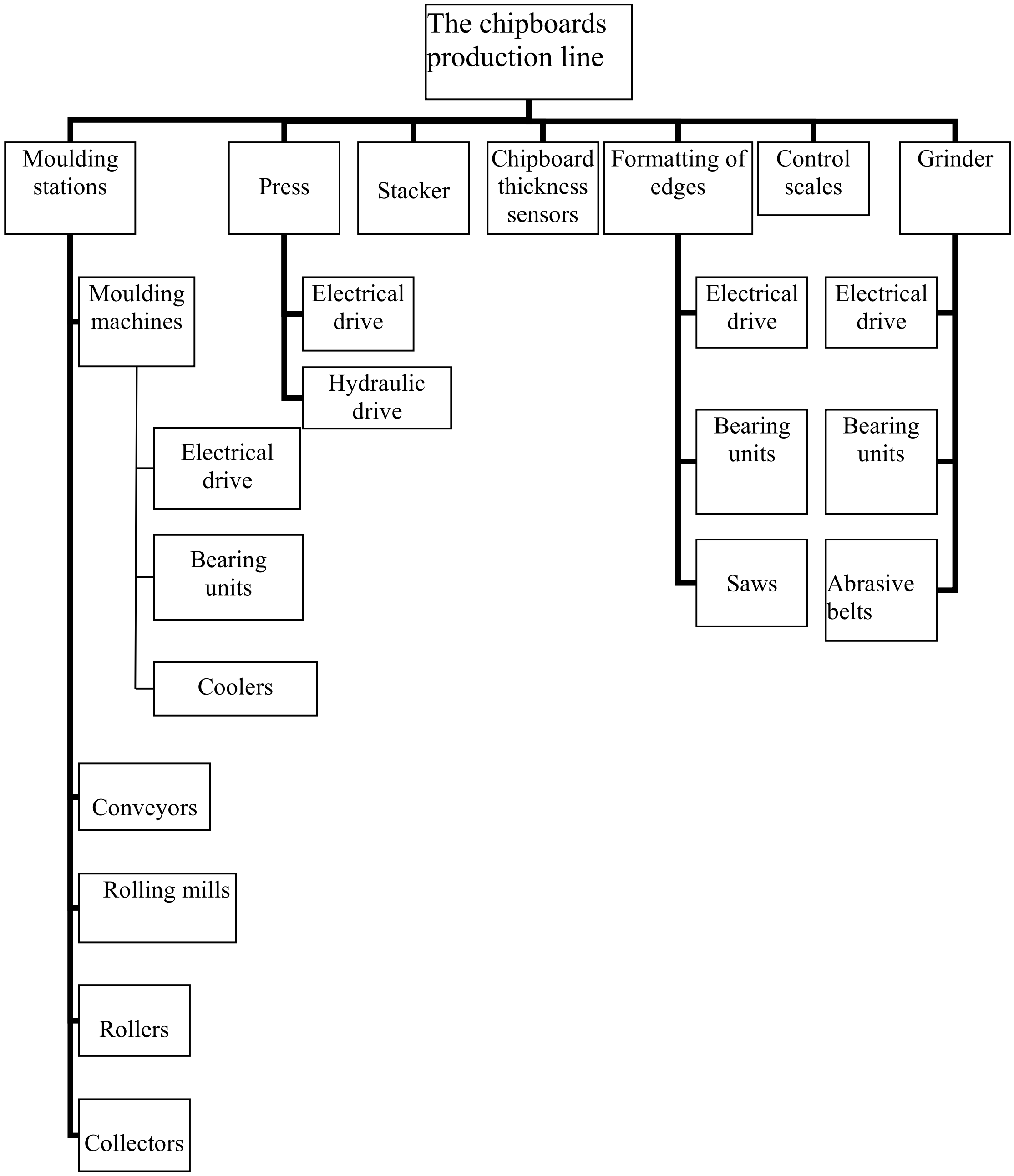

Fig. 4.1 - Block scheme of the technological lien for chipboard production

The list of drive devices of the forming machine for the chipboard production line is illustrated in Table 4.1. The performance and the synchronous frequency of electric motors are shown in Table 4.2.

Table 4.1
List of drive devices of the forming machine for the chipboard production line

Type of drive	Type of device	Name of device with the drive	Availability of mechanical gears and sensors
231M1 - gear motor (asynchronous motor with frequency changer)	Large chips conveyor belt	Large chips conveyor belt	Rotation sensor, Capacity level sensors for moulds filling (8 pcs.)
231M2, 231M3 - gear motor (asynchronous motor with frequency changer)	Drive of cleaning worms of the conveyor belt	Cleaning worms of the conveyor belt	Rotation sensor
231M4 - gear motor (asynchronous motor with frequency changer)	Cleaning conveyor belt with large bristles	Cleaning conveyor belt with large bristles	Rotation sensor
233M1 - gear motor (asynchronous motor with frequency changer)	Drive of worms with large chips	Drill point with large chips	Rotation sensor
234M1 - gear motor (asynchronous motor with frequency changer)	Large chips conveyor belt	Large chips conveyor belt	Rotation sensor
235 M1 - gear motor (asynchronous motor with frequency changer)	Oscillation of large chips conveyor belt	Large chips conveyor belt	Chain gear Sensors of extreme position, rotation sensor
236M1, 237M1, 238M1 - gear motor (asynchronous motor with frequency changer)	Drive of ”rack“ chips	Moulding machine	Chain drive Rotation sensors
251M1 - gear motor (asynchronous motor with frequency changer)	Belt conveyor for soft chips	Belt conveyor for soft chips	Rotation sensor, Capacity level sensors for moulds filling (8x2 pcs.)
251M2, 251M3 - gear motor (asynchronous motor with frequency changer)	Drive of cleaning worms of the conveyor	Cleaning worms of the conveyor	Rotation sensor
251M4 - gear motor (asynchronous motor with frequency changer)	Cleaning of soft chips by brushing conveyor	Cleaning of soft chips by brushing conveyor	Rotation sensor
252-pneumatic cylinder	Drive of distributor damper (distribution of soft chip flows) Capacity level sensors for moulds filling (8x2 pcs.)	Forming machine	Capacity level sensors for moulds filling (8x2 pcs.)
253M1, 254M1 - gear motor (asynchronous motor with frequency changer)	Drive of feeding worms of soft chips	Forming machine	Rotation sensor
255M1, 256M1 - gear motor (asyn-	Distributor Bendix	Forming machine	Chain drive Rotation

chronous motor with frequency changer)	drive		sensor
257M1, 258M1 - gear motor (asynchronous motor with frequency changer)	Drive of distributor	Forming machine	Chain drive Extreme position sensors
302M1,312M1, 322M1 gear motors (asynchronous motors with frequency changers)	Drive of capillary shaft	Forming machine	Belt drive. Rotation sensors for each shaft
303M1, 313M1, 323M1 - gear motors (asynchronous motors with frequency changers)	Bottom belt drive	Forming machine	Chain drive for each belt
304M1, 314M1, 324M1 - gear motors (asynchronous motors with frequency changers)	Bottom brush drive	Forming machine	Sensors of weight gain per 1 shaft
305M1, 306M1, 315M1, 316M1 – low voltage electric motors	”Vibrator“ on filter grid	Forming machine	Balancing adjustable boards
325M1, 326MH, 327MH, 328MH, 329MH, 330MH1 - gear motors (asynchronous motors with frequency changers) Classical axle drive shaft	Classical axle drive shaft	Forming machine	Cam belt, Rotation sensor
308M1, 318M1 – gear motors (asynchronous motors with frequency changers)	Conveyor drive	Forming machine	Rotation sensor
331M1, 332M1	Conveyor drive	Forming machine	Rotation sensor
321M1 - gear motor (asynchronous motor with frequency changer)	Forming machine – drive of height adjustable drive of a secondary form	Forming machine	Shaft with stars at the ends, adaptor joint based on twin-row chain, gearbox
364M1 - gear motor (asynchronous motor with frequency changer)	Actuator of main conveyor	Main conveyor	Chain gear (twin-row chain). Rotation sensor, sensor of pallets availability
365M1 - gear motor (asynchronous motor with frequency changer)	Actuator of pallet brush	Main conveyor	Rotation sensor

Table 4.2
Performance and synchronous frequency of electric motors

№	**Type of motor**	**Performance in kW**	**Synchronous frequency rev/.min-1**
1	Gross motor for chip mixing	90	1000
2	Soft/ Fine motor for chip mixing	30	1500
3	Electric motor of first grinder	90	1500
4	Electric motor of second grinder	90	1500
5	Electric motor of third grinder	90	1500
6	Electric motor of first forming machine	22	1500
7	Electric motor of third forming machine	22	1500

8	Electric motor of crusher	75	1500
9	Electric motor of pneumatic classifier	45	1500
10	Self-cutter with electric motor	45	1500

The tables of the idle time periods in the production show exactly which idle times occur during the emergency production stop. Fig. 4.2 illustrates the comparison of idle time in 2008-2012 years for the production line in the Bizon Company. The analysis of idle times shows their most frequent occurrence as a result of mechanical components´ accidents.

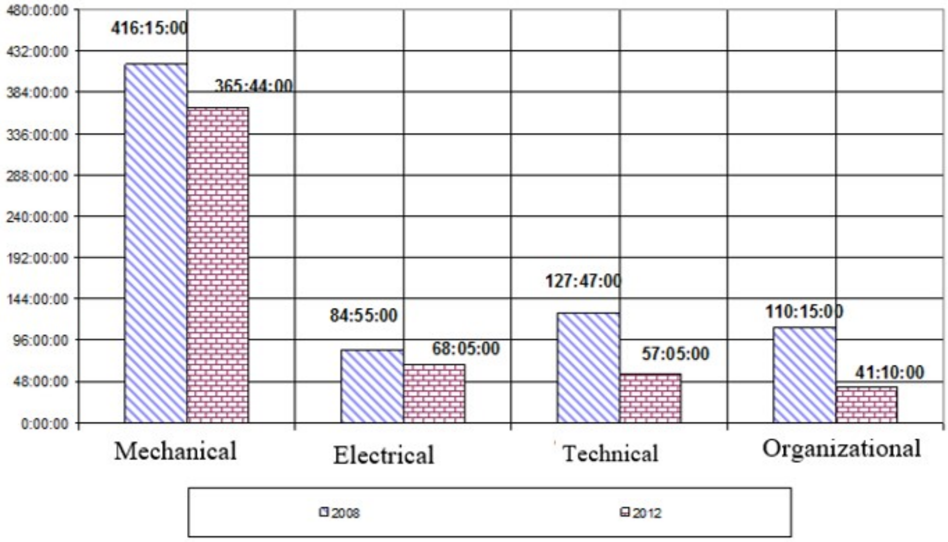

Fig. 4.2 - Scheme of production line idle times; comparison of downtimes for the production line in Bizon Company in years 2008 and 2012

The basics for the analysis of the production line components for chipboards were represented by the data from the activity log, where the information on the executed repair activities were recorded. A sample including the data from 2008-2012 years was compiled.

The analysis of the device reliability in the time period of five years shows that a lot of failures have occurred as a result of wear: roller bearings, chain gears, or electric motors, whereas the nodes generate 50% of the guarantee in average and 18.2% of the operational life of the general repair. At the same time, the operation of devices shows that in favourable operational conditions of drives (quality assembly, following the technical operation rules, etc.) they could have full guarantee, repair, and the estimated overall operational life.
The particularity of failures caused by the component damage (roller bearing, electric motor) is represented by the fact that this type of failures means the replacement of the whole device units without the possibility of further recovery, which is the most expensive operation. The losses on products and the wage costs during the emergency switch-offs as well as failures in the general operational regime are at the same time unconditional. This all determines the problem imperativeness of the drives´ diagnostics, which determine the reliability and operational life of technological devices.

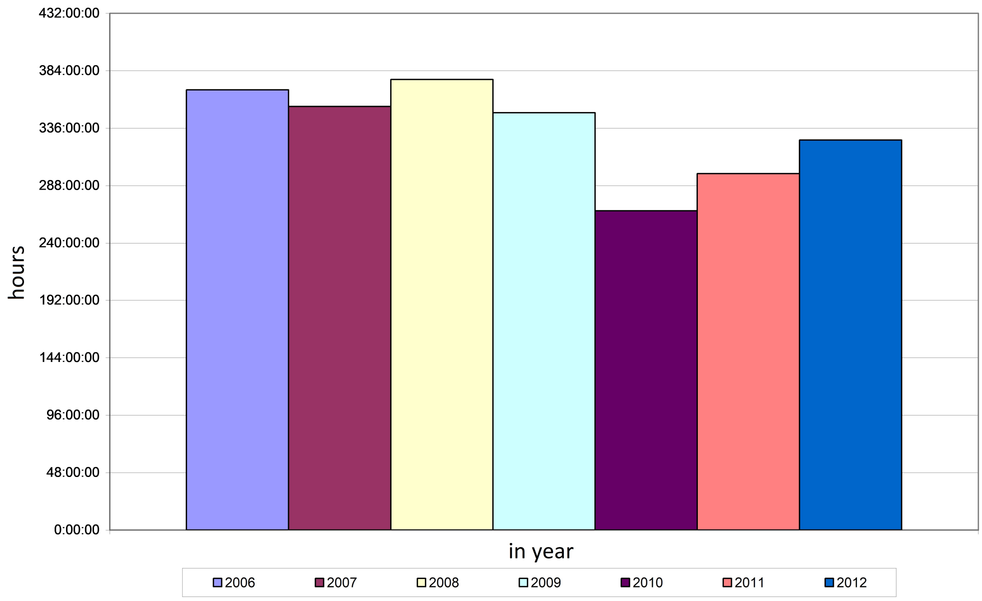

Fig. 4.3 – Time spent by preventive maintenance from 2006 to 2012

”Uvadrev OAO“ selected the planned time period for the preventive repair once a week. At the same time, all devices are stopped due to repairs and maintenance. The repair is managed by the main workshop mechanic, who decides on the change of the parts of the device in question. All the lubricating and cleaning work is done. In the end of a particular shift, each working shift carries out many specific operations such as cleaning of the device, lubrication of specific components, setting the device into an operative state as well as they record all these activities. Fig. 4.3 shows the time spent by planned preventive maintenance in years 2006-2012.

The analysis of the time spent by planned preventive maintenance of the technological devices allowed us to conclude that after the modernisation of the devices in 2009, the time for repairs was shortened from 350 hours a year to 260 hours a year (26%). Since 2010 there has been the tendency to increase the time for repairs by 30 hours a year.

4.2 Model development of the diagnostic system for the technological devices drives for chipboard manufacturing

Figures 4.4–4.13 present the measurement results of devices electric motors vibrations on Bizon production line for manufacturing the chipboard plates in Uvadrev Company, LLC.

The measurements results of vibrations are shown in the interval of 7 days.

As shown, the measurement results of vibrations acceleration of actuators are non-informative and do not allow the evaluating the change of their technical state.

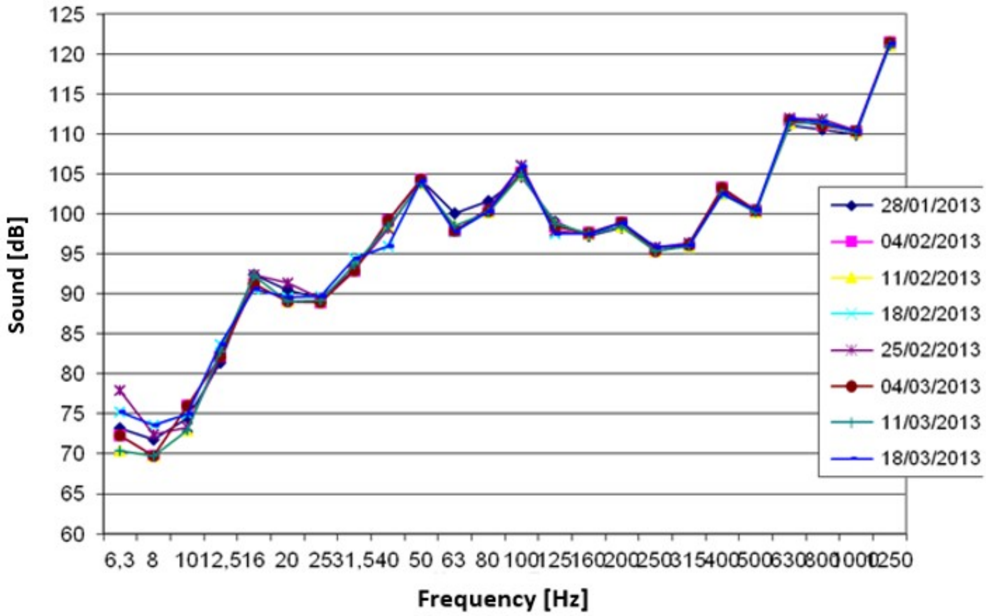

Fig. 4.4 - Vibration measurement results of the thick chip mixer motor

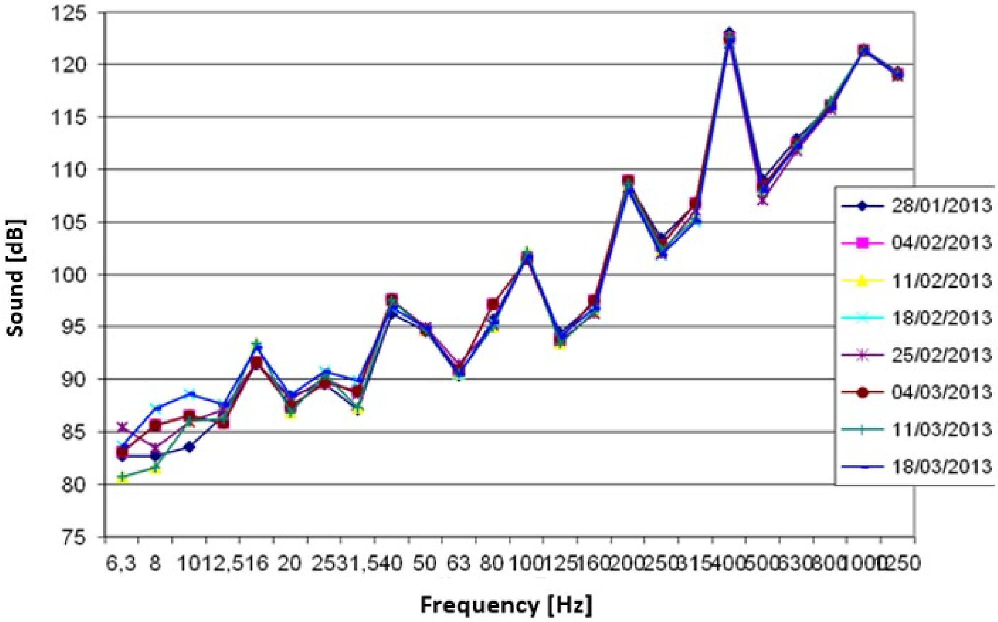

Fig. 4.5 - Vibration measurement results of the soft chip mixer motor

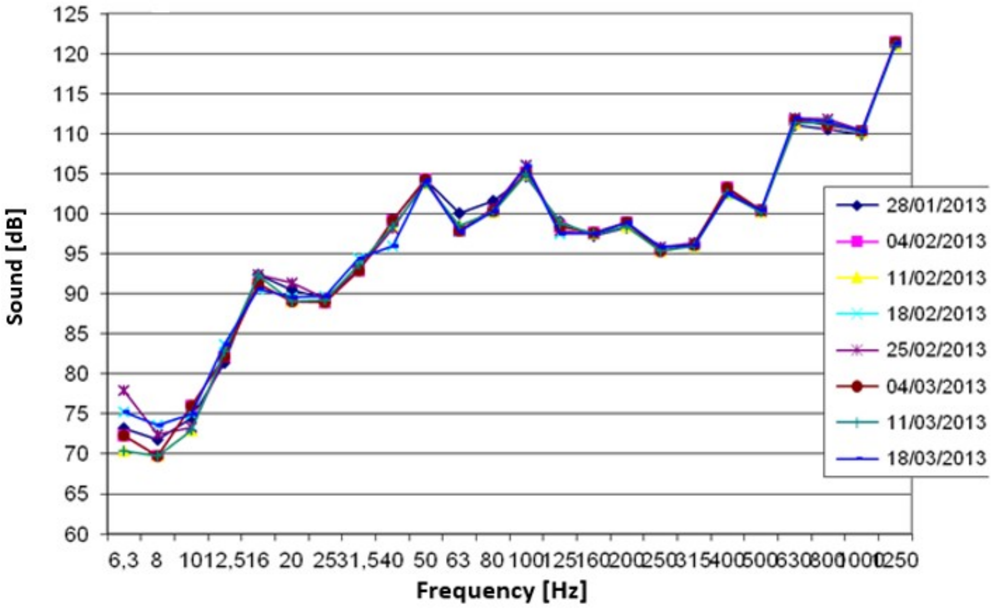

Fig. 4.6 - Vibration measurement results of the first grinder electric motor

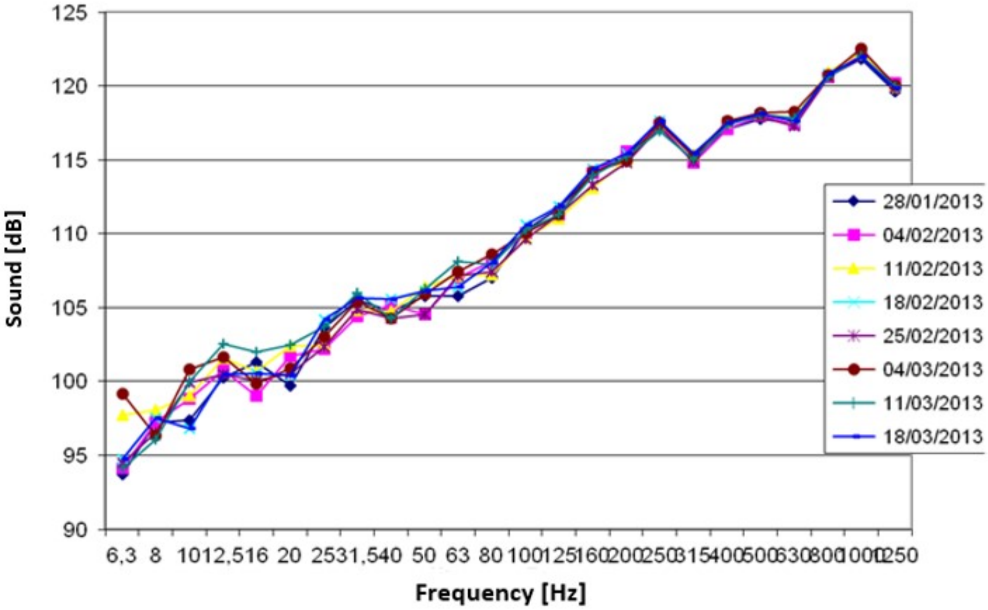

Fig. 4.7 - Vibration measurement results of the second grinder electromotor

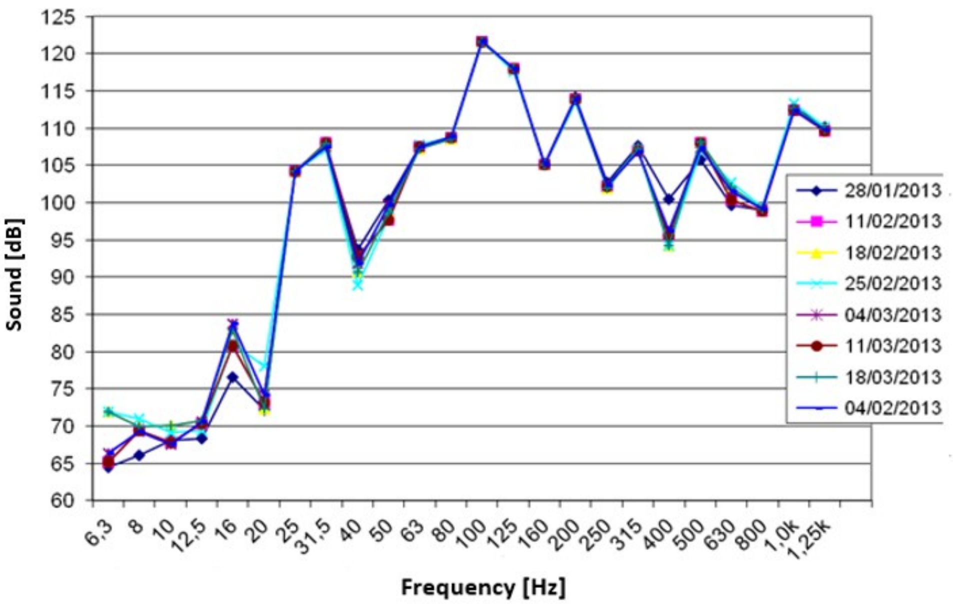

Fig. 4.8 - Vibration measurement results of the third grinder electric motor

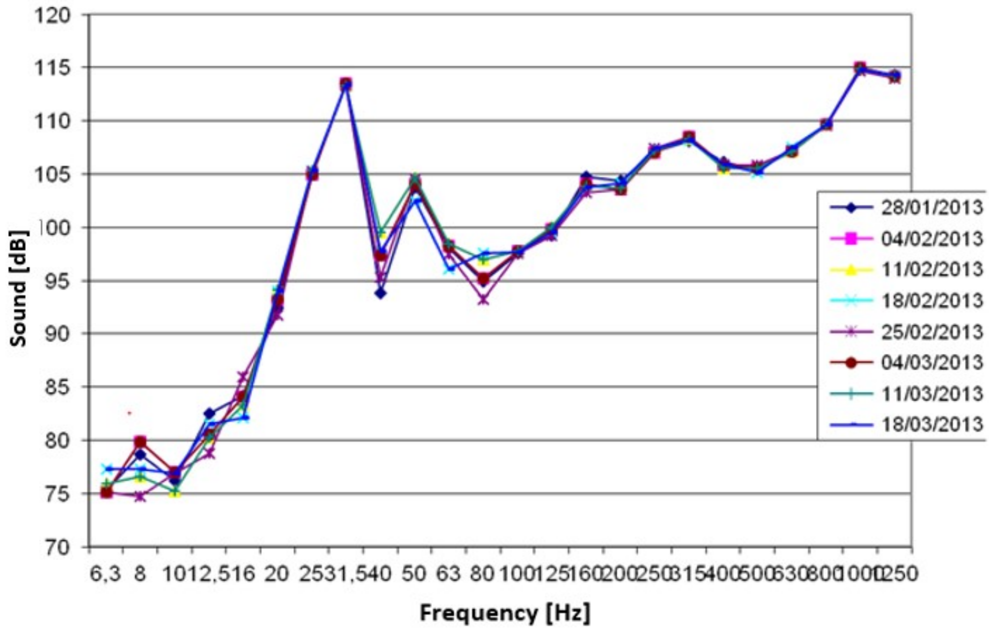

Fig. 4.9 - Vibration measurement results of the first forming machine electric motor

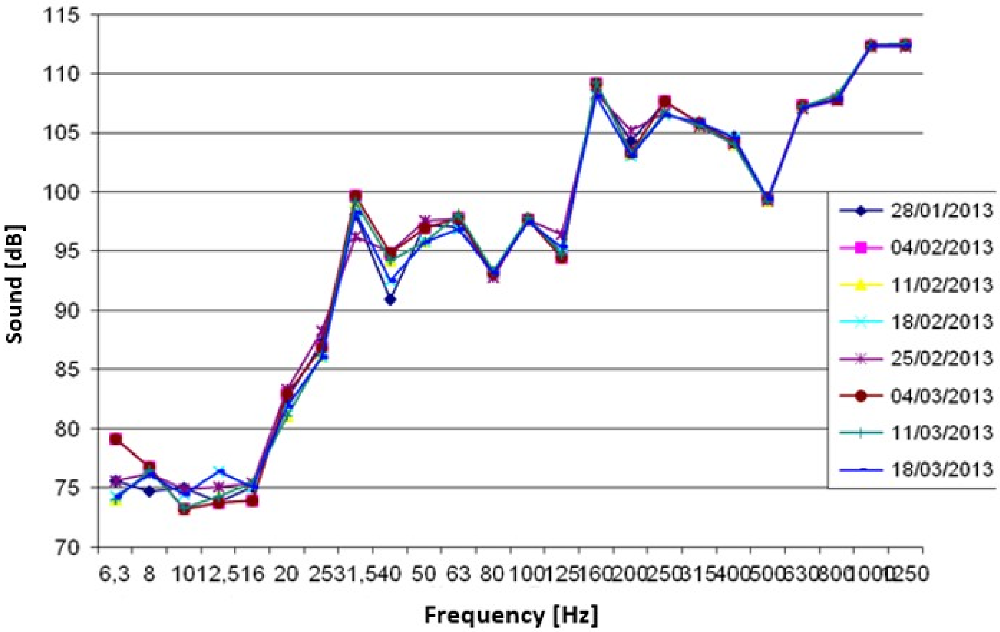

Fig. 4.10 - Vibration measurement results of the third forming machine electric motor

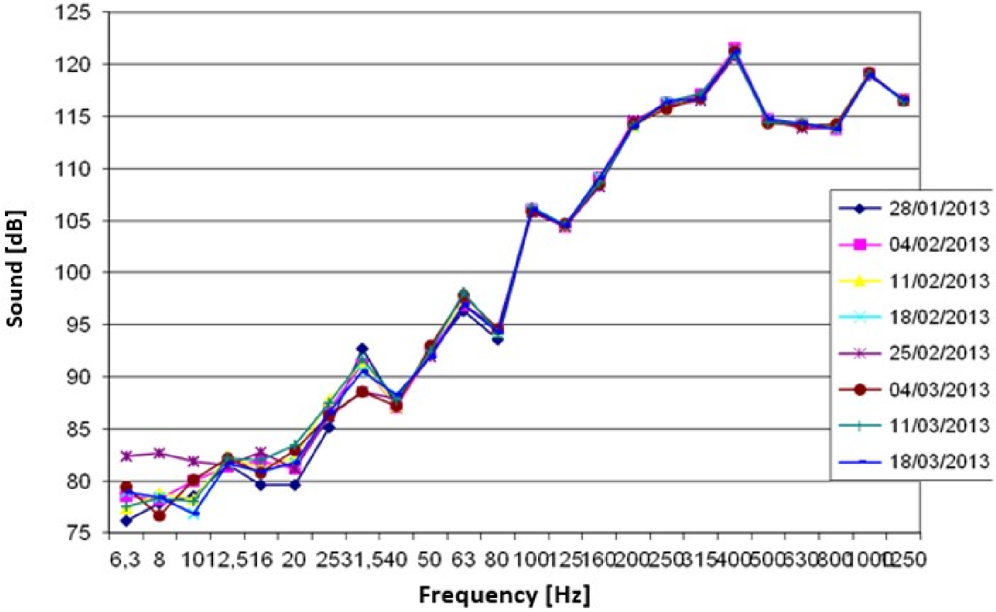

Fig. 4.11 - Vibration measurement results of the crusher electric motor

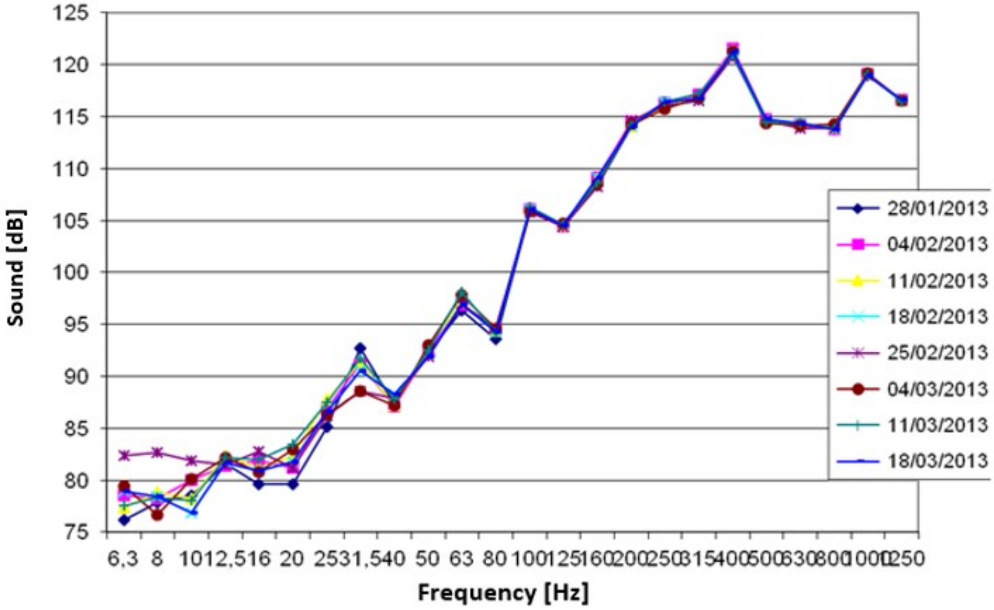

Fig. 4.12 - Vibration measurement results of the pneumatic classifier electric motor

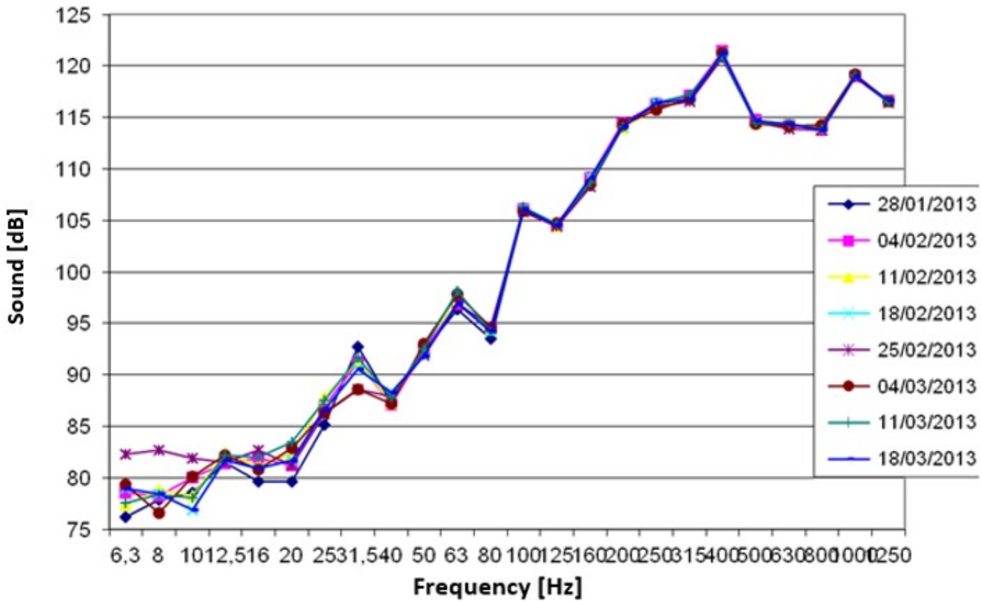

Fig. 4.13 – Vibration measurement results of the self-cutter electric motor

The analysis of the experiments aimed at vibrations measurement showed that it is suitable to consider the vibrations of the nodes in three frequency ranges: to 12.5 Hz (low frequency), from 12.5 Hz to 630 Hz (medium frequency), and from 630 Hz to 1250 Hz (high frequency).

The parameters of the input language variables of the ”Engine“ fuzzy system are in Table 4.3.

Table 4.3
Parameters of input language variables of the ”Engine“ fuzzy system

	Low level of vibrations	**Medium level of vibrations**	**High level of vibrations**
low frequency	75-95 dB	85-110 dB	100-115 dB
medium frequency	85-110 dB	90-115 dB	105-125 dB
high frequency	100-115 dB	105-130 dB	120-135 dB

In the fuzzy system ”Engine“ the trapezoid function is used as a member function of the input variables as the highest value level of the compliance is reached quite quickly, and this level has several values. The function of the input variable is represented by Gaussian division, the highest level is reached once, and with a quite fluent access to it. Fig. 4.14 shows the editor of the input and output parameters of the motor diagnostic system. Fig. 4.15 illustrates the editor of member system functions of the motor fuzzy inference. Fig. 4.16 shows the knowledge database editor of the ”Engine“ fuzzy diagnostic system.

The number of rules is equal to the number of expressions in the grade of the number of input variables, i.e. 27. Table 4.4 summarizes the input and output conditions of the fuzzy inference system for motor diagnostics (n – low level of the diagnostic parameter, s – average level of the diagnostic parameter, v – high level of the diagnostic parameter, i – drive in good state, d – defect occurrence start, h – defect drive state).

Table 4.4
Input and output conditions of the fuzzy inference system for motor diagnostics

No.	**low frequency**			**medium frequency**			**high frequency**			**technical state of actuators**		
	n	s	v	n	s	v	n	s	v	i	d	h
1	+			+			+			+		
2	+			+				+			+	
3	+			+					+			+
4	+				+		+				+	
5	+				+			+			+	
6	+				+				+			+
7	+					+	+				+	
8	+					+		+			+	
9	+					+			+			+

10		+		+			+				+	
11		+		+				+			+	
12		+		+					+			+
13		+			+		+				+	
14		+			+			+			+	
15		+			+				+			+
16		+				+	+				+	
17		+				+		+			+	
18		+				+			+			+
19			+	+			+				+	
20			+	+				+			+	
21			+	+					+			+
22			+		+		+				+	
23			+		+			+			+	
24			+		+				+			+
25			+			+	+				+	
26			+			+		+				+
27			+			+			+			+

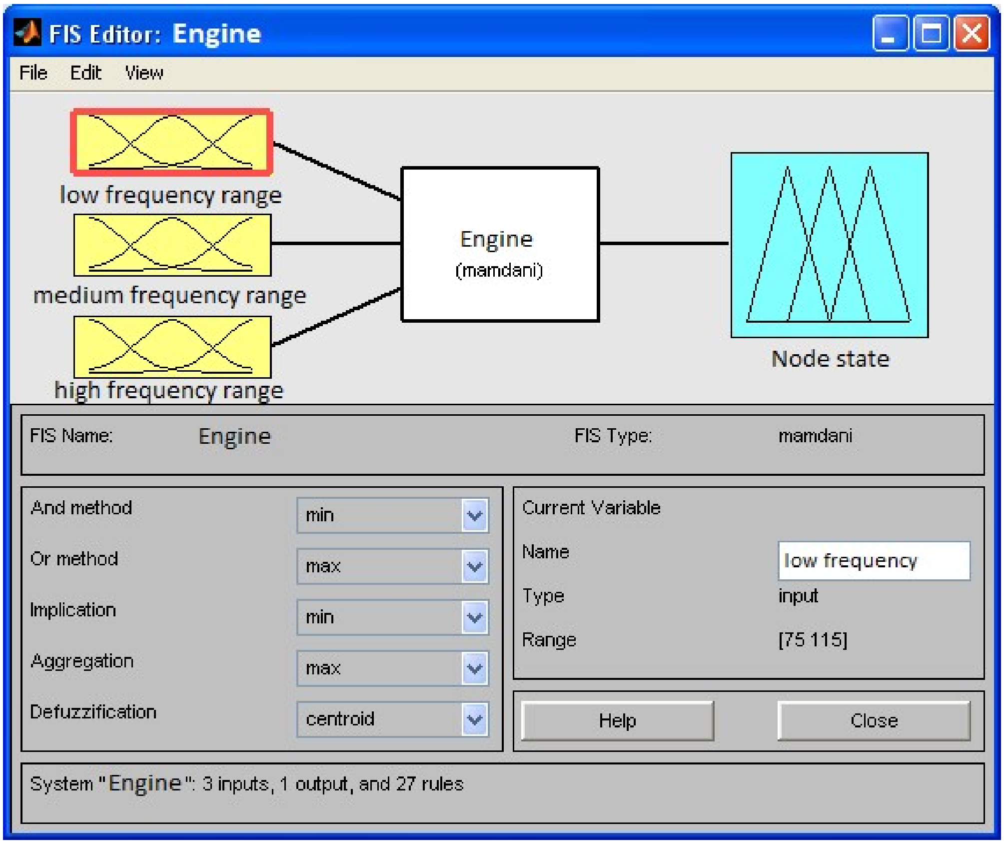

Fig. 4.14 - Editor of input and output parameters of a motor diagnostic system

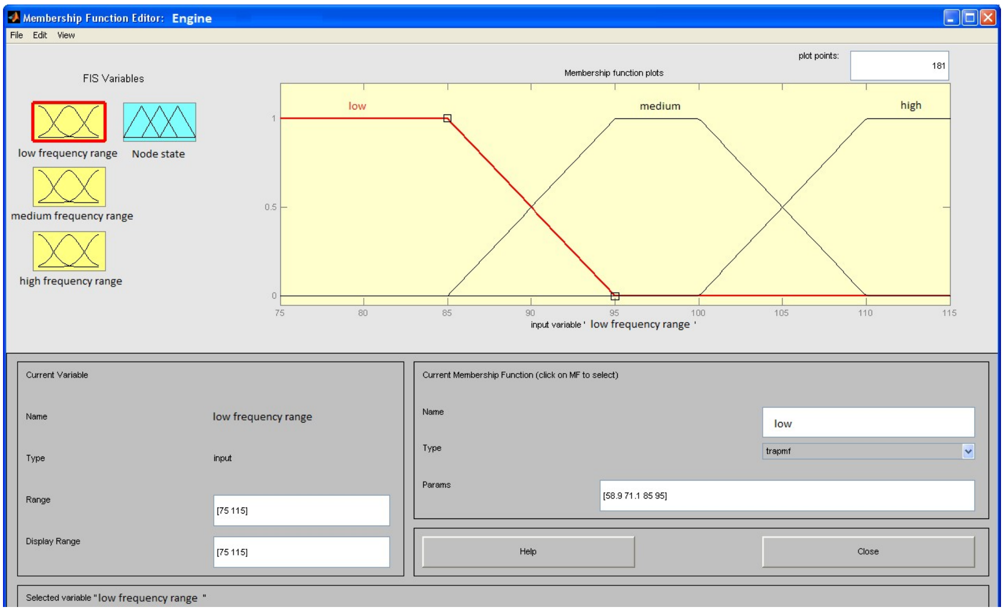

Fig. 4.15 - Editor of relevant functions of the ”Engine“ fuzzy diagnostic system

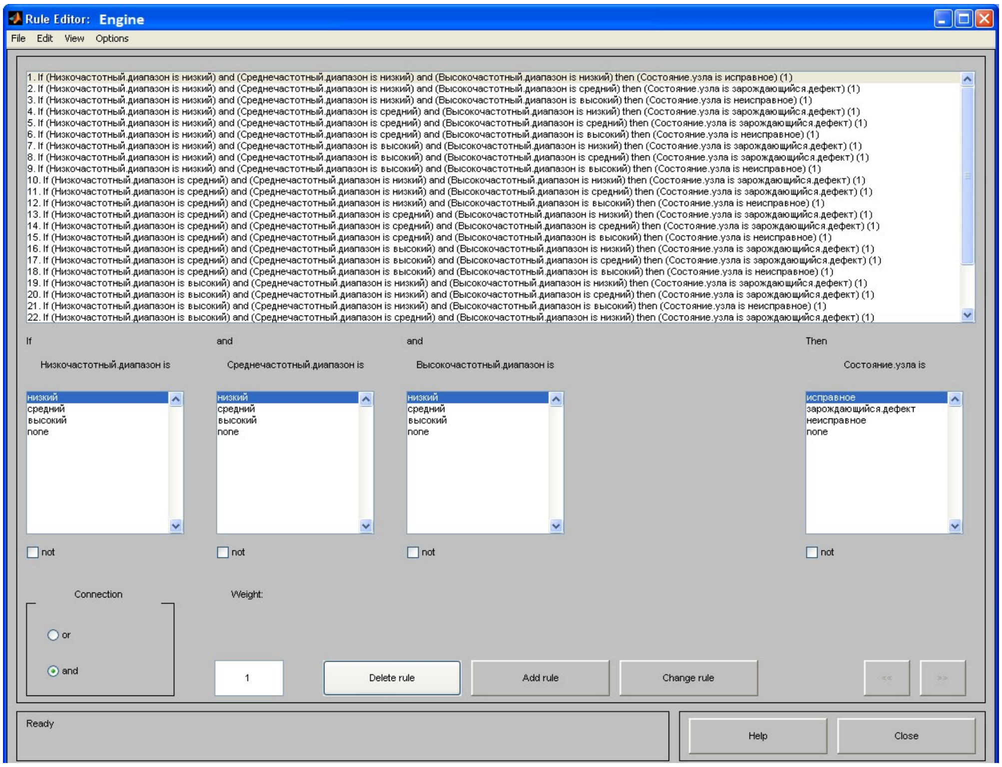

Fig. 4.16 – Knowledge database editor of the ”Engine“ fuzzy diagnostic system. (translation: “Низкочастотный диапазон” = low frequency range; “Среднечастотный диапазон” = medium frequency range; “Высокочастотный диапазон” = high frequency range; “низкий” = low; “средний” = medium; “высокий” = high; “Состояние узла” = Node status; “исправное” = serviceable; “зарождающийся дефект” = incipient defect; “неисправное” = faulty)

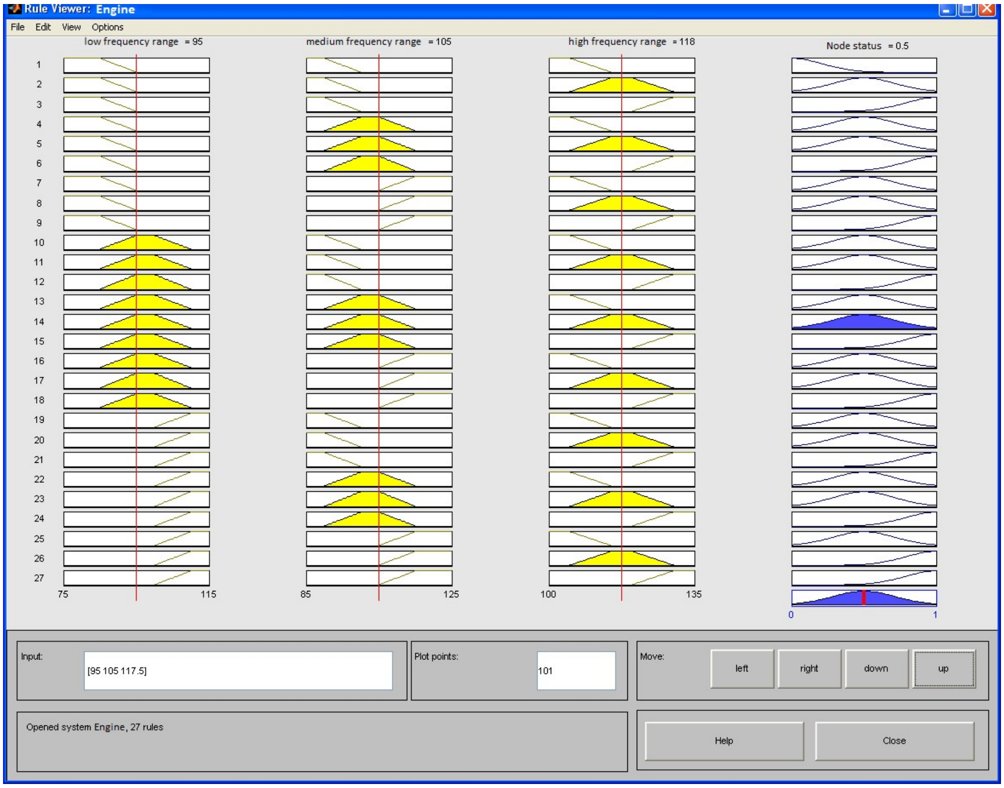

Fig. 4.17 – Visualisation of the "Engine" fuzzy logic inference

Fig. 4.17 presents a necessary conclusion of the "Engine" fuzzy diagnostic system.

The examples of the technical state evaluation of the soft chip mixer electric motor are shown in Figs. 4.18–4.20.

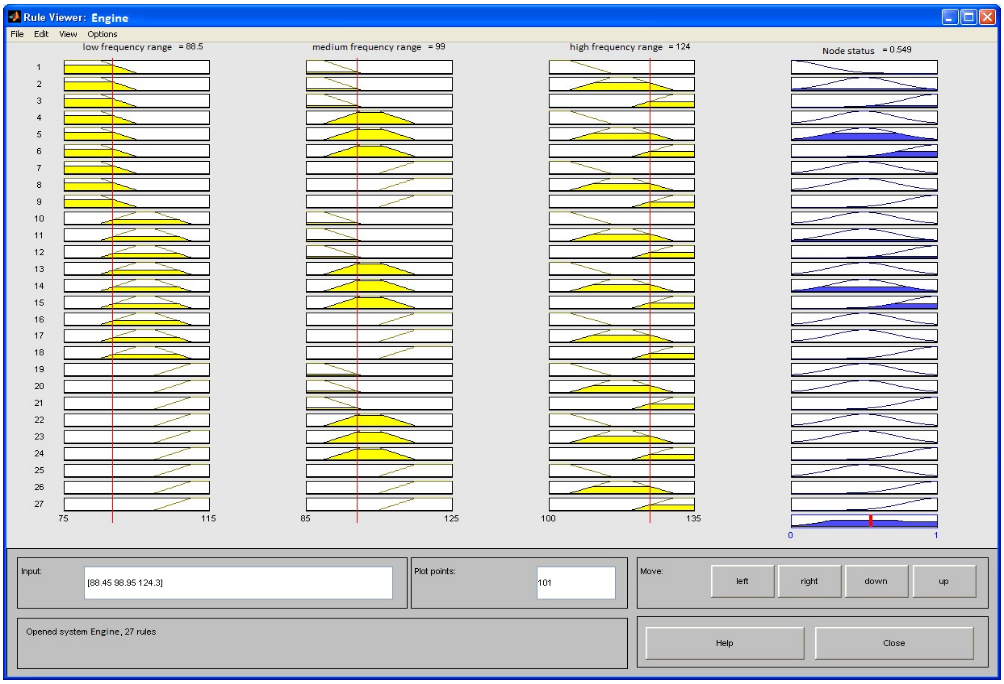

Fig. 4.18 - Results of the technical state evaluation of the soft chip mixer – 0.549 (01/28/13)

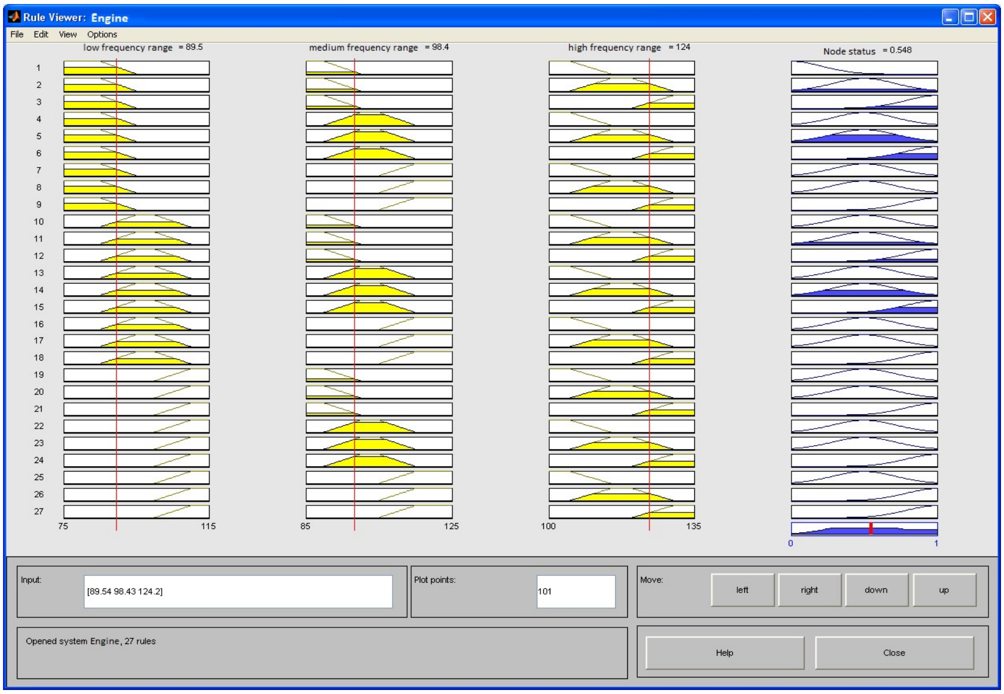

Fig. 4.19 - Results of the technical state evaluation of the soft chip mixer – 0.548 (02/20/13)

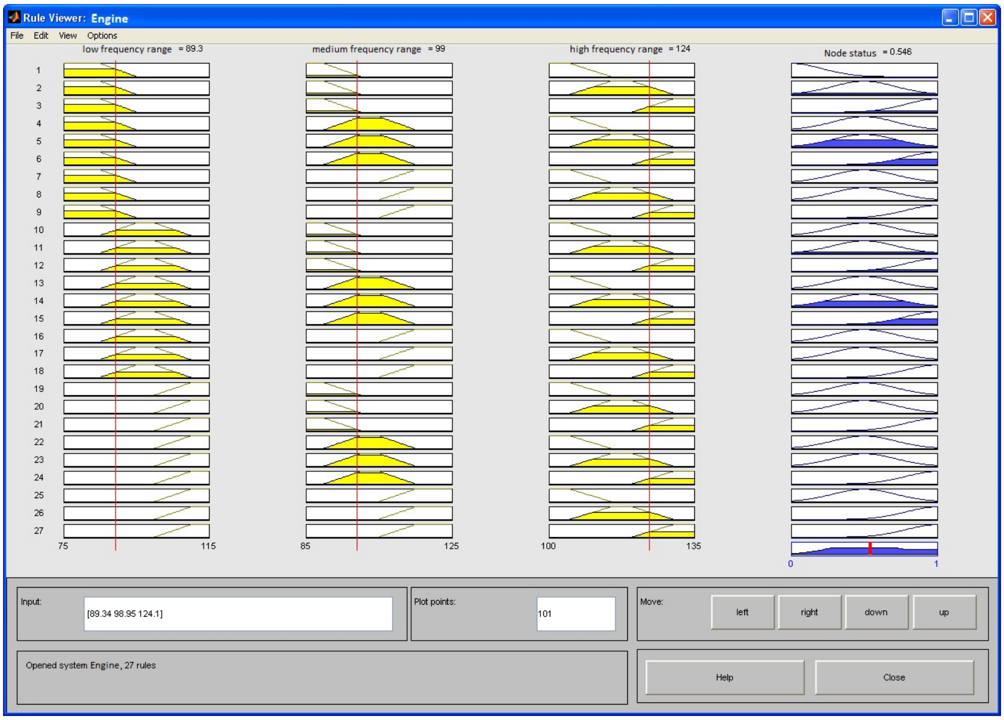

Fig. 4.20 - Results of the technical state evaluation of the soft chip mixer – 0.546 (03/22/13)

The technical state analysis of the soft chip mixer electric motor showed that it is in a sufficient state. By high frequencies the level of vibrations reaches a significant value, therefore, it is necessary to plan its replacement.

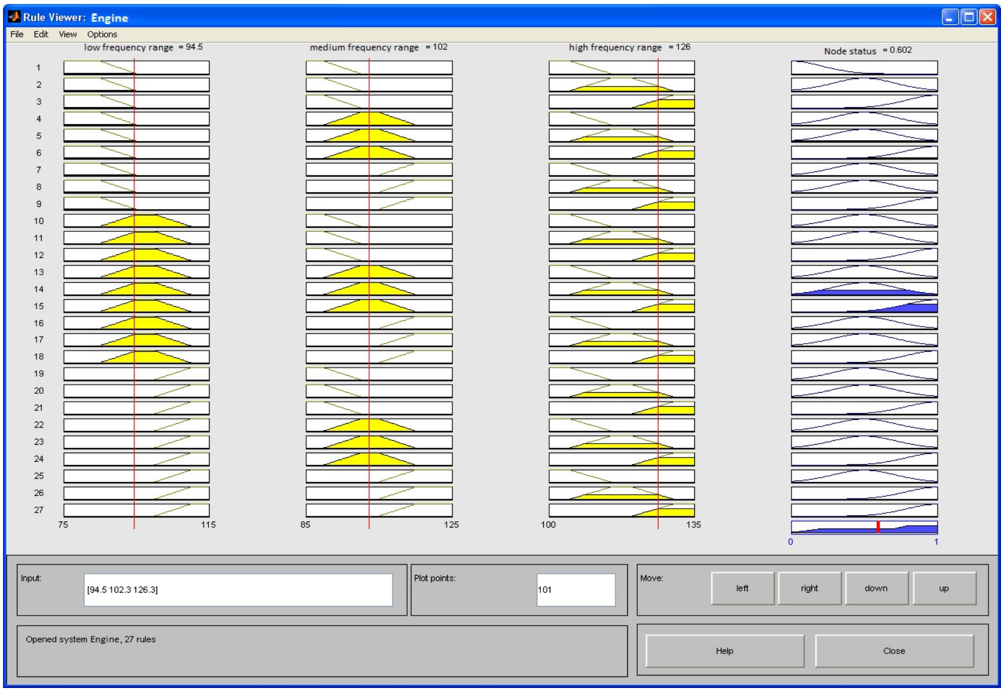

Fig. 4.21 - Results of the technical state evaluation of the thick chip mixer – 0.602 (01/28/13)

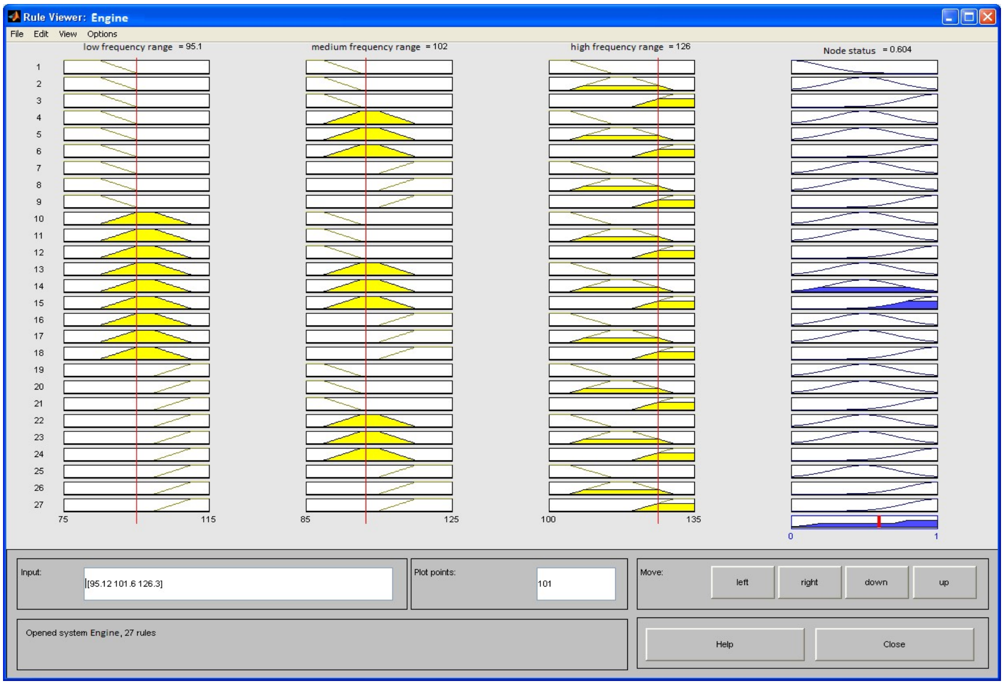

Fig. 4.22 - Results of the technical state evaluation of the thick chip mixer – 0.604 (02/20/13)

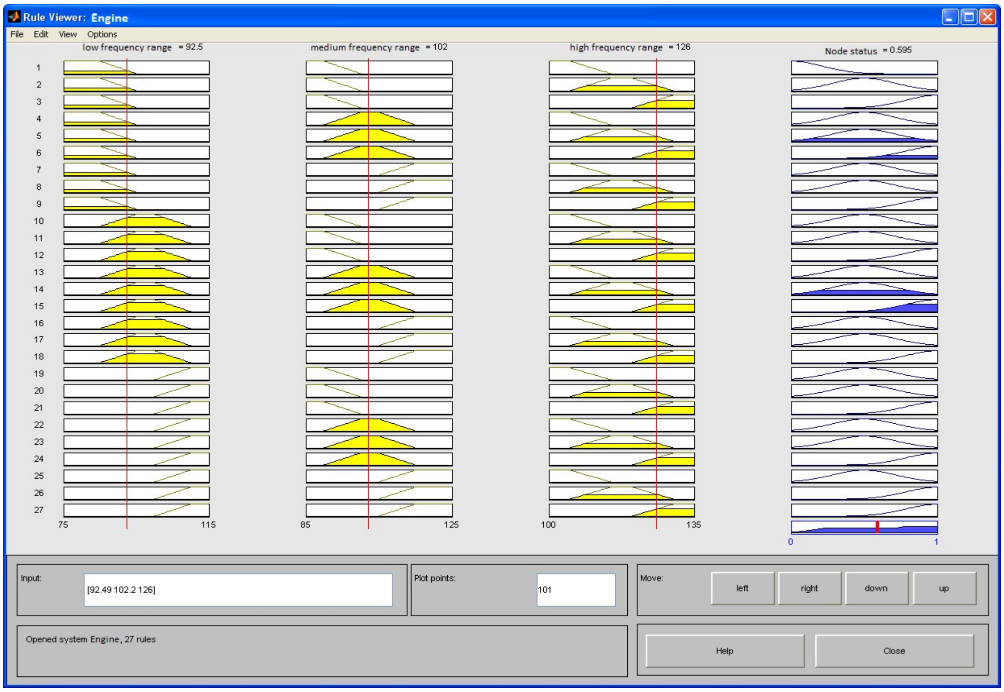

Fig. 4.23 - Results of the technical state evaluation of the thick chip mixer – 0.595 (03/22/13)

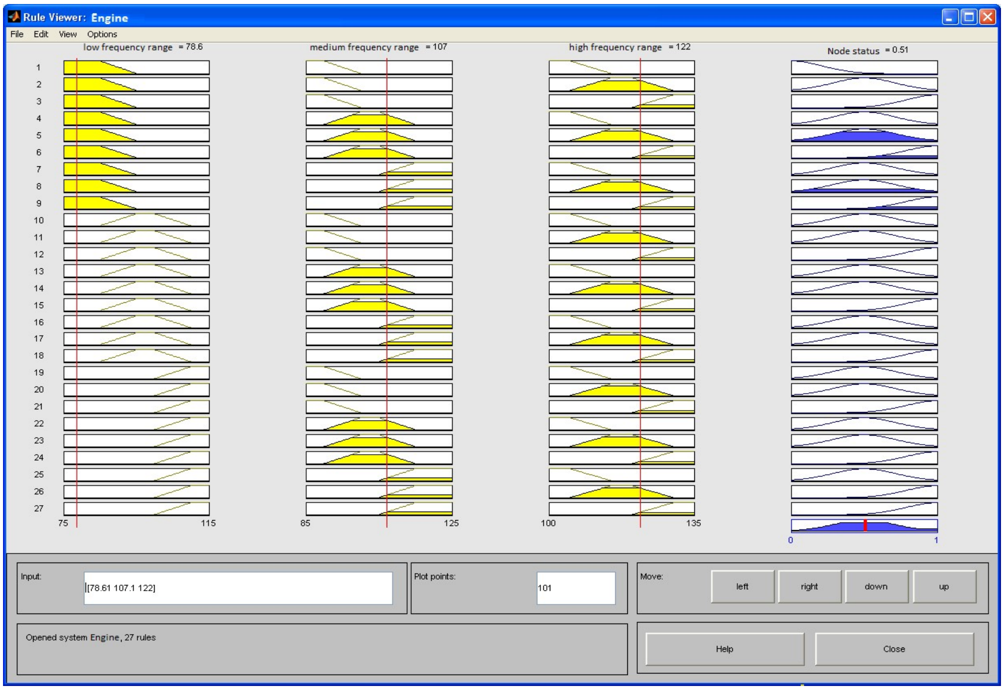

Fig. 4.24 - Results of the technical state evaluation of the first grinder electric motor – 0.51 (01/28/13)

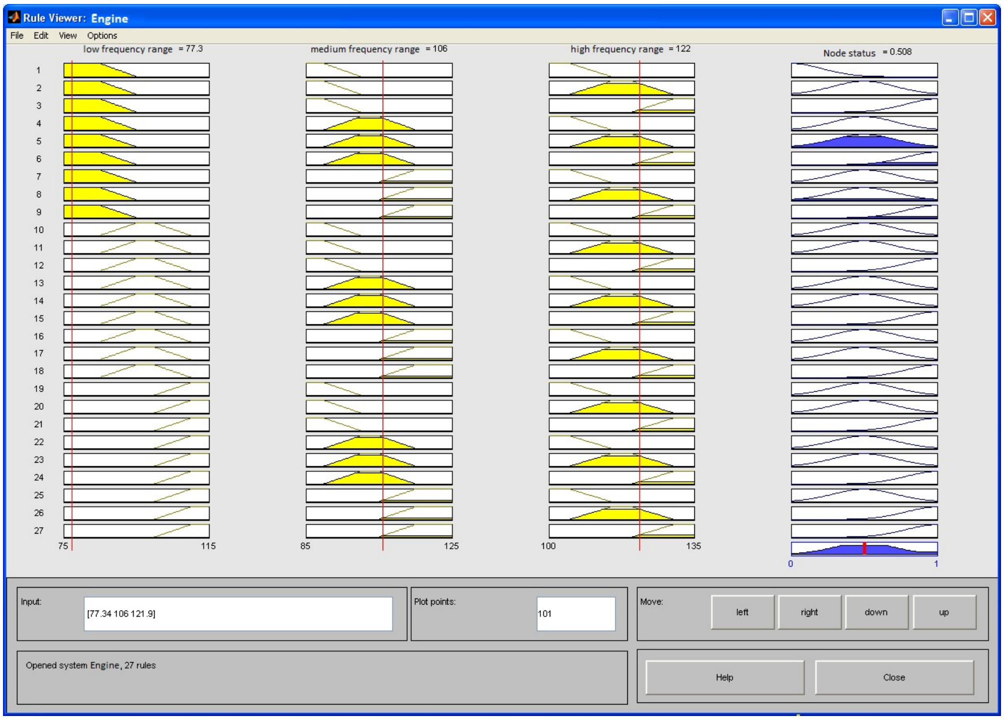

Fig. 4.25 - Results of the technical state evaluation of the first grinder electric motor – 0.508 (02/20/13)

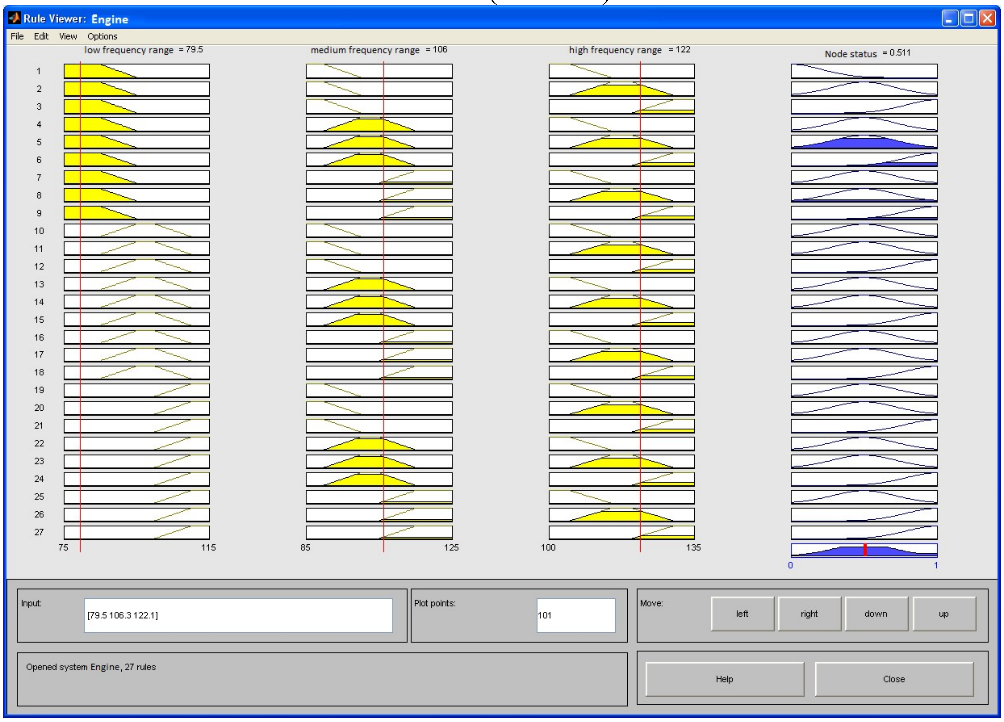

Fig. 4.26 - Results of the technical state evaluation of the first grinder electric motor – 0.511 (03/22/13)

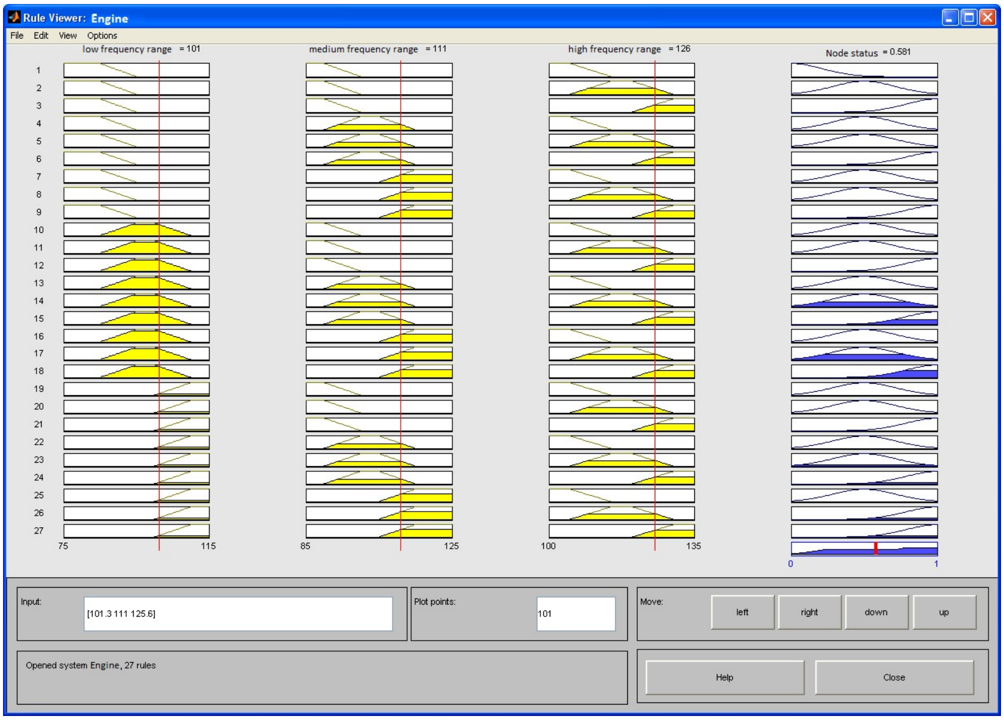

Fig. 4.27 - Results of the technical state evaluation of the second grinder electric motor – 0.581 (01/28/13)

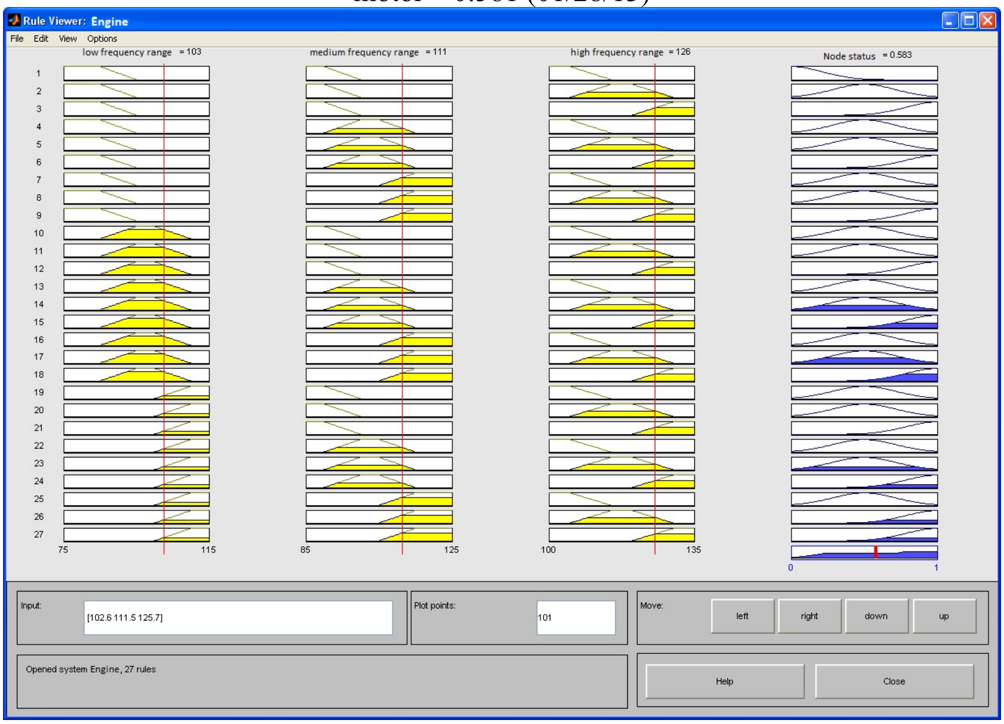

Fig. 4.28 - Results of the technical state evaluation of the second grinder electric motor – 0.583 (02/20/13)

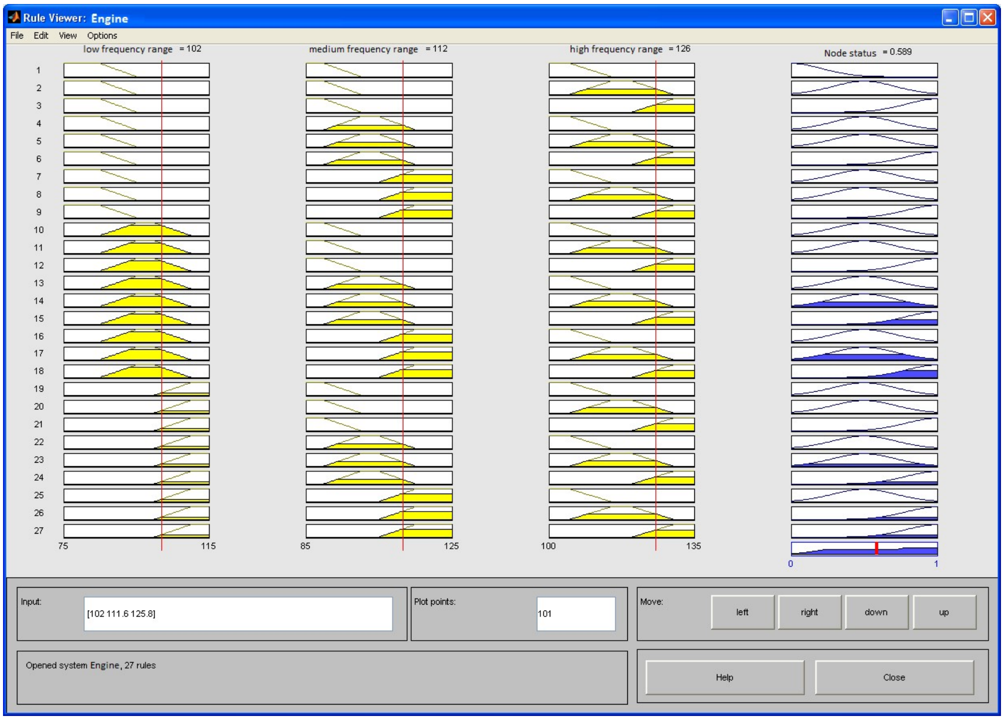

Fig. 4.29 - Results of the technical state evaluation of the second grinder electric motor – 0.589 (03/22/13)

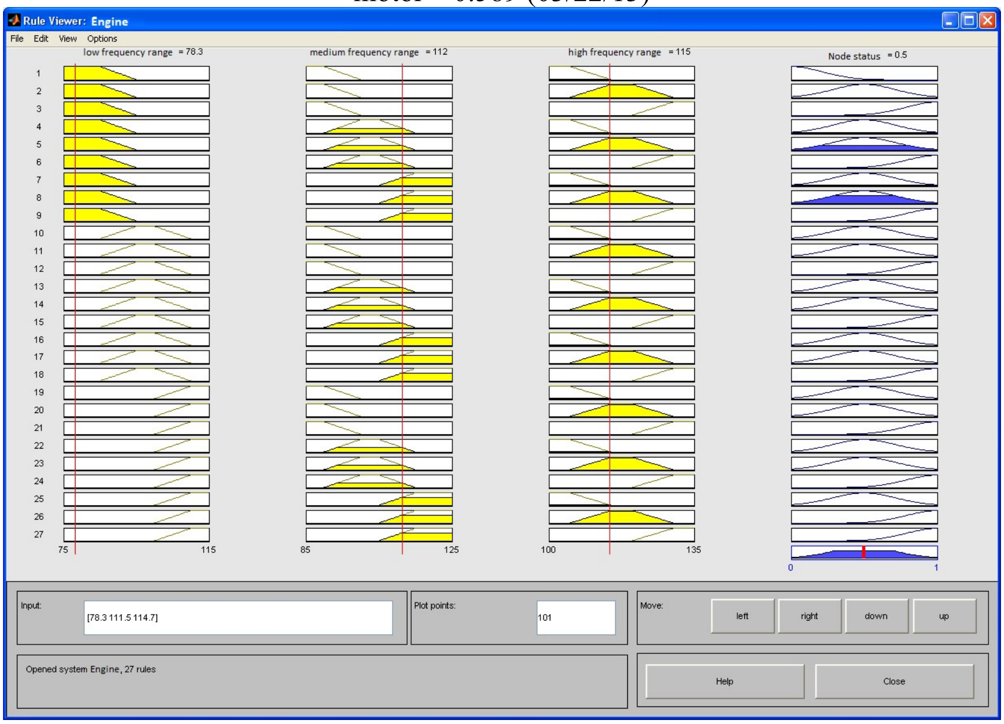

Fig. 4.30 - Results of the technical state evaluation of the third grinder electric motor – 0.5 (01/28/13)

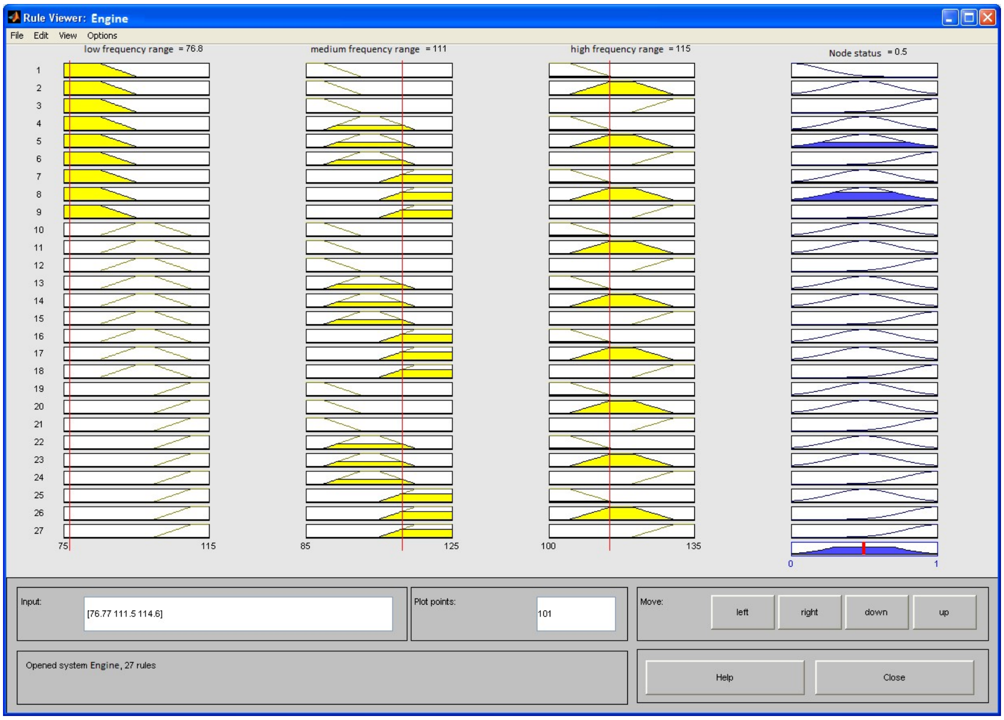

Fig. 4.31 - Results of the technical state evaluation of the third grinder electric motor – 0.5 (02/20/13)

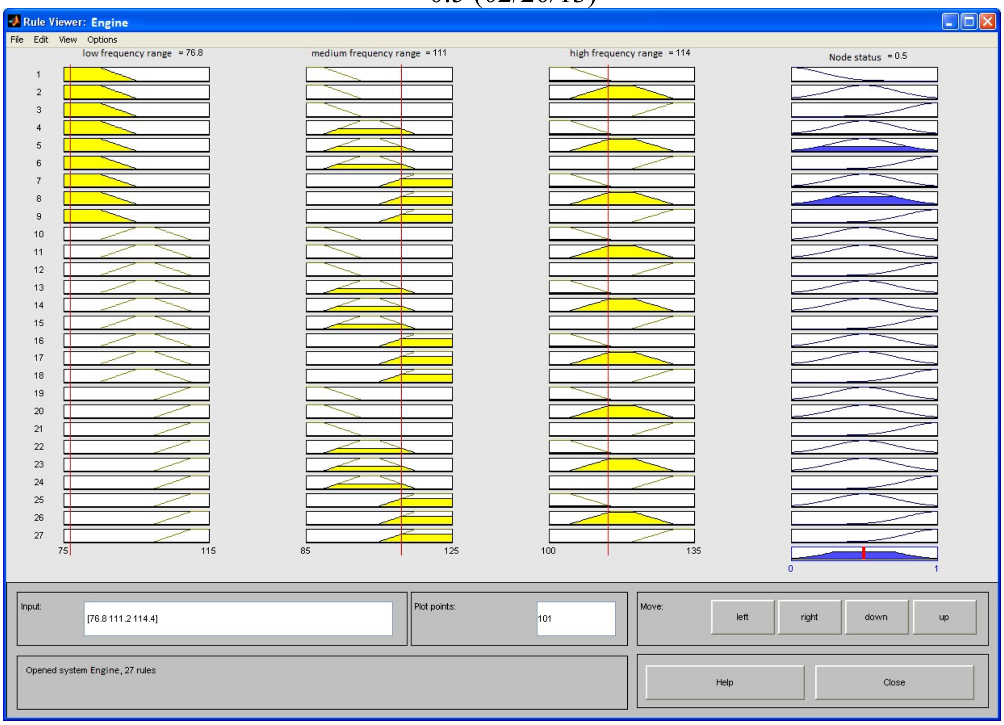

Fig. 4.32 - Results of the technical state evaluation of the third grinder electric motor – 0.5 (03/22/13)

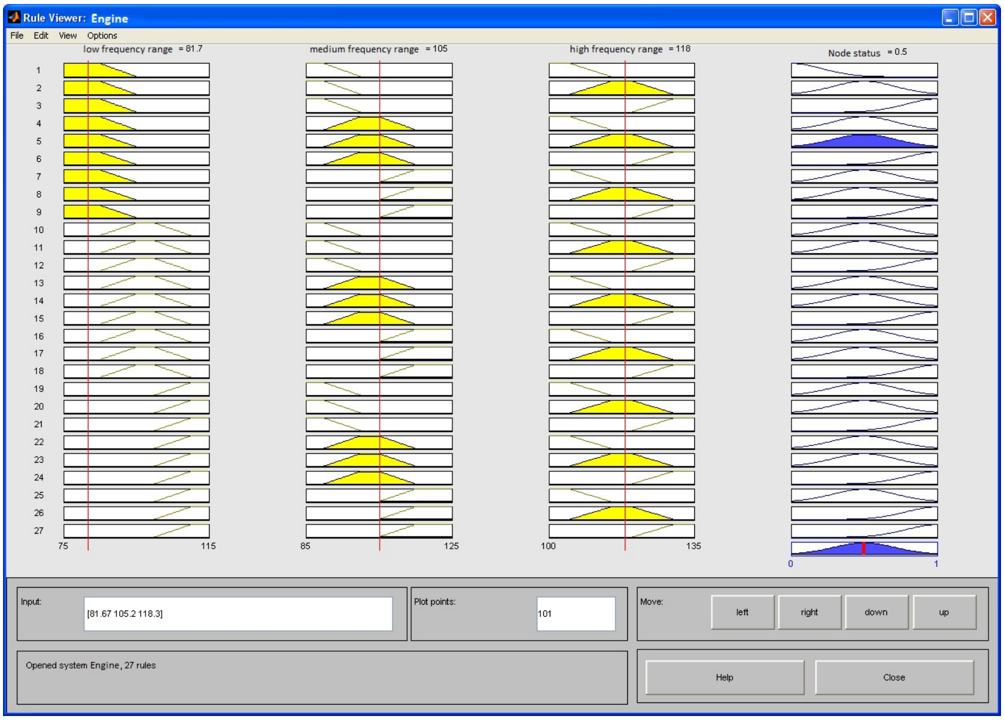

Fig. 4.33 - Results of the technical state evaluation of the first forming machine electric motor – 0.5 (01/28/13)

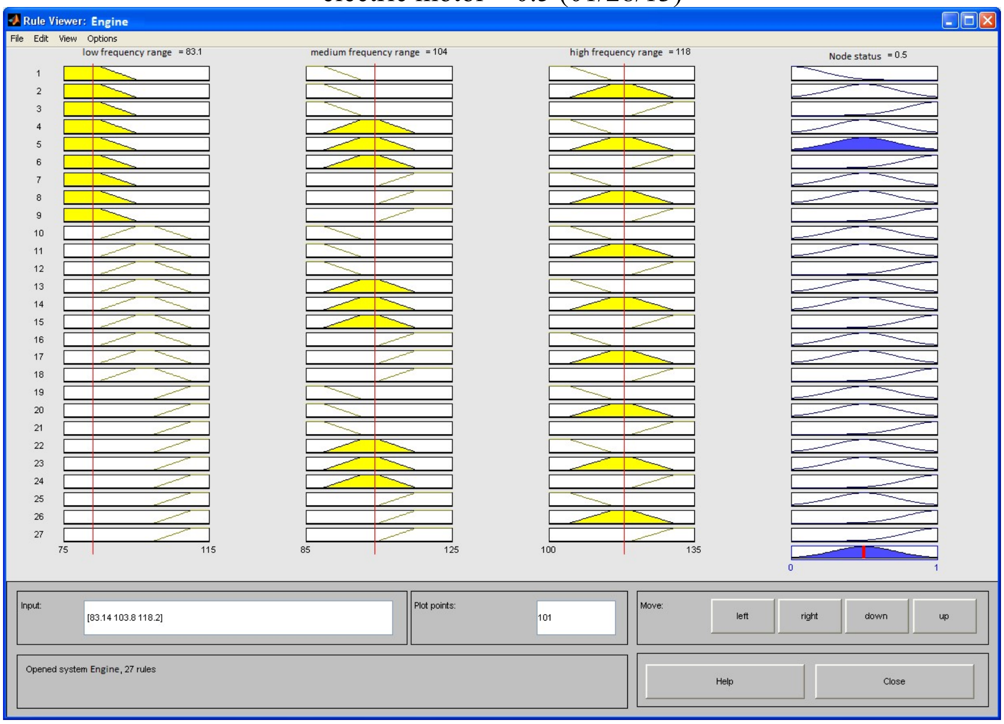

Fig. 4.34 - Results of the technical state evaluation of the first forming machine electric motor – 0.5 (02.20.13)

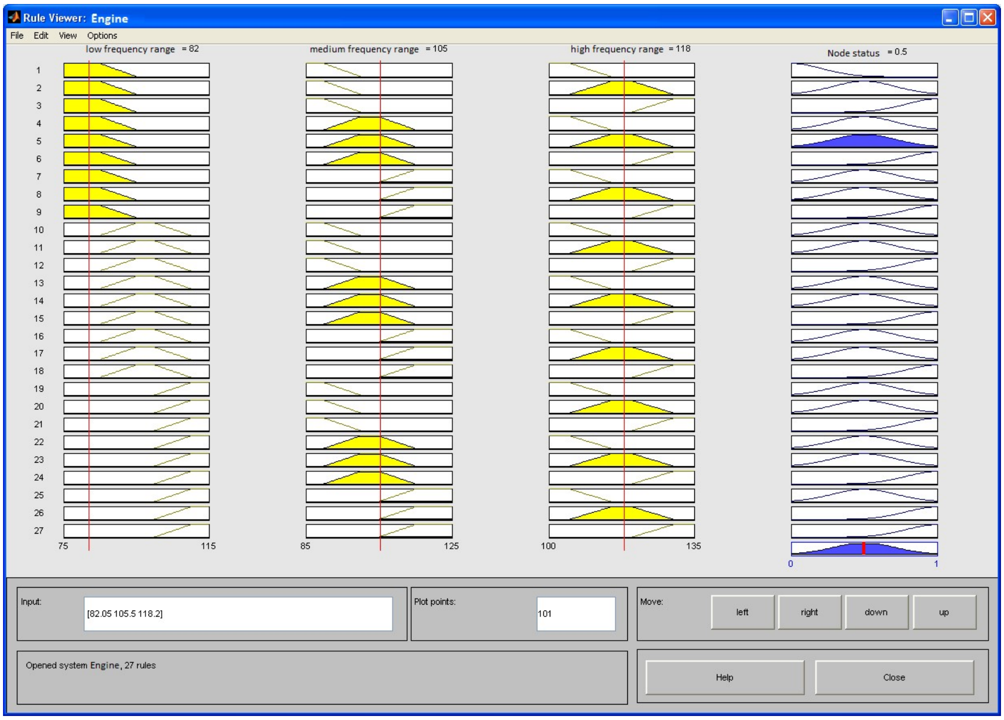

Fig. 4.35 - Results of the technical state evaluation of the first forming machine electric motor – 0.5 (03/22/13)

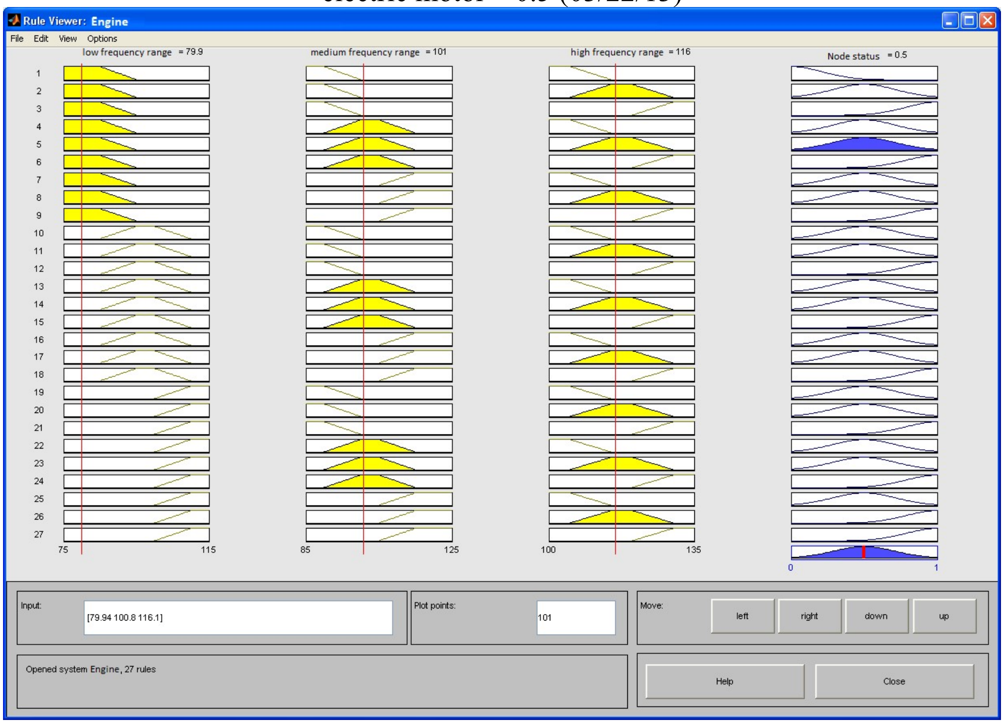

Fig. 4.36 - Results of the technical state evaluation of the third forming machine electric motor – 0.5 (28/28/13)

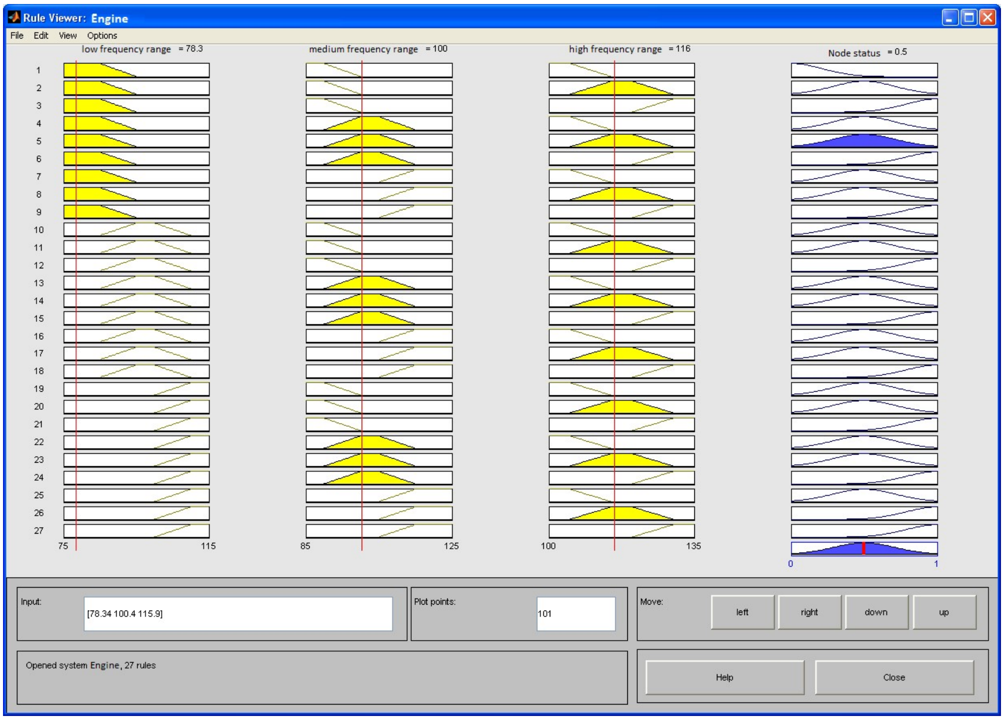

Fig. 4.37 - Results of the technical state evaluation of the third forming machine electric motor – 0.5 (02/20/13)

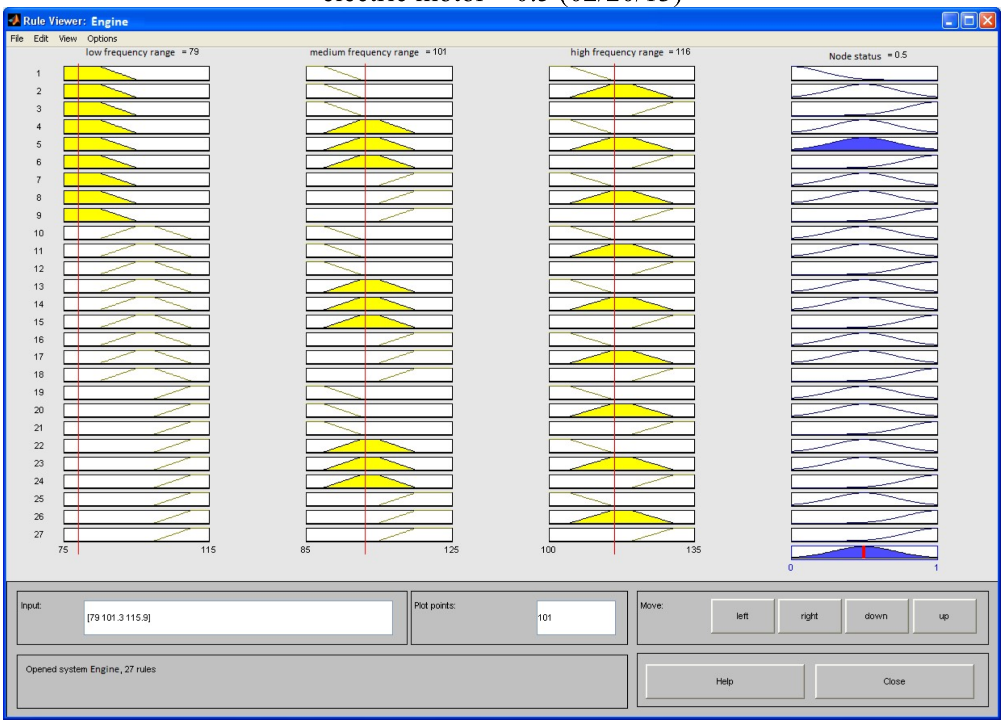

Fig. 4.38 - Results of the technical state evaluation of the third forming machine electric motor – 0.5 (03/22/13)

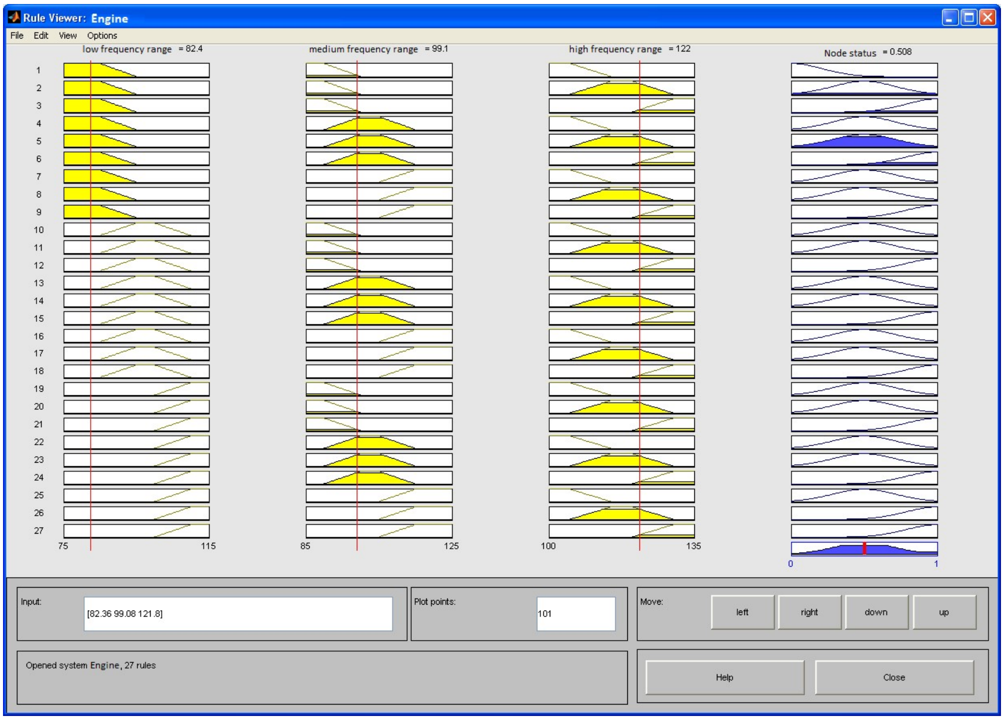

Fig. 4.39 - Results of the technical state evaluation of the crusher electric motor – 0.508 (01/28/13)

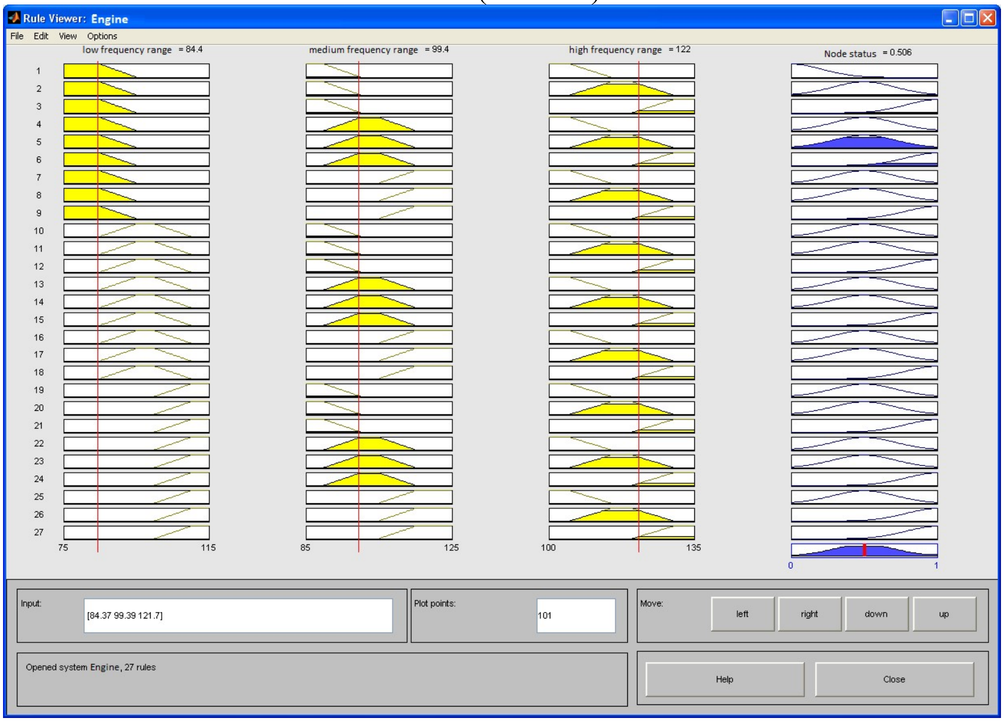

Fig. 4.40 - Results of the technical state evaluation of the crusher electric motor – 0.506 (02.20.13)

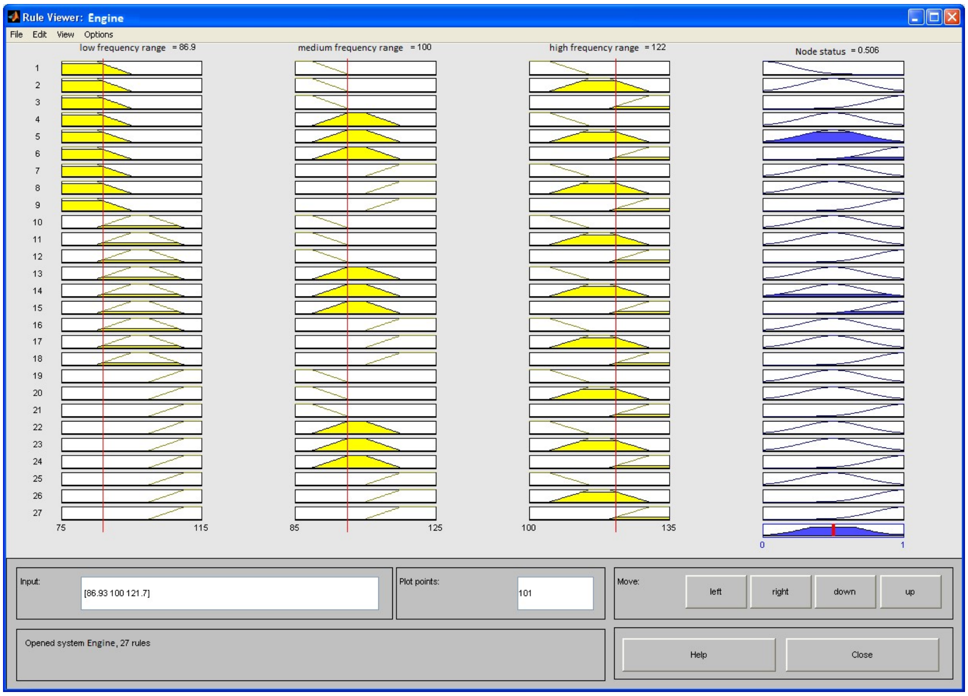

Fig. 4.41 - Results of the technical state evaluation of the crusher electric motor – 0.506 (03/22/13)

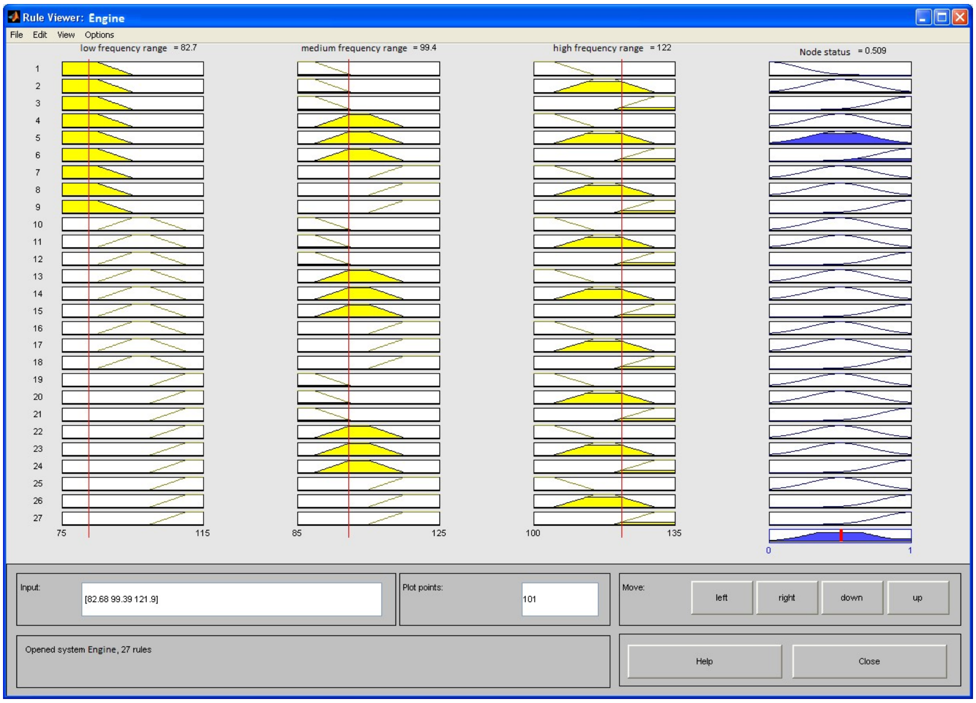

Fig. 4.42 - Results of the technical state evaluation of the pneumatic classifier electric motor – 0.509 (01/28/13)

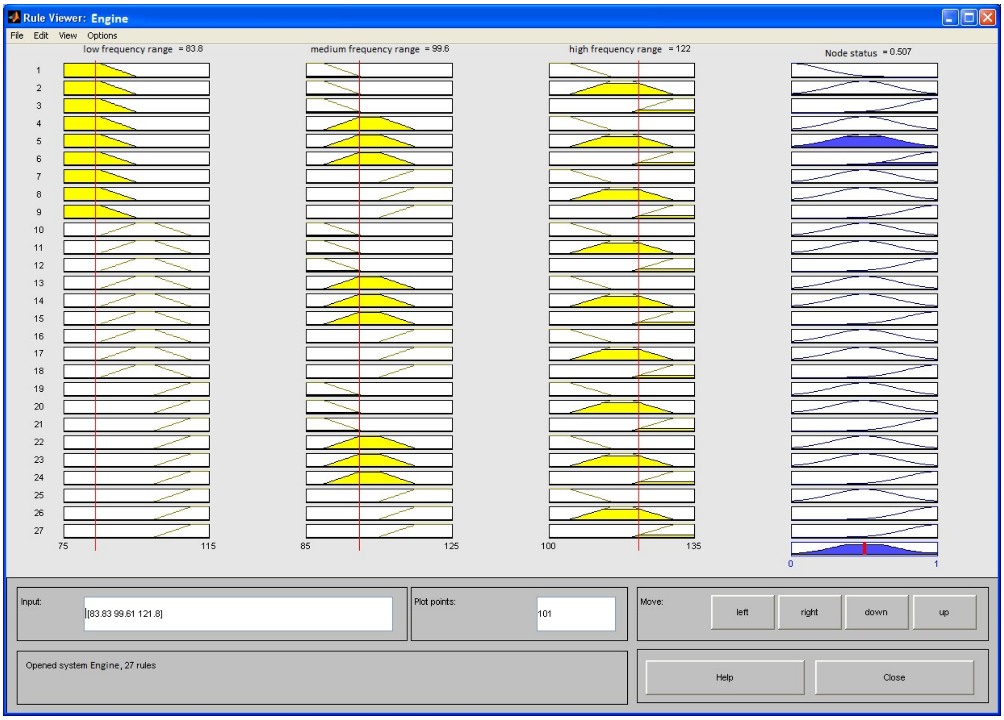

Fig. 4.43 - Results of the technical state evaluation of the pneumatic classifier electric motor – 0.507 (02/20/13)

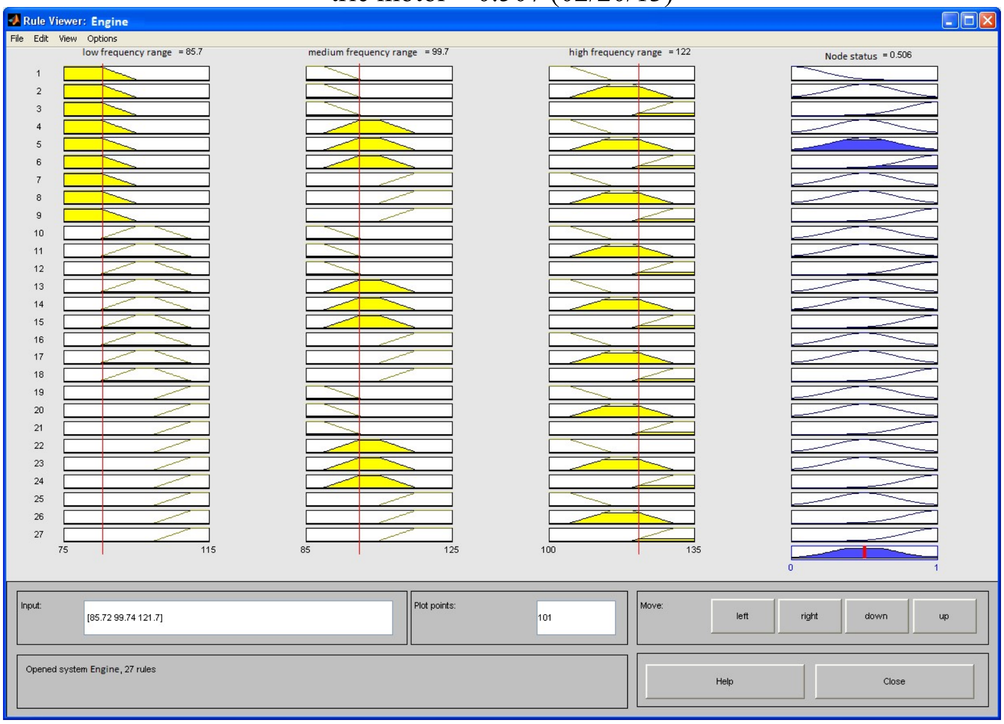

Fig. 4.44 - Results of the technical state evaluation of the pneumatic classifier electric motor – 0.506 (03/22/13)

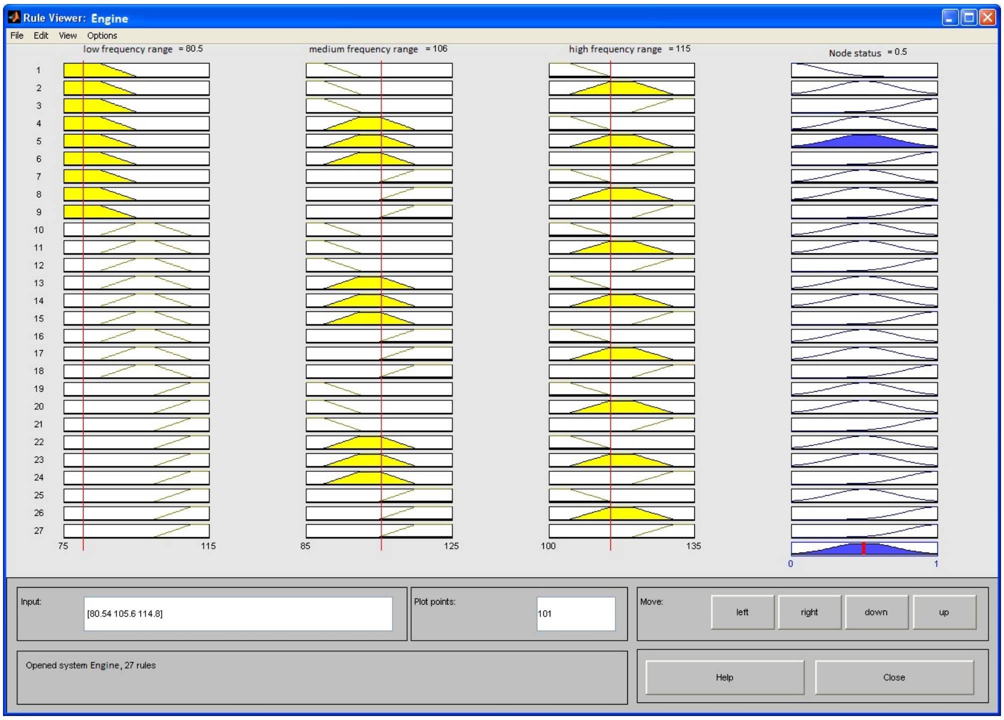

Fig. 4.45 - Results of the technical state evaluation of the self-cutter electro-drive – 0.5 (01/28/13)

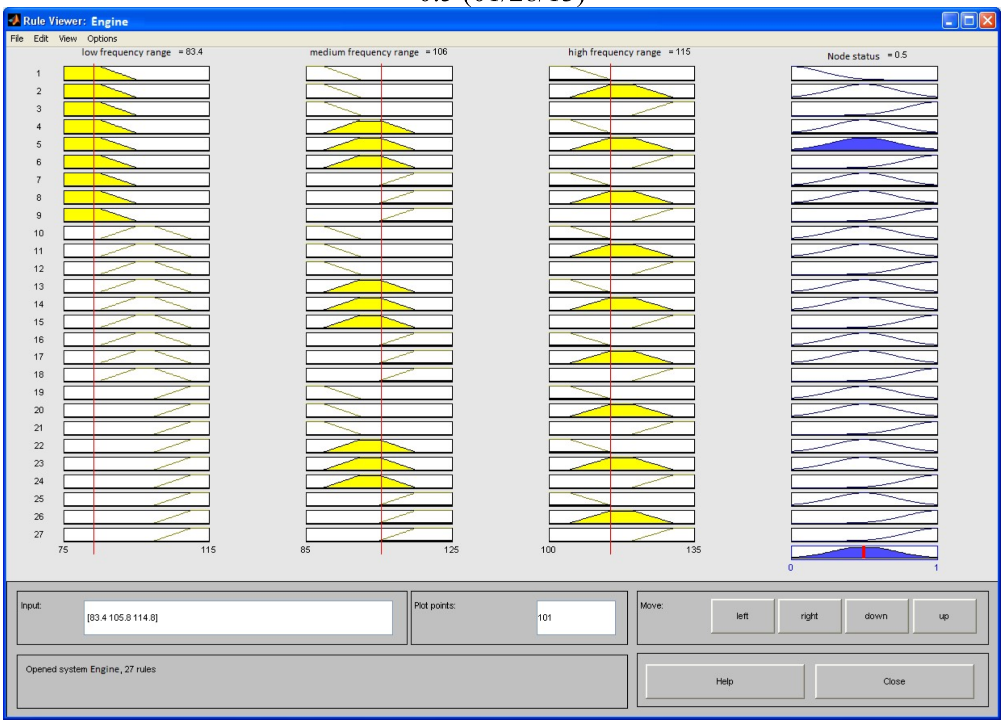

Fig. 4.46 - Results of the technical state evaluation of the self-cutter electro-drive – 0.5 (02/20/13)

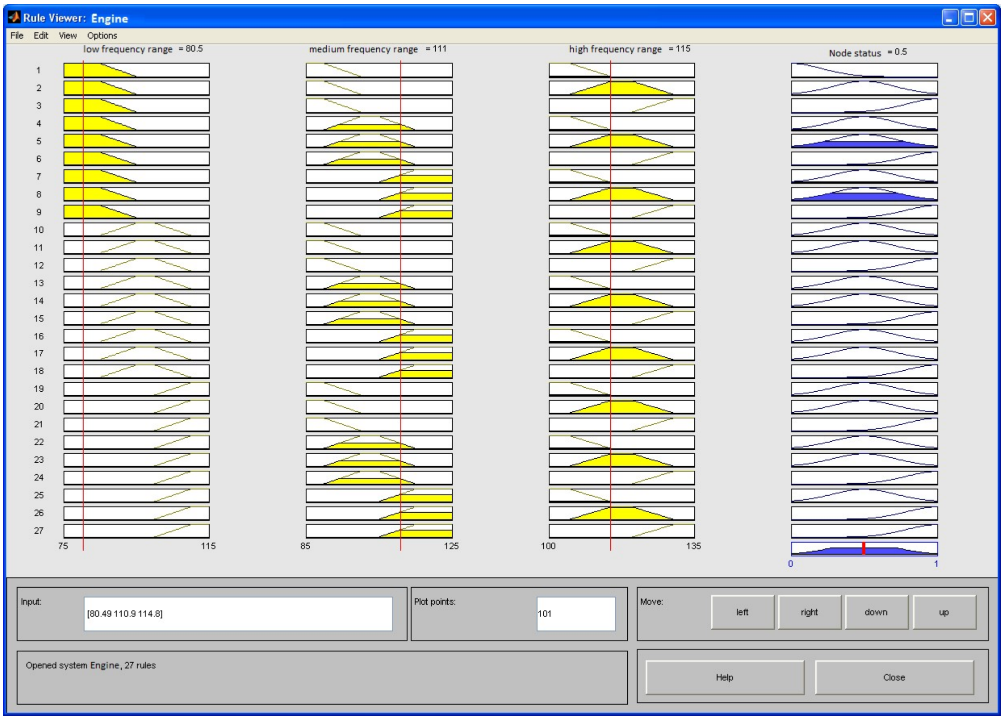

Fig.4.47 – Results of the technical state evaluation of the self-cutter electro-drive – 0.5 (03/22/13)

The diagnostics results of the devices for chipboard manufacturing are shown in Table 4.5.

The presented model of drives and motors´ diagnostics is based on the fuzzy inference system. The basic rules for the technical state evaluation are developed, the technical state of a device is evaluated by the vibration parameters via MatLab software. The analysis of experiment results of vibrations measurement showed that it is suitable to consider the vibrations of the device nodes in three frequency ranges: to 12.5 Hz, from 12.5 Hz to 630 Hz and from 630 Hz to 1250 Hz in compliance with the vibrations level, so that the technical state can be evaluated via fuzzy logic. In the evaluated time period from 28 January 2013 to 22 March 2013 the level of vibrations did not change more than by 6%, which indicates that no significant defects were present. The presented diagnostic model represents the grounds for the diagnostic algorithms' development.

Table 4.5
Results of technical devices actuators diagnostics for chipboard manufacturing

№	Diagnosed object	Evaluation of technical state	Recommendation
13	Electric motor for thick chip mixing	Initial defect (0.6)	Increase the state monitoring
14	Electric motor for soft chip mixing	Initial defect (0.548)	Increase the state monitoring
15	Electric motor of the first grinder	Initial defect (0.509)	Monitoring the state in normal regime
16	Electric motor of the second grinder	Initial defect (0.584)	Increase the state monitoring
17	Electric motor of the third grinder	Initial defect (0.5)	Monitoring the state in normal regime
18	Electric motor of the first forming machine	Initial defect (0.5)	Monitoring the state in normal regime
19	Electric motor of the third forming machine	Initial defect (0.5)	Monitoring the state in normal regime
20	Electric motor of crusher	Initial defect (0.506)	Monitoring the state in normal regime
21	Pneumatic classifier with electro-drive	Initial defect (0.507)	Monitoring the state in normal regime
22	Self-cutter machine with electro-drive	Initial defect (0.5)	Monitoring the state in normal regime

The dependence of current technical state anticipated residual operational life, diagnostics frequency on the diagnostic parameters value, speed growth of diagnostic parameters and developed source are presented in the form of fuzzy inference system. The input variables of the fuzzy inference system as well as the results are shown in Table 4.6.

Table 4.6

Dependence of current technical state, predicted residual life, diagnostics frequency on the diagnostic parameters value, speed of diagnostic parameters growth and exhausted supplies.

	Input data of fuzzy inference system			**Results of fuzzy inference system**		
No. of rule	**Values of diagnostic parameters**	**Speed of diagnostic parameters growth**	**Generated source**	**Current technical state**	**Predicted residual life**	**Diagnostics frequency**
1	L	L	L	L	H	L
2	L	L	M	M	M	M
3	L	L	H	H	L	H
4	L	M	L	M	M	M
5	L	M	M	M	M	M
6	L	M	H	H	L	H
7	L	H	L	H	L	H
8	L	H	M	H	L	H
9	L	H	H	H	L	H
10	M	L	L	M	M	M
11	M	L	M	M	M	M
12	M	L	H	H	L	H
13	M	M	L	M	M	M
14	M	M	M	M	M	M
15	M	M	H	H	L	H
16	M	H	L	H	L	H
17	M	H	M	H	L	H
18	M	H	H	H	L	H
19	H	L	L	M	M	H
20	H	L	M	M	M	H
21	H	L	H	H	L	H
22	H	M	L	H	L	H
23	H	M	M	H	L	H
24	H	M	H	H	L	H
25	H	H	L	H	L	H
26	H	H	M	H	L	H
27	H	H	H	H	L	H

To develop the fuzzy inference rules for this Table, the logic operations of input data by AND operation were needed. As diagnostic parameters the vibrations acceleration in the frequency ranges of the third octave filter is used.

Terms of diagnostic parameters values: L – low level of diagnostic parameters values; M – average diagnostic parameters values; H – high diagnostic parameters values. Terms of diagnostic parameters growth speed: L – low diagnostic parameters growth speed; M – average diagnostic parameters growth speed; H – high diagnostic parameters growth speed. Conditions for developed supply: L – developed supply is low; M – exhausted supply is of average value of the almost half of the operational lifetime; H – developed source is high and close to the lifetime. Conditions of current technical state: L – free of defects; M – with minor defects; H – with serious defects. Terms for anticipated residual source: L – anticipated source is low; M – anticipated supply is of average value close to the half of the operational lifetime; H – anticipated source is high and close to the lifetime. Terms for diagnostics frequency: L – low diagnostics frequency; M – average diagnostics frequency; H – high diagnostics frequency.

The analysis of the soft chip mixer electric motor vibrations acceleration (Fig. 4.5) showed that the vibrations acceleration in the low-frequency range (6.3, 8, 10, and 31.5 Hz) is different in the largest change of vibrations acceleration values. Figures 4.48-4.51 illustrate the measurement results of the soft / fine chip mixer electric motor vibrations acceleration in the independent frequency ranges (6.3, 8, 10, and 31.5 Hz) by 40 changes.

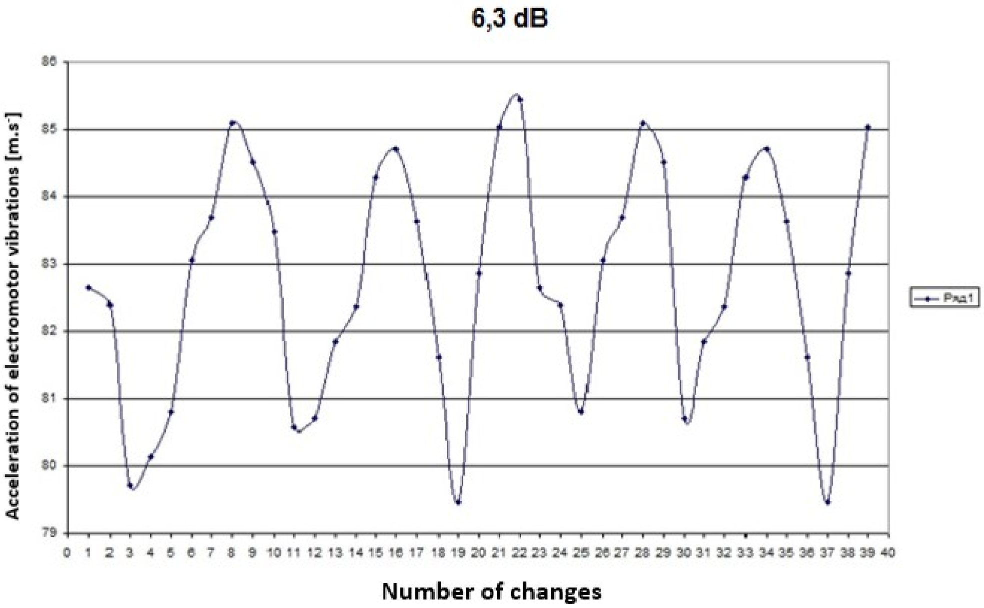

Fig. 4.48 - Measured results of a soft chip mixer electric motor vibrations in 6.3 Hz frequency range by 40 changes

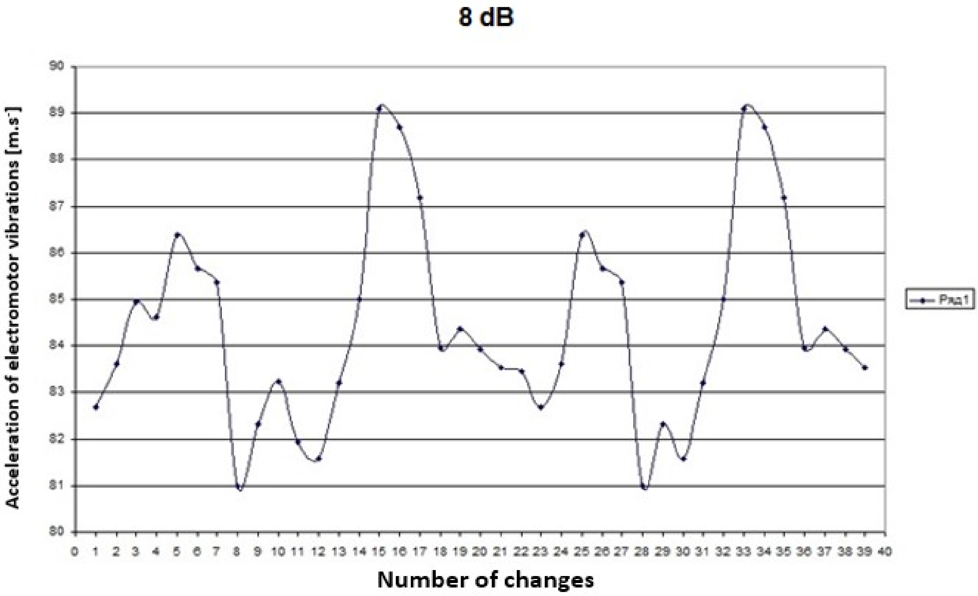

Fig. 4.49 - Measured results of a soft chip mixer electric motor vibrations in 8 Hz frequency range by 40 changes

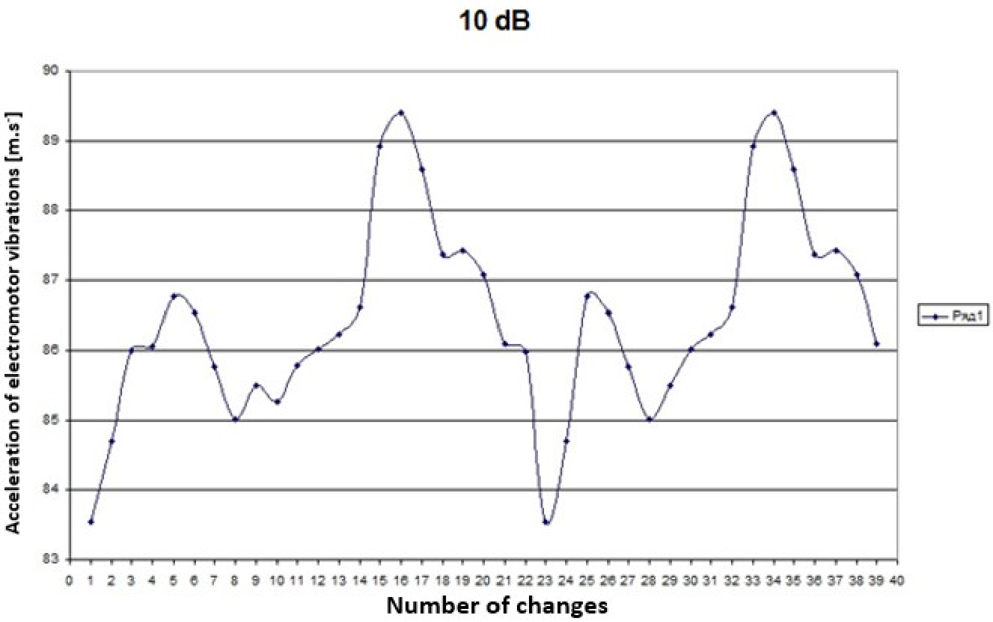

Fig. 4.50 - Measured results of a soft chip mixer electric motor vibrations in 10 Hz frequency range by 40 changes

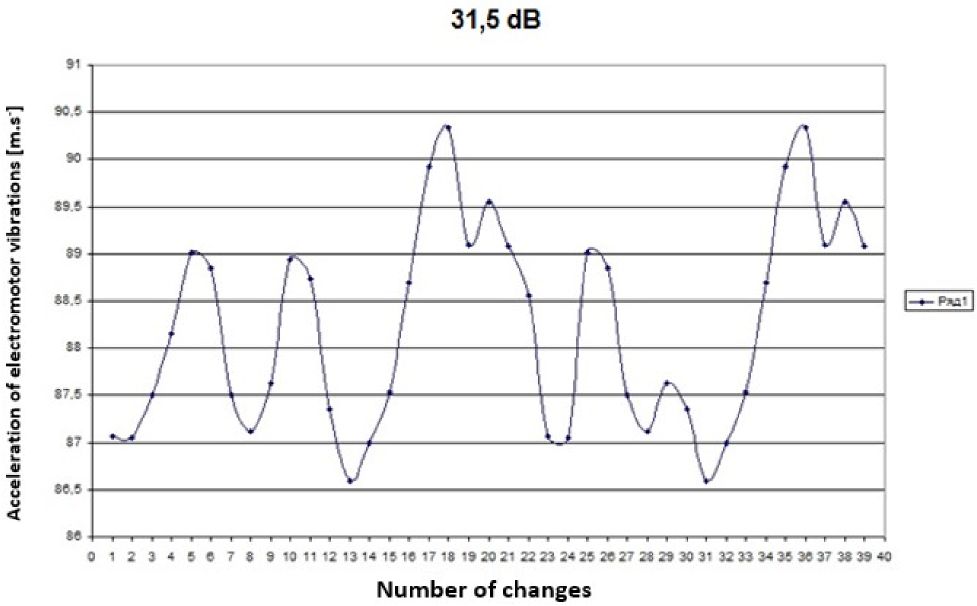

Fig. 4.51 – Measured results of a soft chip mixer electric motor vibrations in 31.5 Hz frequency range by 40 changes

The obtained results allow estimating the maximum range of vibrations acceleration in the low-frequency area up to 8 dB and the period of the vibrations acceleration increase and decrease up to 10 changes.

Such changes of vibration acceleration in the low-frequency area are explained by the fact that the low-frequency vibrations are well transferred through the base and joints of the mechanical components of a technological device. Therefore, to prevent an incorrect diagnosis, it is necessary either to exclude the data on low-frequency vibrations, or to average them through 10 measurements by 10 changes.

The diagnostic rules are continuously updated when the information on a specific monitoring object is gathered. First, all known diagnostic properties are used, and after complementing the statistic material the rules for the qualitative changes of the most informative vibration characteristics and the operational regime indicators for all main classes of the object state are determined (for the possible list of failures in changing the operational regime and structural parameters characterising its technical state it is possible to carry out the diagnostics by comparing the current most informative diagnostic parameters to standard ones, and thus determine the possible object´s conditions (i.e. determine the nature of the failure as well as the list of possible defects).

The following terms were used for the diagnostic model development, prediction of the residual operational lifetime and diagnostics of electric actuator diagnostics.

Terms of diagnostic parameters: L – low level of diagnostic parameters values; M – average level of diagnostic parameters values; H – high level of diagnostic parameters values.

Terms of diagnostic parameters: L – low rate of diagnostic parameters growth; M – average speed of diagnostic parameters growth; H – high rate of diagnostic parameters growth.

Terms of diagnostic parameters: L – exhausted resource is low; M – exhausted resource is of average value at about half of service life; H – exhausted resource is large, approaching length of the service life.

Terms of diagnostic parameters of current technical state: L – free of encumbrances; M – with small defects; H – with serious defects.

Terms for anticipated operating residual life: L – anticipated operating life is small; M – anticipated operational life is of average value close to the half of the lifetime; H – anticipated operational life is high and close to the whole lifetime.

Terms for diagnostics frequency: L – low diagnostics frequency; M – average diagnostics frequency; H – high diagnostics frequency.

The equation of diagnostic parameters is solved either by the fuzzy set method or by neural networks if the values of diagnostic parameters are greater than 5. The solution to the trendy equation of diagnostic parameters, evaluation of technical state, estimation of residual operational life, calculation of diagnostic intervals is executed by the fuzzy set method. The input data of fuzzy inference and the results of technical state evaluation are shown in Table 4.7. The input data of the fuzzy inference system and the results of the residual operational life are in Table 4.8. The input data of the fuzzy inference system and the results of diagnostic intervals calculation are in Table 4.9.

Table 4.7
Dependence of current technical state on the diagnostic parameters' values, the trend of diagnostic parameters and residual life

No. of rule	Values of diagnostic parameters	Development of diagnostic parameters	Generated source	Current technical state
1	L	L	L	L
2	L	L	M	M
3	L	L	H	H
4	L	M	L	M
5	L	M	M	M
6	L	M	H	H
7	L	H	L	H
8	L	H	M	H
9	L	H	H	H
10	M	L	L	M
11	M	L	M	M
12	M	L	H	H
13	M	M	L	M
14	M	M	M	M
15	M	M	H	H
16	M	H	L	H
17	M	H	M	H
18	M	H	H	H
19	H	L	L	M
20	H	L	M	M
21	H	L	H	H
22	H	M	L	H
23	H	M	M	H
24	H	M	H	H
25	H	H	L	H
26	H	H	M	H
27	H	H	H	H

Table 4.8
Dependence of diagnostic frequency on the diagnostic parameters' values, the trend of diagnostic parameters, technical state, and residual life

No. of rule	Values of diagnostic parameters	Development of diagnostic parameters	Generated source	Current technical state	Predicted residual life
1	L	L	L	L	H
2	L	L	M	M	M
3	L	L	H	H	L
4	L	M	L	M	M
5	L	M	M	M	M
6	L	M	H	H	L
7	L	H	L	H	L
8	L	H	M	H	L
9	L	H	H	H	L
10	M	L	L	M	M
11	M	L	M	M	M
12	M	L	H	H	L
13	M	M	L	M	M
14	M	M	M	M	M
15	M	M	H	H	L
16	M	H	L	H	L
17	M	H	M	H	L
18	M	H	H	H	L
19	H	L	L	M	M
20	H	L	M	M	M
21	H	L	H	H	L
22	H	M	L	H	L
23	H	M	M	H	L
24	H	M	H	H	L
25	H	H	L	H	L
26	H	H	M	H	L
27	H	H	H	H	L

Table 4.9

Dependence of diagnostic frequency on the diagnostic parameters' values, the trend of diagnostic parameters and residual life

No. of rule	Values of diagnostic parameters	Development of diagnostic parameters	Generated source	Current technical state	Diagnostic frequency
1	L	L	L	L	L
2	L	L	M	M	M
3	L	L	H	H	H
4	L	M	L	M	M
5	L	M	M	M	M
6	L	M	H	H	H
7	L	H	L	H	H
8	L	H	M	H	H
9	L	H	H	H	H
10	M	L	L	M	M
11	M	L	M	M	M
12	M	L	H	H	H
13	M	M	L	M	M
14	M	M	M	M	M
15	M	M	H	H	H
16	M	H	L	H	H
17	M	H	M	H	H
18	M	H	H	H	H
19	H	L	L	M	H
20	H	L	M	M	H
21	H	L	H	H	H
22	H	M	L	H	H
23	H	M	M	H	H
24	H	M	H	H	H
25	H	H	L	H	H
26	H	H	M	H	H
27	H	H	H	H	H

The diagnostic parameters values characterised by x (t), vector of diagnostic parameters is determined by the measurement of vibrations acceleration and the calculation of a standard deviation and maximum factor in one third octave frequency ranges.

The location of the sensor assembly on the unit are indicated by a cross. The acceleration measurements were carried out by OKTAVA-110A-EKO device with AR2082M vibration converter measuring the vibrations acceleration with the measuring error of ± 0.5 dB. The vibrator was mounted to a magneto. The vibration acceleration measurement method by OKTAVA-110A-ECO device is a direct method. The corresponding levels of vibrations acceleration are shown directly on the device indicator.

The photograph of the soft/fine chip mixer electric motor with 30kW capacity and the synchronous frequency of 1 500 rev/min -1 indicating the installation of the vibration's acceleration sensor is in Fig. 4.52.

Fig. 4.52 – Soft chip mixer electric motor

The measurement results of the soft / fine chip mixer electric motor acceleration in independent frequency ranges (6.3, 8, 10, and 31.5 Hz) by 40 changes are in Figures 4.53-4.56. The development of the diagnostic parameters vector on the example of a soft chip mixer electric motor is in Tables 4.10-4.13.

Table 4.10
Acceleration of a soft chip mixer electric motor obtained by a filter with one octave third (measurement time interval 10 s, RMS, max., peak factor, date 28/01/2013)

Frequency (Hz)	**amplitude RMS, (dB)**	**amplitude max, (dB)**	**peak factor (-)**
6.3	82.38	85.67	3.29
8	84.61	84.61	0.00
10	85.96	86.41	0.45
12.5	87.34	87.34	0.00
16	91.70	91.70	0.00
20	87.77	87.88	0.11
25	89.76	89.76	0.00
31.5	88.02	88.10	0.08
40	96.83	96.98	0.15
50	94.74	94.74	0.00
63	90.94	91.17	0.23
80	96.15	96.16	0.01
100	101.70	101.72	0.02
125	94.17	94.36	0.19
160	97.18	97.18	0.00
200	108.65	108.72	0.07
250	103.61	103.74	0.13
315	106.24	106.24	0.00
400	122.95	122.95	0.00
500	108.83	108.83	0.00
630	112.77	112.77	0.00
800	116.57	116.68	0.11
1000	121.57	121.57	0.00
1250	119.42	119.42	0.00

The addition of the maximum factor was 4.84 dB, which indicates the good state of the electric actuator.

Table 4.11

Acceleration of a soft chip mixer electric motor obtained by a filter with one octave third (measurement time interval 10 s, RMS, max., peak factor, date 22/30/2013)

Frequency (Hz)	**amplitude RMS, (dB)**	**amplitude max, (dB)**	**peak factor (-)**
6.3	83.32	85.67	2.35
8	83.80	87.38	3.58
10	86.68	88.53	1.85
12.5	87.34	87.36	0.02
16	93.13	94.00	0.87
20	86.95	88.30	1.35
25	89.85	90.16	0.31
31.5	89.41	89.86	0.45
40	96.48	97.71	1.23
50	94.82	95.09	0.27
63	90.64	91.32	0.68
80	95.16	97.89	2.73
100	101.66	102.34	0.68
125	93.76	94.71	0.95
160	96.59	97.62	1.03
200	108.42	108.99	0.57
250	102.05	103.74	1.69
315	106.01	107.13	1.12
400	122.13	122.98	0.85
500	107.66	109.01	1.35
630	111.96	112.81	0.85
800	115.82	116.68	0.86
1000	121.42	121.57	0.15
1250	119.09	119.42	0.33

The addition of the maximum factor was 26.12 dB, which indicates the worsening of the electric actuator state (in comparison to 4.84 dB on 01/28/2013).

Table 4.12
Acceleration of a soft chip mixer electric motor obtained by a filter with one octave third (measurement time interval 10 s, maximum factor, changes of maximum factor, dates 28/01/2013 and 22/03/2013)

Frequency, amplitude Hz	amplitude RMS 28/01/2013, dB	amplitude RMS 22/03/2013, dB	change of RMS
6.3	82.38	83.32	0.94
8	84.61	83.80	-0.81
10	85.96	86.68	0.72
12.5	87.34	87.34	0.00
16	91.70	93.13	1.43
20	87.77	86.95	-0.82
25	89.76	89.85	0.09
31.5	88.02	89.41	1.39
40	96.83	96.48	-0.35
50	94.74	94.82	0.08
63	90.94	90.64	-0.30
80	96.15	95.16	-0.99
100	101.70	101.66	-0.04
125	94.17	93.76	-0.41
160	97.18	96.59	-0.59
200	108.65	108.42	-0.23
250	103.61	102.05	-1.56
315	106.24	106.01	-0.23
400	122.95	122.13	-0.82
500	108.83	107.66	-1.17
630	112.77	111.96	-0.81
800	116.57	115.82	-0.75
1000	121.57	121.42	-0.15
1250	119.42	119.09	-0.33

The addition of changes in is -5.71 dB, which indicates a good state of the electric motor.

Table 4.13

Acceleration of a soft chip mixer electric motor obtained by a filter with one octave third (measurement time interval 10 s, maximum factor, changes of maximum factor, dates 28/01/2013 and 22/03/2013)

Frequency, amplitude Hz	**amplitude RMS 28/01/2013, dB**	**amplitude RMS 22/03/2013, dB**	**peak factor**
6.3	3.29	2.35	-0.94
8	0.00	3.58	3.58
10	0.45	1.85	1.40
12.5	0.00	0.02	0.02
16	0.00	0.87	0.87
20	0.11	1.35	1.24
25	0.00	0.31	0.31
31.5	0.08	0.45	0.37
40	0.15	1.23	1.08
50	0.00	0.27	0.27
63	0.23	0.68	0.45
80	0.01	2.73	2.72
100	0.02	0.68	0.66
125	0.19	0.95	0.76
160	0.00	1.03	1.03
200	0.07	0.57	0.50
250	0.13	1.69	1.56
315	0.00	1.12	1.12
400	0.00	0.85	0.85
500	0.00	1.35	1.35
630	0.00	0.85	0.85
800	0.11	0.86	0.75
1000	0.00	0.15	0.15
1250	0.00	0.33	0.33

The addition of maximum factor changes was 21.28 dB, which indicates the worsening of the electric actuator state.

The photograph of a 90 kW electric motor and a synchronous frequency of 1,000 rev/min of the thick chip mixer with the vibration acceleration sensor location is in Fig. 4.26. The measurements results of electric motor vibrations are in Fig. 4.4.

Fig. 4.53 - Thick chip mixer electric motor

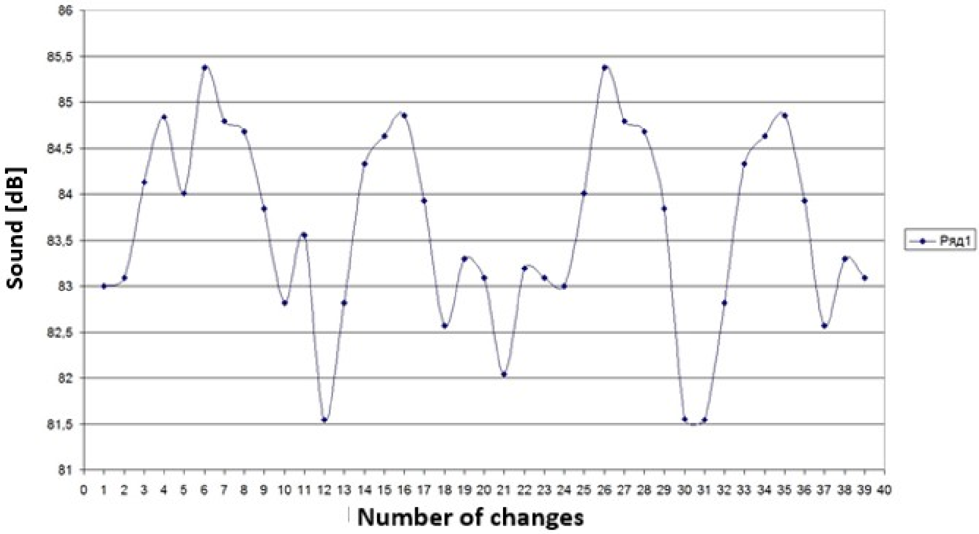

Fig. 4.54 - Measured results of a thick chip mixer electric motor vibrations in 6.3 Hz frequency range by 40 changes

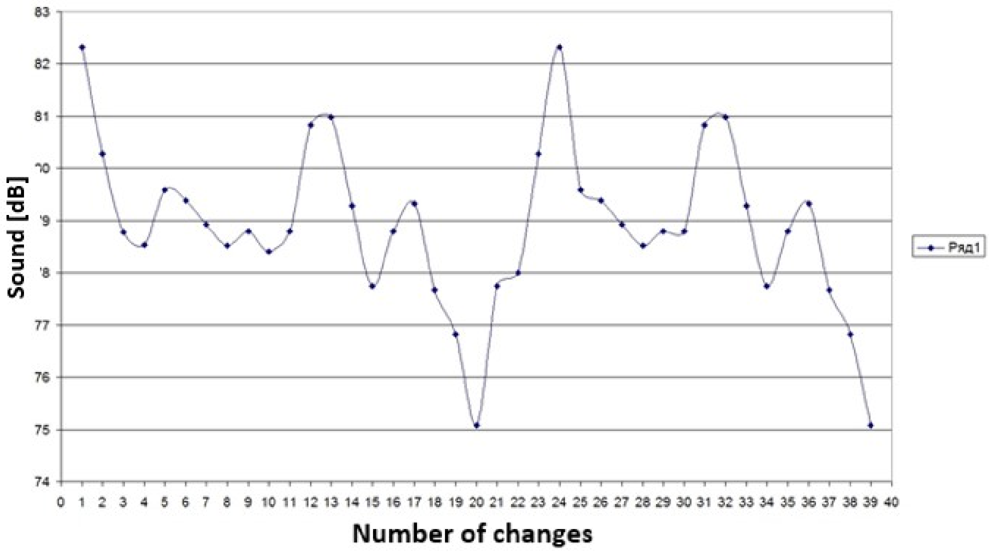

Fig. 4.55 – Measured results of a thick chip mixer electric motor vibrations in 8 Hz frequency range by 40 changes

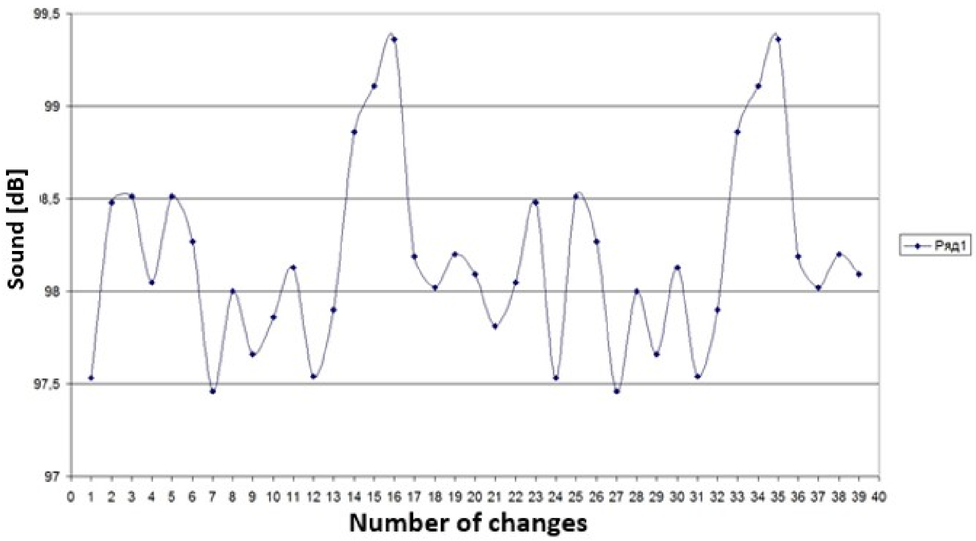

Fig. 4.56 – Measurements results of a thick chip mixer electric motor vibrations in 25 Hz frequency range by 40 changes

Measurements results of electric motor vibrations in independent frequency ranges (6.3, 8, 10, and 31.5 Hz) by 40 changes are illustrated in Figs. 4.27–4.30. The development of diagnostic parameters vector on an example of a thick chip mixer electric motor is shown in Tables 4.14–4.17.

Table 4.14
Acceleration of electric motor vibrations of a thick chips' mixer obtained by a filter with one octave third (measurement time interval 10 s, RMS, max., peak factor, date 28/01/2013)

Frequency (Hz)	RMS amplitude, (dB)	max amplitude, (dB)	peak factor (-)
6.3	83.25	83.89	0.64
8	81.15	81.33	0.18
10	94.64	94.73	0.09
12.5	102.89	103.23	0.34
16	101.46	101.68	0.22
20	94.80	94.80	0.00

25	97.67	97.67	0.00
31.5	95.36	95,36	0,00
40	94.84	95.02	0.18
50	95.32	95.32	0.00
63	98.85	98.93	0.08
80	97.40	97.53	0.13
100	91.23	91.33	0.10
125	89.98	90.13	0.15
160	96.07	96.23	0.16
200	99.41	99.52	0,11
250	103.12	103.15	0.03
315	102.92	102.92	0.00
400	100.91	100.91	0.00
500	102.02	102.02	0.00
630	110.81	110.81	0.00
800	121.43	121.54	0.11
1000	123.26	123.32	0.06
1250	119.67	119.75	0.08

Addition of maximum factor was 2.55 dB, which indicates a good state of the electric drive.

Table 4.15

Acceleration of electric motor vibrations of a thick chip mixer obtained by a filter with one octave third (measurement time interval 10 s, RMS, max., peak factor, date 03/22/2013)

Frequency (Hz)	RMS amplitude, (dB)	max amplitude, (dB)	peak factor (-)
6.3	83.30	84.99	1.69
8	77.35	81.33	3.98
10	93.40	95.48	2.08
12.5	102.75	103.54	0.79
16	102.53	102.53	0.00
20	94.01	95.76	1.75
25	98.17	98.84	0.67
31.5	95.20	96.17	0.97
40	95.20	95.94	0.74
50	95.26	95.64	0.38
63	98.85	98.93	0.08
80	96.67	97.84	1.17
100	92.40	92.40	0.00
125	89.96	90.53	0.57
160	96.31	96.53	0.22
200	99.60	99.65	0.05
250	103.64	103.64	0.00
315	103.10	103.19	0.09
400	101.27	101.27	0.00
500	102.95	102.98	0.03
630	110.91	111.35	0.44
800	121.59	121.69	0.10
1000	122.88	123.32	0.44
1250	118.95	119.75	0.80

The addition of the maximum factor was 17.04 dB, which indicates the worsening of the electric drive state (in comparison to 2.55 dB on 01/28/2013).

Table 4.16
Acceleration of electric motor vibrations of the soft chip mixer obtained by a filter with one octave third (measurement time interval 10 s, RMS, changes in RMS, dates 28/01/2013 and 22/03/2013)

Frequency, Hz	RMS amplitude 28/01/2013, dB	RMS amplitude 22/03/2013, dB	change of RMS
6.3	83.25	83.30	0.05
8	81.15	77.35	-3.80
10	94.64	93.40	-1.24
12.5	102.89	102.75	-0.14
16	101.46	102.53	1.07
20	94.80	94.01	-0.79
25	97.67	98.17	0.50
31.5	95.36	95.20	-0.16
40	94.84	95.20	0.36
50	95.32	95.26	-0.06
63	98.85	98.85	0.00
80	97.40	96.67	-0.73
100	91.23	92.40	1.17
125	89.98	89.96	-0.02
160	96.07	96.31	0.24
200	99.41	99.60	0.19
250	103.12	103.64	0.52
315	102.92	103.10	0.18
400	100.91	101.27	0.36
500	102.02	102.95	0.93
630	110.81	110.91	0.10
800	121.43	121.59	0.16
1000	123.26	122.88	-0.38
1250	119.67	118.95	-0.72

The addition of changes in RMS was -2.21 dB, which indicates a good state of the electric drive.

Table 4.17
Acceleration of an electric motor of a thick chips' mixer obtained by a filter with one octave third (measurement time interval 10 s, maximum factor, changes of maximum factor, dates 28/01/2013 and 22/03/2013)

Frequency, Hz	Change of maximum factor 28/01/2013, (dB)	Change of maximum factor 22/03/2013, (dB)	Change of maximum factor
6.3	0.64	1.69	1.05
8	0.18	3.98	3.80
10	0.09	2.08	1.99
12.5	0.34	0.79	0.45
16	0.22	0.00	-0.22
20	0.00	1.75	1.75
25	0.00	0.67	0.67
31.5	0.00	0.97	0.97
40	0.18	0.74	0.56
50	0.00	0.38	0.38
63	0.08	0.08	0.00
80	0.13	1.17	1.04
100	0.10	0.00	-0.10
125	0.15	0.57	0.42
160	0.16	0.22	0.06
200	0.11	0.05	-0.06
250	0.03	0.00	-0.03
315	0.00	0.09	0.09
400	0.00	0.00	0.00
500	0.00	0.03	0.03
630	0.00	0.44	0.44
800	0.11	0.10	-0.01
1000	0.06	0.44	0.38
1250	0.08	0.80	0.72

The addition of maximum factor was 14.38 dB, which indicates the worsening of the electric drive´s state.

Conclusions

The most important perspectives for the development of automated technological systems are represented by the intellectualisation, increased reliability, and design via modular structures. The diagnostics of technological drives improves the level of their intellectualisation and reliability. Regarding the analysis of the methods of the technological drives, it could be concluded that the following diagnostic methods are suitable to be used: by the vibrations, temperature, and electric current via artificial intelligence methods. The analysis of the algorithms and software products current state showed that there is the tendency to develop the diagnostic programs based on artificial intelligence methods and built on a modular basis. The analysis of the diagnostic systems for the technological drives also showed that the promising way is represented by the development of small diagnostic devices based on a microcontroller, or a digital signals processor with excellent computer knowledge and a standard operation system for fast diagnostics, which are server connected and can provide us with deep diagnostics, and thus can calculate the trends in the field as well as it can calculate the parameters, the residual operational life of mechatronic systems, and archive the data. For the diagnostics of critical drives of technological systems, for the accidents, which could lead to casualties, technological disasters, or significant economic damage, it is recommended to utilise continuous diagnostic systems.

The diagnostic systems classification is designed regarding its dependence on the cost of accidents consequences and speed of processes degradation in the diagnostic object (portable devices, stationary systems, continuous diagnostic systems).

A logic-linguistic model for diagnosing and predicting the residual operational life of the technological drives is proposed. The logic-linguistic model for diagnosing and predicting the residual sources of the technological drives is a complex consisting of the: description of initial linguistic variables and technical conditions, laws of physical degradation processes in mechanical, electrical, electromechanical, and electronic devices, laws related to failures and diagnostic parameters, operation and operational regimes, basic rules of fuzzy inference system to determine the technical state.

There are also the change patterns of the diagnostic parameters by the changing technical state of drives, which is explained by the example of a technological device for chipboards production.

Once the diagnostics is implemented, the economic efficiency is improved by the lower number of failures, decreased costs for maintenance, and repairs as well as by the decreased number of idle times of an expensive device.

References

Abramov, I. et al. (2014) Monitoring of technical condition of motors and bearings of woodworking equipment. *Acta Facultatis Xylologiae*, 56(2), pp. 97-104.

Abramov, I., Nikitin, Y., Abramov, A., Sosnovich, E., Božek, P. (2014) Control and diagnostic model of brushless DC motor. *Journal of Electrical Engineering,* 65(5), pp. 277-282.

Abramov, I. et al. (2015) Diagnostics of electrical drives. In: *18th Int. Conf. on Electrical Drives and Power Electronics. EDPE 2015*; Sept. 21-23, 2015; High Tatras, Slovakia. IEEE, pp. 364-367.

Abramov, I., Božek, P., Abramov, A., Sosnovich, E., Nikitin, Y. (2017) Diagnostics brushless DC motors. In: *Proc. of 55th Int. Sci. Conf. Experimental Stress Analysis 2017: EAN 2017*; May 30th - June 1st, 2017, Nový Smokovec, Slovakia. Košice: TUKE, pp. 156-164.

Barkov, A.V., Barkova, N.A., Azovcev, A.Y. (2000) *Monitoring i diagnostika rotornyh mashin po vibracii (Monitoring and diagnostics of rotary machines by vibration)*. SPb: SPb Gosudarstvenny morskoy tekhnichesky universitet, 169 p. (in Russian)

Bartelmus, W. (2003) Diagnostic information on gearbox condition for mechatronic systems. *Transactions of the Institute of Measurement and Control*, 25(5), pp. 451-465, ISSN 0142-3312.

Bencsik, A.L., Szabo, J.Z., Lendvay, M. (2013) Maintenance and Diagnostic in Mechatronic Systems. In: Szakal, A. (Ed.), *IEEE 9th Iint. Conf. on Computational Cybernetics (ICCC 2013)*; July 08-10, 2013; Tihany, Hungary, pp. 141-146, ISBN 978-1-4799-0063-3.

Blanke, M., Kinnaert, M., Lunze, J., Staroswiecki, M. (2003) *Diagnosis* *and Fault Tolerant Control*. Springer-Verlag, Berlin. 2003. 571 p.

Blatnicky, M., Dizo, J., Saga, M., Gerlici, J., Kuba, E. (2020) Design of a Mechanical Part of an Automated Platform for Oblique Manipulation. *Applied Sciences*, 10(23), Art. No: 8467, DOI: 10.3390/app10238467.

Božek, P., Nikitin, Y., Krenický, T. (2021) *Diagnostics of Mechatronic Systems*. Cham: Springer, 2021, 79 p.

Božek, P., Nikitin, Y., Krenický, T. (2021) Model Systems for Diagnosticing of Mechatronic Objects. *Studies in Systems, Decision and Control,* 345, pp. 27-61, DOI: 10.1007/978-3-030-67055-9_3.

Costa, B.S.J. (2016) Fuzzy Fault Detection and Diagnosis. In: *Handbook on Computational Intelligence in 2 Volumes. Volume 1: Fuzzy Logic, Systems, Artifical Neural Networks and Learning Systems*. World Scientific Publishing, pp. 251-288.

Dalla Vedova, M.D.L. (2018) Diagnostic/Prognostics Strategies Applied to Physical Dynamic Systems: Critical Analysis of Several Model-Based Fault Identification Methods. In: Bardis, N. (Ed.), *2nd Int. Conf. on Mathematical Methods & Computational Techniques in Science & Engineering*, Feb. 16-18, 2018, Cambridge, GB. *AIP Conference Proceedings*, 2018, Vol. 1982.

Dietel, F., Schulze, R., Richter, H., Jakel, J. (2012) Fault detection in rotating machinery using spectral modelling. In: *13th Int. Workshop on Research and Education in Mechatronics (REM)*, Nov. 21-23, 2012, Supmeca, Paris, 2012, pp. 353-357, ISBN 978-1-4673-4771-6.

Ding, S.X. (2008) *Model-based Fault Diagnosis Techniques. Design Schemes, Algorithms, and Tools*. Springer, 473 p.

Gulyashinov, A.N., Tenenev, V.A., Yakimovich, B.A. (2005) *Decision theory in complex socio-technical systems (Teoriya prinyatiya reshenij v* *slozhnykh sociotekhnicheskikh sistemakh)*. Izhevsk: IzhGTU, 280 p. (in Russian)

Gutierrez-Carvajal, R.E., de Melo, L.F., Rosario, J.M., Machado, J.A.T. (2016) Condition-based diagnosis of mechatronic systems using a fractional calculus approach. *Int. J. of Systems Science*, 47(9), pp. 2169-2177.

Hannius, O., Ring, D., Karlsson, J. (2006) Derivation of diagnostic requirements for a distributed UAV turbofan engine control system. In: *Proc. of 51st ASME Turbo Expo 2006*; May 06-11, 2006; Barcelona, Spain, Vol. 2, 2006, pp. 469-477, ISBN 0-7918-4237-1.

Isermann, R. (2006) *Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerance*. Berlin: Springer-Verlag, 475 p.

Isermann, R. (2011) *Identification of Dynamic Systems. An Introduction with Applications*. Berlin Heidelberg: Springer-Verlag, 705 p.

Janda, O., Hammer, M., Ministr, M., Ertl, J. (2011) Adaptive Neuro-Fuzzy Inference System for Power Oil Transformer Diagnostics. *MM Science Journal*, 4(3), pp. 325-331.

Klyuev, V.V. et al. (1995) *Non-destructive testing and diagnostics (Nerazrushayushchij kontrolj i diagnostika: Spravochnik)*. Moscow: Mashinostroyenie, 487 p. (in Russian)

Kopas, P., Blatnický, M., Sága, M., Vaško, M. (2017) Identification of mechanical properties of weld joints of AlMgSi07.F25 aluminium alloy. *Metalurgija*, 56(1-2), pp. 99-102.

Krenicky, T. (2011) Implementation of Virtual Instrumentation for Machinery Monitoring. In: *Scientific Papers: Operation and Diagnostics of Machines and Production Systems Operational States: Vol. 4*, RAM-Verlag, Lüdenscheid, pp. 5-8, ISBN 978-3-942303-10-1.

Krenický, T., Jacko, P. (2011) Real-time monitoring of technical systems operation, *Strojárstvo Extra* 5, pp. 32/1-32/2.

Krenický, T., Fabian, S. (2013) *Basics of vibrodiagnostics (Základy vibrodiagnostiky.* Prešov: FVT TU, 105 p. (in Slovak)

Mascenik, J., Pavlenko, S. (2018) Innovative broad - spectrum testing and monitoring of belt transmissions. *MM Science Journal,* No. December, pp. 2706-2709, ISSN 1803-1269.

Mascenik, J. (2019) Implementation of the designed program for calculation and check of chain gears. *MM Science Journal*, No. December, pp. 3431-3434.

Matveev, S.A., et al. (2020) Diagnostic and Monitoring System for Technical Condition of Electromechanical Section of Thermal Control Systems in Spacecraft. *Int. J. of Mathematical Engineering and Management Sciences*, 5(1), pp. 181-192, ISSN 2455-7749.

Mayer, D., Atzrodt, H., Herold, S., Thomaier, M. (2008) An approach for the model based monitoring of piezoelectric actuators. In: *Thematic Conf. on Smart Structures and Materials - Computers & Structures II ECCOMAS;* July 18-21, 2005; Tech Univ Lisbon, Portugal, 86(3-5), pp. 314-321.

Muller, T., Lange, K., Breuer, A., Krieger, O., Form, T. (2007) Automatic and expierence-based diagnostics using distributed data and neural networks. In: *VDI BERICHTE 13th Int. Congress on Electronic Systems Vehicles*; Oct. 10-11, 2007; Baden Baden, Germany, Vol. 2000, pp. 593-605, ISBN 978-3-18-092000-9.

Murcinkova, Z., Krenicky, T. (2013) Implementation of virtual instrumentation for multiparametric technical system monitoring. In: *SGEM 2013: 13th Int. Multidisciplinary Sci. Geoconf. Vol. 1*; 16-22 June 2013; Albena, Bulgaria. Sofia: STEF92 Technology, pp. 139-144, ISBN 978-954-91818-9-0.

Nikitin, Y. (2010) *Diagnostics of mechatronic systems on the basis of neural networks. State-of-the-Art in Mechatronics, Vol. 2*. Alphen aan den Rijn: Simulation Research Press, pp. 167-188.

Nikitin, Y.R., Abramov, I.V. (2010) CNC machines diagnostics. In: *Proc. of 13th Int. Symp. on Mechatronics*; 2-4 June 2010; Trenčianske Teplice, Slovakia, pp. 89-91.

Nikitin, Y., Abramov, I. (2011) Mechatronic modules diagnosis by use of fuzzy sets. In: *Proc. of 14th Int. Conf. on Mechatronics*; 1-3 June 2011; Trenčianske Teplice, Slovakia, pp. 109-111.

Nikitin, Y.R., Abramov, I.V. (2011) Models of information processes of mechatronic systems diagnosis. *University Review*, 5(1), pp. 12-16.

Nikitin, Y., Turygin, Yu., Sosnovich, E., Božek, P. (2016) Trends in control of NC machines. *Procedia Engineering*, 149, pp. 352-358.

Nikitin, Y., Bozek, P., Peterka, J. (2020) Logical-Linguistic Model of Diagnostics of Electric Drives with Sensors Support. *Sensors*, 20(16), ISSN 1424-8220.

Nurieva, E., Nikitin, Y. (2012) Intelligent diagnostic system of mechatronic modules. *Acta facultatis forestalis*, 54(1), pp. 173-176.

Panda, A., Jurko, J., Pandová, I. (2016) *Monitoring and Evaluation of Production Processes. An Analysis of the Automotive Industry*. Springer Int. Pub., Switzerland, 117 p., ISBN 978-3-319-29441-4.

Panda, A., Olejárová, Š., Valíček, J., Harničárová, M. (2018) Monitoring of the condition of turning machine bearing housing through vibrations. The *Int J of Adv Manuf Technol*, 97(1-4), pp. 401-411, ISSN 0268-3768.

Panda, A. et al. (2019) Development of the method for predicting the resource of mechanical systems. *Int J of Adv Manuf Technol*, 105(1-4), pp. 1563-1571.

Panda, A., Nahornyi, V. (2021) *Forecasting Catastrophic Events in Technology, Nature and Medicine*. Springer Nature Switzerland AG, Cham, 2021, 110 p., ISBN 978-3-030-65327-9.

Prislupcak, M. et al. (2014) Diagnostic and Experimental Valuation on Progressive Machining Unit. *Applied Mechanics and Materials*, 616, p. 191, DOI: 10.4028/www.scientific.net/AMM.616.191.

Rafajdus, P., Peniak, A., Brandt, M. (2012) Parametrical Model of Power Transformers Used for Diagnostics Systems. In: *Proc. of 15th Int. Conf. on Mechatronics*; 5-7 December, Prague; 2012, pp. 42-48.

Repko, A., Saga, M., Sentyakov, B., Sviatskii, V. (2020) Development and Testing of a Block Hydrocyclone. *Processes*, 8(12), Art. No. 1577, DOI: 10.3390/pr8121577.

Rothe, S., Soffker, D. (2015) Development of a State-related Evaluation for Diagnostic-oriented Data Filtering Approach. In: Chang, F.K. & Kopsaftopoulos, F. (Eds.) *10th Int. Workshop on Structural Health Monitoring (IWSHM)*; Sept. 01-03, 2015; Stanford, USA. Stanford Univ, 2015, pp. 593-600, ISBN 978-1-60595-275-8.

Saga, M., Jakubovicova, L. (2014) Simulation of vertical vehicle non-stationary random vibrations considering various speeds. *Sci. J. of Silesian Uni. of Technology – series Transport*, 84, pp. 113-118.

Saga, M., Vasko, M., Pechac, P. (2014) Chosen numerical algorithms for interval finite element analysis. *Procedia Engineering*, 96, pp. 400-409.

Saga, M., Blatnicka, M., Blatnicky, M., Dizo, J., Gerlici, J. (2020) Research of the Fatigue Life of Welded Joints of High Strength Steel S960 QL Created Using Laser and Electron Beams. *Materials*, 13(11), Art. No: 2539, DOI: 10.3390/ma13112539.

Sinopaljnikov, V.A. (2005) *Reliability and diagnostics of technological systems (Nadezhnostj i diagnostika tekhnologicheskikh sistem)*. Moscow, Vysshaya shkola, 343 p. (in Russian)

Skhirtladze, A.G. (2008) *Reliability and diagnostics of technological systems: textbook (Nadezhnostj i diagnostika tekhnologicheskikh sistem: ucheb)*. Moscow: Novoye znanie, 518 p. (in Russian)

Soffker, D., Wolters, K., Ozbek, M., Dettmann, K.U. (2007) Feature-based diagnosis and prognosis for an integrated diagnostic approach. In: Chang, F.K. (Ed.), *6th Int. Workshop on Structural Health Monitoring*; Sept. 11-13, 2007; Stanford Univ., Stanford, USA. Stanford Univ., pp. 754-761, ISBN 978-1-932078-71-8.

Stepanov, P., Lagutkin, S., Božek, P. (2014) Comprehensive Approach to Technical Conditions of Electromechanical Units in Mechatronic Systems. *American J. of Mechanical Engineering*, 2(7), pp. 278-281.

Stepanov, P., Nikitin, Y. (2014) Diagnostics of Mechatronic Systems on the Basis of Neural Networks with High-Performance Data Collection. *Mechatronics 2013: Recent Technological and Scientific Advances*. Springer, pp. 433-440.

Stepanov, P., Bozek, P., Lagutkin, S., Nikitin, Y. (2021) Development of a decision box of diagnostic system for electric drives. *MM Science Journal*, November, pp. 4954-4961.

Straka, L., Panda, A. (2018) Optimal Preventive Maintenance Schedule of Sleeving Rings for Demanding Production Machine. *MM Science Journal,* No. December, pp. 2696-2700.

Timofeev, A.V. (2003) Physical diagnostics and fault relevant feedback control. In: *Int. Conf. on Physics and Control (PHYSCON 2003)*, Aug. 20-22, 2003, St. Petersburg, Russia, 2003, pp. 253-258, ISBN 0-7803-7939-X.

Trefilov, S.A., Nikitin, Y.R. (2019) Robot drives diagnostics by identifiability criterion based on state matrix. In: *Proc. of the 5th Int. Forum Instrumentation Engineering, Electronics and Telecommunications 2019*; November 20-22, 2019; Izhevsk, Russia. Izhevsk: Publishing House of Kalashnikov ISTU, pp. 105-114.

Turygin, Y., Božek, P., Nikitin, Y., Sosnovich, E., Abramov, A. (2016) Enhancing the reliability of mobile robots control process via reverse validation. *Int J of Advanced Robotic Systems,* 13(6), pp. 1-8.

Turygin, Y., Božek, P., Abramov, I., Nikitin, Y. (2018) Reliability determination and diagnostics of a mechatronic system. *Advances in Science and Technology Research Journal*, 12(2), pp. 274-290.

Vekteris, V., Cereska, A. (2006) Diagnostical measurements of elements of mechatronical system. In: Kyttner, R. (Ed.), *Proc. 5th Int. Conf. of the Danube-Adria-Association-for-Automation-Manufacturing*; Apr. 20-22, 2006; Tallinn, Estonia, pp. 183, ISBN 9985-894-92-8.

Vrban, A. (1983) *The production machines and systems reliability*. Course literature. SVŠT Bratislava, Slovakia.

Vrban, A. (1985) *The technical systems diagnostics*. Course literature. SVŠT Bratislava, Slovakia.

Vrban, A., Božek, P., Janíček, D. (1988) *The machines reliability determin-*

ing methods research. Research task No. F 2106-745, Trnava, Slovakia.

Yavlensky, K.N., Yavlensky, A.K. (1983) *Vibrodiagnostics and prediction of the quality of mechanical systems (Vibrodiagnostika i prognozirovanie kachestva mekhanicheskikh sistem)*. Leningrad: Mashinostroenie, 239 p. (in Russian)

Zhang, Y., Bingham, C., Gallimore, M., Yang, Z., Stewart, J. (2012) Fault Detection and Diagnosis Based on Y-indices and Residual Errors. In: *Proc. of 15th Int. Conf. on Mechatronics*, 5-7 December 2012, Prague, pp. 119-127.

Zhang, Y., Bingham, C., Yang, Z., Gallimore, M., Stewart, P. (2012) Applied Sensor Fault Detection and Identification Using Hierarchical Clustering and SOMNNs, with Faulted-Signal Reconstruction. In: *Proc. of 15th Int. Conf. on Mechatronics*, 5-7 December 2012, Prague, pp. 107-113.

Zhirabok, A., Shumsky, A. (2016) Fault Diagnosis in Nonlinear Mechatronic Systems via Linear Methods. In: *Proc. 42nd Annual Conf. of the IEEE-Industrial-Electronics-Society (IECON)*; Oct. 24-27, 2016; Florence, Italy. IEEE Industrial Electronics Society, pp. 406-411, ISBN 978-1-5090-3474-1.

Zhirabok A.N., Shumskii A.E., Solyanik S.P., Suvorov A.Y. (2017) Design of nonlinear robust diagnostic observers. *Autom. Remote Control*, 78(9), pp. 1572-1584.

Zykina, I.A., Nikitin, Y.R. (2008) Intelligent fault diagnosis for tools. In: *Proc. of 1st Forum of Young Researchers*; 23 April 2008; Izhevsk, Russia, pp. 129-132.

Zykina, I.A., Nikitin, Y.R. (2009) Application of neural networks for mechatronic systems diagnosing. In: *Proc. of 3rd Conf. of PhD students KONDOR 2009*; 13-15 May 2009; Trenčianske Jastrabie, Slovakia, pp. 1-4.

Appendix A

Diagnostic objects of technological devices for manufacturing of chipboard plates

Figures A.1-A.5 illustrate the drives – objects for the diagnostics of technological devices for manufacturing of chipboard plates by Bizon production line in Uvadrev Company, LLC. The assembly spot is marked by a cross. The tests were carried out by OKTAVA-110-A Eco with AR 2082M vibration converter measuring the vibrations acceleration with the measurement default of ± 0.5 dB. The sensor was mounted to the magneto.

Fig. A.1 - Electric motor 1 of the forming machine

Fig. A.2 – Machines for forming of electric motor 3

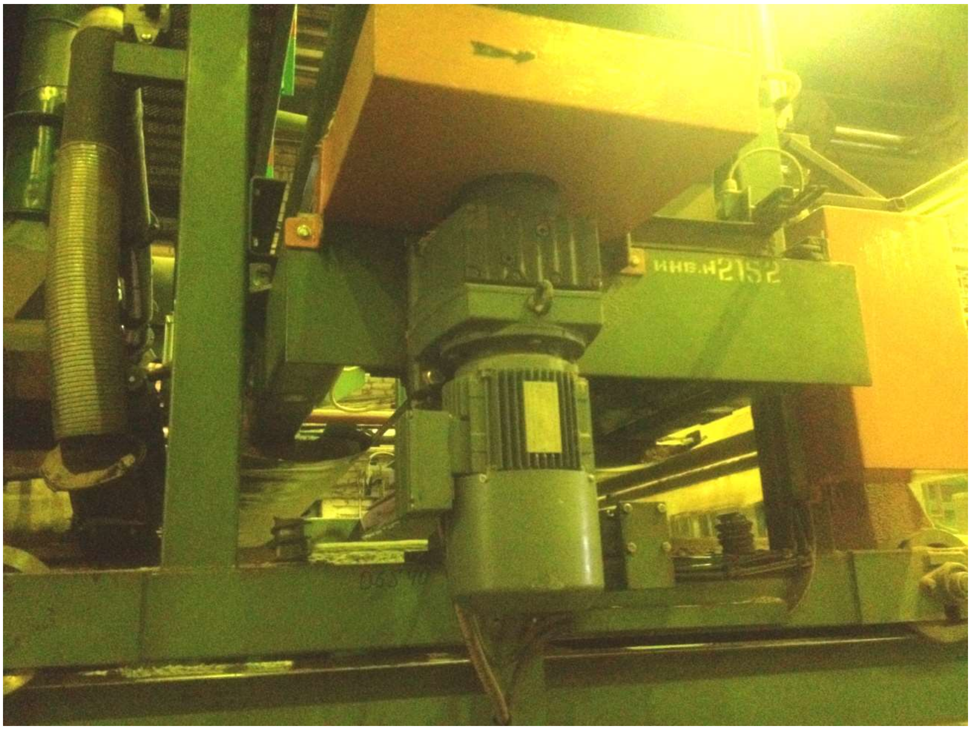

Fig. A.3 – Self drilling motor

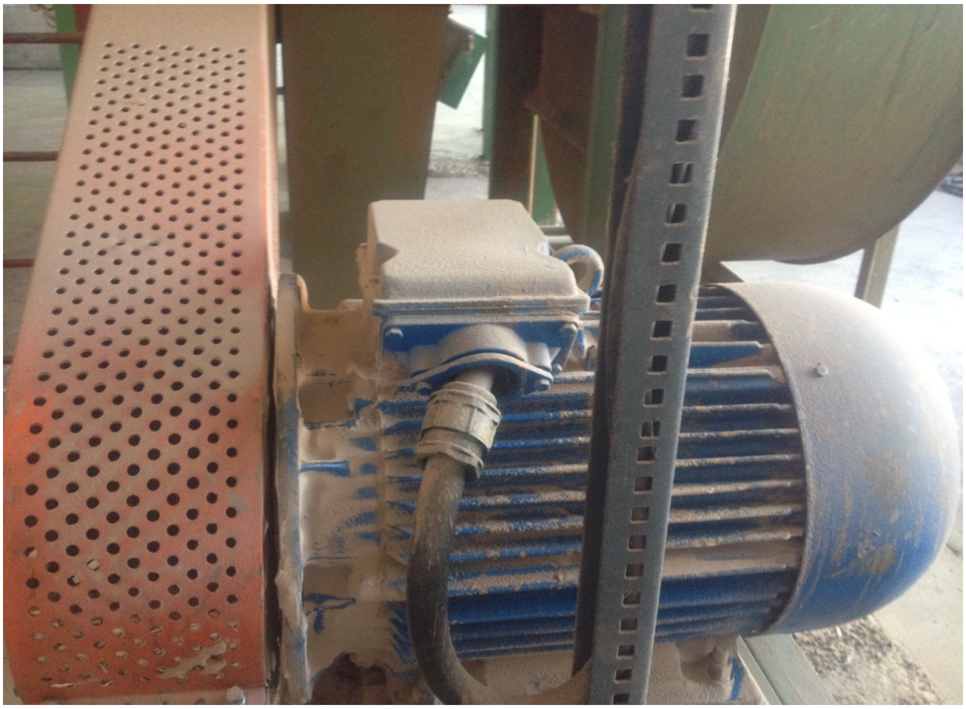

Fig. A.4 - Electric motor of pneumatic classifier

Fig. A.5 - Electric motor of crushing machine

DIAGNOSTICS OF AUTOMATED TECHNOLOGICAL DRIVES

by

Yury NIKITIN, Assoc. Prof. PhD.
Tibor KRENICKÝ, Assoc. Prof. PhD.
Pavol BOŽEK, Dr.h.c. Prof. PhD.

Edition:	1st
Published by:	RAM-Verlag
Number of pages:	148
No. of copies:	120

© Copyright 2022 by RAM-Verlag, D-58515 Lüdenscheid

Publisher:

RAM-Verlag

Stüttinghauser Ringstr. 44

D-58515 Lüdenscheid

Germany

RAM-Verlag@t-online.de

https://ram-verlag.eu

The publisher cannot be held responsible for any linguistic errors in the book: such responsibility is only up to the authors.

ISBN: 978-3-96595-018-4