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A FUZZY LOGIC-BASED MULTI-SENSOR DIAGNOSTIC SYSTEM FOR TRACTION MOTOR BEARINGS IN RAILWAY APPLICATIONS

Summary. This article focuses on the diagnosis of the bearings of the traction motors of electric railway and subway trains. One of the main sources of mechanical failures in a traction motor is its bearings. The failure of traction motor bearings, the factors that cause these failures, and the diagnostic methods for detecting them are investigated. At this time, faults in traction motor bearing monitoring systems are determined only by temperature. In this work, it is proposed to use a system with temperature, vibration, and noise to determine the technical condition of bearings. Such a multi-parameter system, unlike traditional ones, will help determine specific defects at an early stage. The expert system's model, based on fuzzy logic and diagnostic parameters, can accurately predict the likelihood of bearing faults in real-time under changing operating conditions. A fuzzy expert system represents knowledge in the form of fuzzy productions and linguistic variables. The expert system model was developed using the Mamdani fuzzy inference algorithm of the Fuzzy Logic Toolbox package in the MATLAB computing environment. The application of fuzzy logic in generating a knowledge base and inference processes enables the formalization of a process for evaluating technical conditions based on incomplete, faulty, and potentially erroneous information and for making decisions about fault identification.

1. INTRODUCTION

High-reliability indicators of traction motors in locomotives enable the stable operation of the rolling stock under various operating conditions. The primary tasks of diagnosing the mechanical part of traction motors in locomotives are to determine the current state and predict changes in the technical condition of bearing parts based on operating time. In production, the sudden failure of the bearings of the traction motors of locomotives can lead to irreparable consequences.

Research conducted by the Institute of Electrical and Electronics and the Electric Power Research Institute (EPRI) has shown that the majority of faults occur in the rotating parts and the stator (Fig. 1) [1].

Bearing diagnostics is one of the most important aspects of monitoring the technical condition of the internal mechanical components of traction motors (Fig. 2). Failures typically begin with minor defects that grow over time, and it is crucial to identify any defect at the earliest stage to prevent serious damage to traction motors. A technical diagnostics system should include periodic assessments of the technical

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condition of traction motors. It should also resolve problems, identify damage, determine the degree of danger posed by defects, and evaluate the residual life of the equipment.

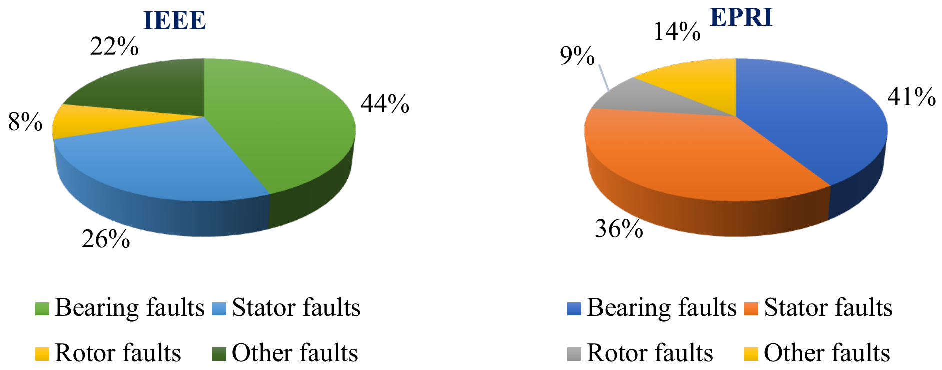

Fig. 1. Overall fault percentage in AC asynchronous motors

2. PROBLEM STATEMENT

The following factors cause bearing failures in traction motors:

- *Mechanical stress* - Overloading, impact of external forces, and vibrations cause physical damage to the bearing components.
- *Installation problems* - The improper installation of bearings on the motor shaft causes uneven load distribution and wear.
- *Contamination* – When dirt, dust, and other particles enter the bearing, it causes abrasion and rapid wear.
- *Lubrication problems* - Insufficient or excessive lubrication and contaminated oils cause defects in bearings.
- *Electrical problems* – Leakage currents cause electrical erosion of bearing surfaces, especially in motors driven by variable frequency drives (VFDs).

According to research, most of the failures are caused by mechanical stress.

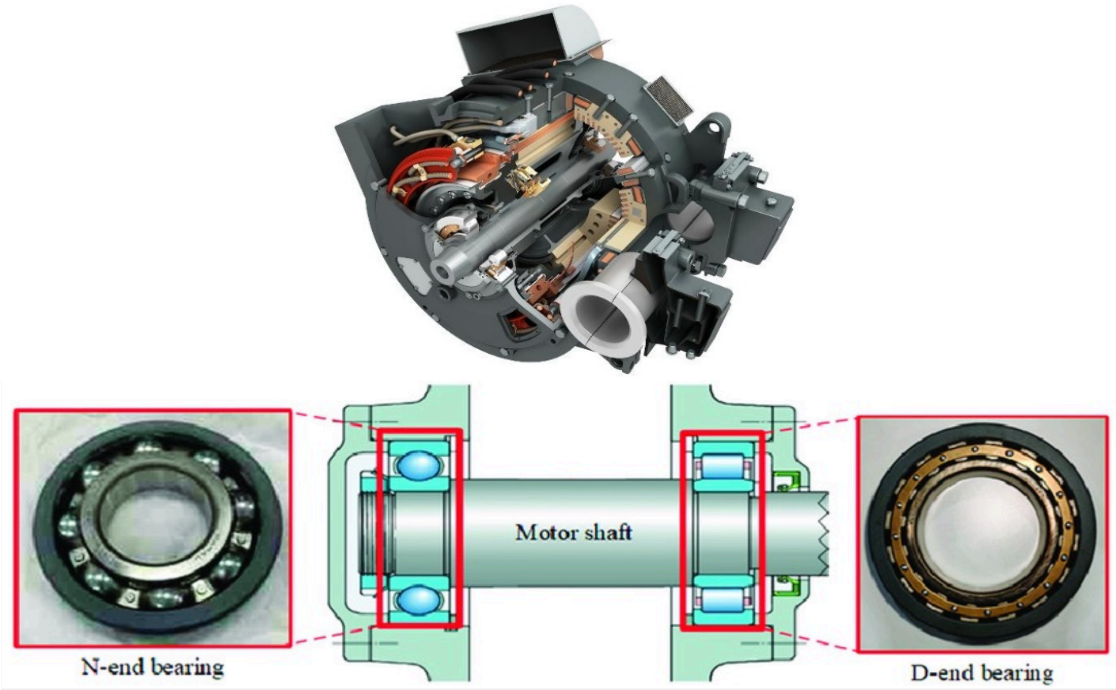

Fig. 2. External view of roller bearing parts used in traction motors

Based on statistical data taken from "Azerbaijan Railways" and "Baku Metro," bearing failures in traction motors were analyzed:

- *Outer ring failures* - Cracks or breaks in the outer ring are caused by excessive radial loads or improper installation.
- *Inner ring failures* - As in the case of the outer ring, these failures are often caused by axial loads or improper installation.
- *Roller faults* - Defects and wear in the rolling elements are caused by contamination, insufficient lubrication, or metal fatigue.
- *Failures in the separator* – These failures are caused by damage to or deformation of the separator that holds the rolling elements, sudden braking at high speeds or a significant moment at the time of starting movement, poor lubrication, or manufacturing defects.
- *Failures related to lubrication* - Insufficient or contaminated lubricant causes increased friction and wear. Poor maintenance or the entry of dirt or water into the bearing will cause failures over time.
- *Faults associated with electrical erosion* - The formation of potholes or unevenness on supporting surfaces due to electrical discharges. Spinning occurs when high-frequency currents pass through the bearings in wide-range variable frequency drives.

The statistics of bearing failures of traction motors are shown in the diagrams below (Figs. 3 and 4) [2].

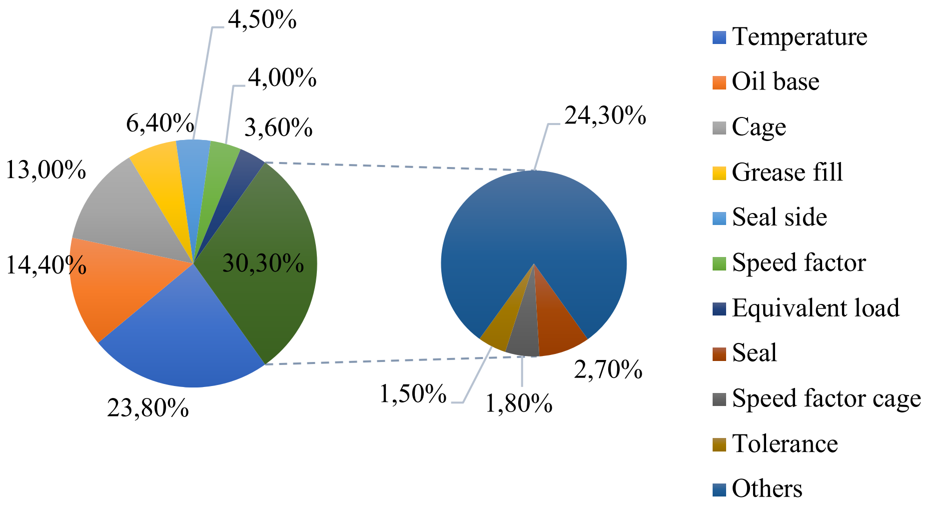

Fig. 3. The impact of specific factors and some aspects of their established interrelated components on bearing life

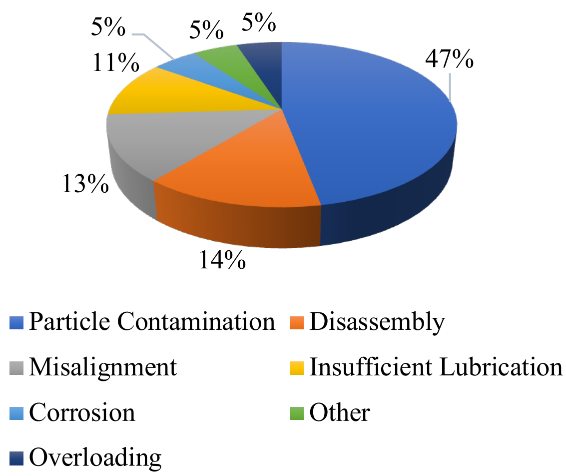

Fig. 4. The main factors affecting bearing failures

According to statistics, failures most commonly occur in the separator and are related to lubrication. The grouping of bearing failures based on the ISO 15243:2004 standard is shown below (Fig. 5).

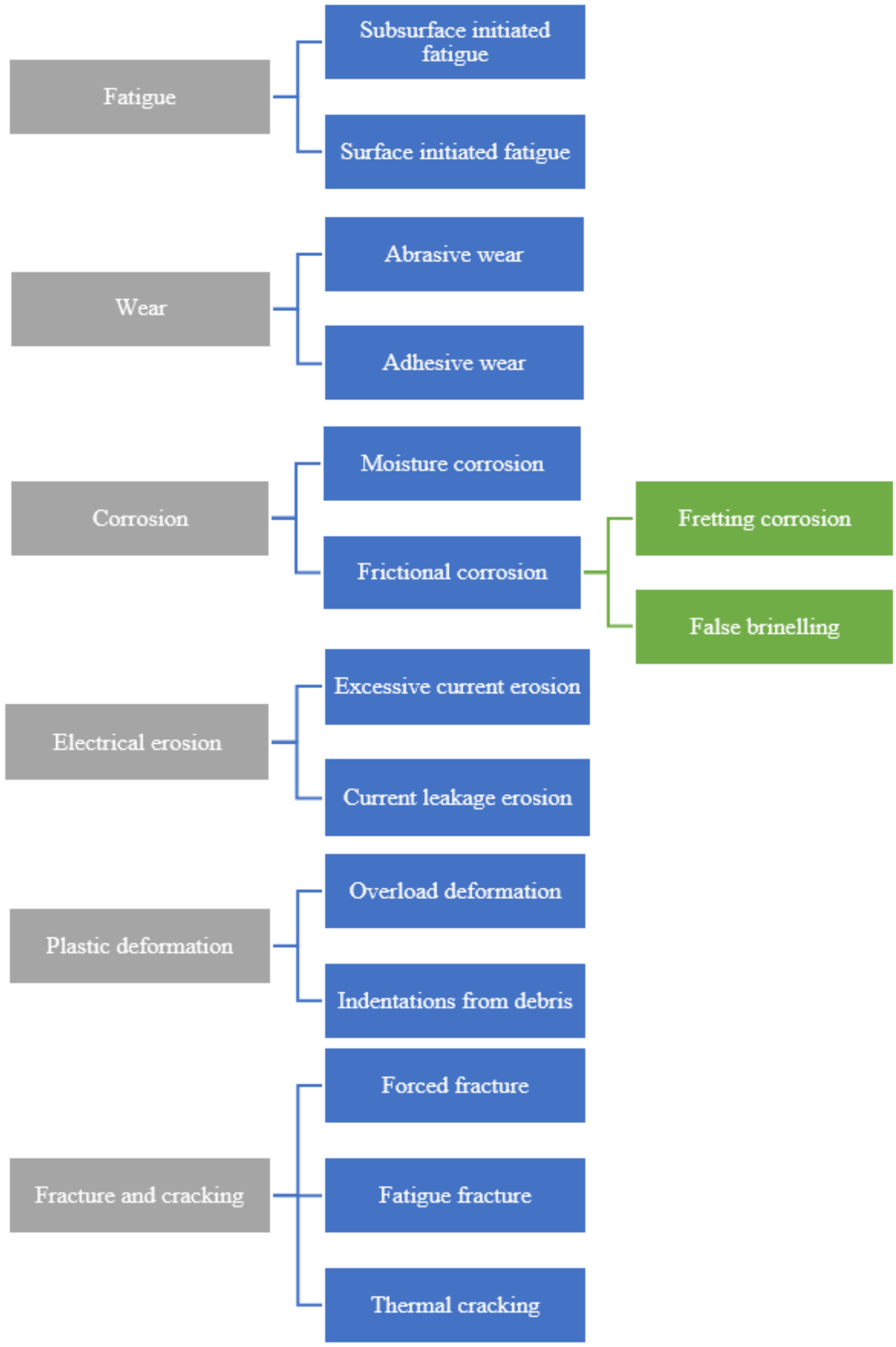

Fig. 5. Grouping of bearing failures according to the ISO 15243:2004 standard

Bearing faults in large traction motors can cause serious problems if not detected and addressed promptly. Currently, only temperature is monitored to detect bearing failures in modern electric traction systems. To build a more accurate diagnostic system, it is necessary to monitor the vibration and noise levels of the bearings in real-world conditions, along with the temperature. For this purpose, an intelligent diagnostic system that controls these three parameters is proposed. This system can detect faults at an early stage, predict their technical condition, and ensure the longevity and reliability of the motor [1–3].

3. PROBLEM SOLVING

In general, in practice, many diagnostic methods are used to detect failures of bearings located in strategic facilities:

- *Vibration analysis.* In this method, vibration signals are monitored to obtain abnormal fluctuations (oscillograms) indicating bearing failures, and then fast Fourier transforms (FFTs) are used to determine the characteristic failure frequencies.
- *Acoustic analysis.* High-frequency acoustic signals caused by bearing failures are obtained. This method is useful for the early detection of defects.
- *Temperature analysis.* Bearing temperature is measured to detect overheating caused by increased friction or lubrication issues. An abnormal temperature rise indicates a bearing failure.
- *Ultrasonic testing.* Ultrasonic sensors are used to detect the high-frequency noise produced by faulty bearings. This method is effective for identifying lubrication problems and defects at an early stage.
- *Electrical signal analysis.* This analysis determines motor electrical signals to identify patterns that indicate bearing failures. This method can be performed when the motor is running.

Analyzing vibrations and noise in bearings in traction motors during operation allows the detection of potential faults at an early stage [4–8].

3.1. Measurement of bearing vibrations and noise level

There are several methods for measuring bearing vibrations and noise levels: *Acoustic emission tests* detect high-frequency acoustic signals generated by bearings and are effective for identifying defects at an early stage. *Vibration analysis* detects abnormalities by monitoring the vibration signals of the bearing. A *stethoscope examination* identifies the noise level of the bearings using a mechanical stethoscope or an electronic stethoscope. Experienced technicians can identify defects based on noise levels. *Noise pressure measurement* indicates the noise pressure level using decibel meters. Abnormalities are identified by comparison with a normal bearing operation. *Ultrasonic tests* detect high-frequency noises of bearings by ultrasonic sensors.

During normal operation, healthy bearings make little noise, and these noises are usually steady. Under conditions of cleanliness, proper lubrication, and proper operation, the normal noise level can reach 70 dB. When there are failures, the noise level in the bearings increases beyond 70 dB, and the noises are variable or unusual (creaking, clicking, humming, etc.). The level of vibration in a normal bearing is around 1–2 mm/s. When there are faults, the vibration level increases above 2 mm/s. This is an indication of mechanical problems.

3.2. Determining the technical condition of the bearings by monitoring temperature

The temperature level of the bearings in traction motors is one of the most important parameters for evaluating the general condition of the bearings and the motor. Temperature analysis is one of the most effective diagnostic methods used to detect and prevent bearing failures. Mechanical damage, lubrication problems, contamination, installation problems, and electrical erosion are among the issues that affect the vibration of the bearings and increase the noise level. Such factors also cause an increase in temperature.

There are several methods for measuring the temperature level of the bearings: *Temperature sensors* measure temperature using temperature sensors (thermocouples or thermistors) installed on the bearings. These sensors are used for real-time temperature monitoring. *Infrared thermometers* measure the surface temperature of the bearings using infrared thermometers or thermal cameras. This is an effective method for quick and non-contact temperature assessments. *Bearing oil temperature measurement* provides bearing temperature information by measuring the oil temperature inside the bearings. Temperature sensors in the lubrication system are used for this purpose.

In healthy bearings, the temperature is usually in the range of 60–90°C. During faults, the temperature level increases and is above 90°C. This is also an indication of many mechanical problems or lack of lubrication.

The vibration and noise analysis and temperature monitoring methods mentioned above are effective in detecting bearing failures at an early stage. It is also possible to increase the longevity and reliability of traction motors by proper maintenance and diagnostics of the bearings.

Table 1

Each of the input parameters has three value ranges for normal and abnormal conditions

Parameters	Value of the parameters		
	low	medium	high
Temperature [ºC]	0–60	60–90	>90
Vibration [mm/s]	0–1	1–2	>2
Noise [dB]	0–30	30–70	>70

4. FAULT DIAGNOSTICS OF TRACTION MOTOR BEARINGS BASED ON FUZZY SET THEORY

The most important application of fuzzy set theory for traction motor diagnostics bearings is fuzzy logic controllers. Their operation is somewhat different from that of conventional controllers. The system is described by expert knowledge rather than differential equations. Fuzzy sets identify linguistic variables that can be used to represent this information.

The general structure of a microcontroller using fuzzy logic consists of a fuzzification block, a knowledge base, a solution block, and a defuzzification block. The fuzzification unit converts clear values measured at the output of bearings into fuzzy values that are described by linguistic variables in the knowledge base. The decision block uses fuzzy conditional (if-then) rules embedded in the knowledge base to transform fuzzy input data into necessary control influences, which are also fuzzy. The defuzzification unit converts fuzzy data from the output of the solution block into a clear value that is used for diagnosis.

A knowledge base created by experts in the field in the form of a collection of fuzzy logic rules of the following format serves as the foundation for the fuzzy decision-making mechanism utilized in multiple expert and control systems [4–10]:

P_1: if x is A_1, then y is B_1

P_2: if x is A_2, then y is B_2

…………………………

P_n: if x is A_n, then y is B_n,

where x is the input variable (levels of temperature, vibration, and noise), y is the output variable (rotation frequency and duration), and A and B are membership functions defined on x and y, respectively. An example of a similar rule: if x is low, then y is high.

Here is a more detailed explanation. The expert's knowledge $A \rightarrow B$ reflects the fuzzy causal relation of the premise and conclusion. Therefore, it can be called a fuzzy relation and denoted by R:

$R = A \rightarrow B$,

where "$\rightarrow$" is called a fuzzy implication. The relation R can be considered a fuzzy subset of the direct product XY of the complete set of premises X and conclusions Y. Thus, the process of obtaining a fuzzy result for the output B' using a given observation A' and knowledge A→B can be represented as the formula B' = A'•R = A'• (A→B), where "•" is the convolution operation introduced above.

Both the composition operation and the implication operation in the algebra of fuzzy sets can be implemented in different ways, although, of course, the final result will vary. In any case, the general logical conclusion is carried out in the following four stages.

1. Fuzziness, sometimes known as "fuzzification" or "fuzziness introduction." The degree of validity of each predicate of each rule is ascertained by applying membership functions specified on input variables to their actual values.

2. Logical conclusion. Each rule's conclusions are based on the truth value that was determined for its premises. As a consequence, each result variable for every rule is allocated a single fuzzy subset. Only the math operations "min" (minimum) and "prod" (multiplication) are often employed as the rules of the logic of inference. The function associated with the result is "cut off" in its logical conclusion min by the height that corresponds to the determined degree of accuracy of the rule's premise (fuzzy logic "And"). The determined degree of truth of the rule's premise is used to scale the function of membership of the logical output in the product inference method of fuzzy logic.

3. Composition. One fuzzy subset for each output variable is created by combining the fuzzy subsets that are allocated to each output variable (in all rules). The algorithms "max" (maximum) or "sum" (sum) are typically employed in such a combination. The max composition uses fuzzy logic (or "OR") to generate the combined result of a fuzzy set as a point-wise maximum across all fuzzy subsets. The sum composition is the process of building the combined result of a fuzzy set as a point-wise sum over all fuzzy sets that the rules of mathematical inference assign to the output variable.

4. Conclusion. Defuzzification, or reduction to clarity, is a technique in which a fuzzy collection of pins is usefully transformed into a clear number [9–20].

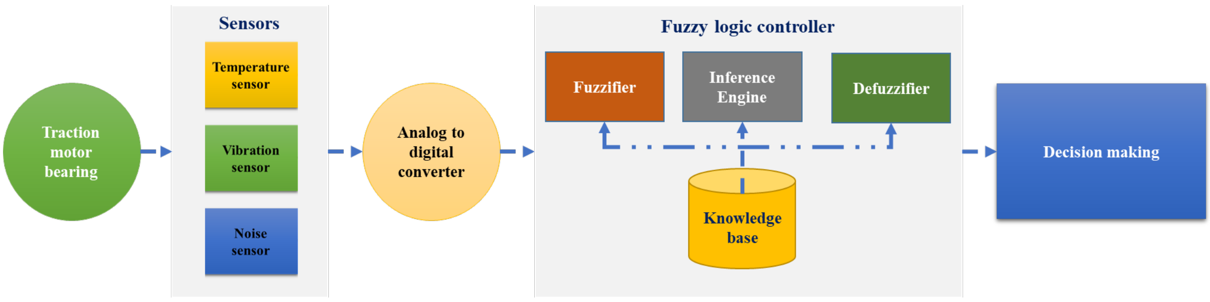

Fig. 6. Block scheme of the fuzzy logic-based bearings diagnostic system of a traction motor

The proposed real-time monitoring system receives analog signals from temperature, vibration, and noise sensors installed in the traction motor bearings and converts and feeds them to the input of a fuzzy logic controller. Based on the values of three diagnostic parameters and using a knowledge base, the controller determines the technical condition (allowable, warning, and dangerous) of the bearings. Such a multi-parameter system, unlike traditional ones, enables the identification of specific defects at an early stage of development (Fig. 6).

To create a model of a fuzzy traction motor diagnostic controller in MATLAB, the user can use the Fuzzy Logic Toolbox package (Fig. 7). We take the temperature, noise, and vibration levels of the bearings in traction motors as input data of the model. Each of the input parameters is divided into three ranges of values according to normal and abnormal conditions: low, medium, and high (Table 1). The frequency and duration of rotation of the bearings are taken as output parameters. Also, we accept three ranges of values for output parameters: low, medium, and high. According to the output parameters, the technical condition of the bearings can be assessed and a decision can be made about their further operation: good or bad. The model is also able to show at what rotational frequency and for how long the bearings can operate in the event of a failure.

In the model, a trapezoidal membership function was used to process the values of the temperature, vibration, and noise levels of the bearings into a fuzzy form. The trapezoid-like function is chosen for the chance that an attribute belonging to the norm is decided by the range of allowable values rather than the variable's value of 1. Fig. 8 illustrates the membership function for input parameters.

After the fuzzification stage, the values of the membership functions for the linguistic terms are determined according to the temperature, vibration, and noise values. These terms are used in rule base conditions for fuzzy output (e.g., parameter n is low, medium, or high). For this, a database consisting of 27 lines was created based on the range of low, medium, and high values of the input parameters (Table 2).

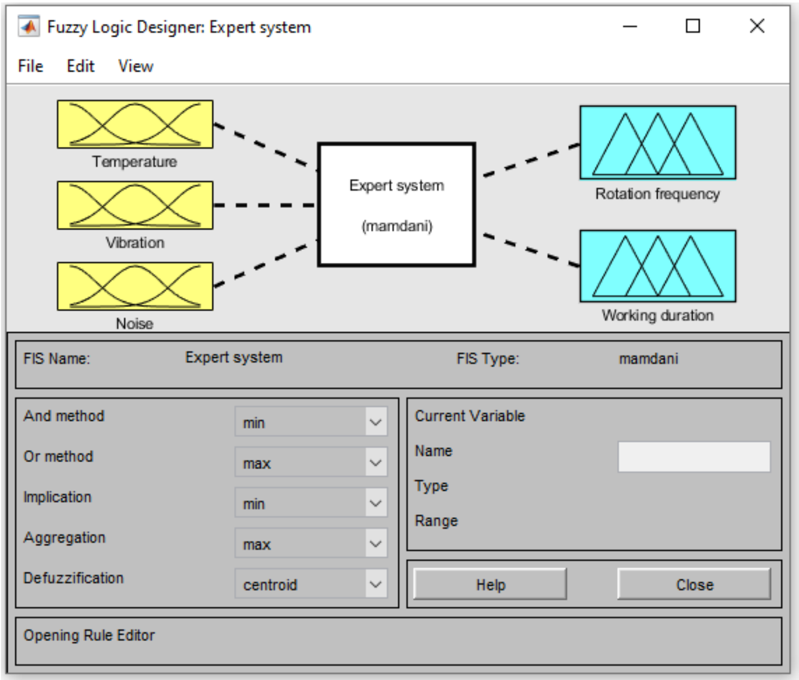

Fig. 7. Block diagram of bearing diagnostics in MATLAB

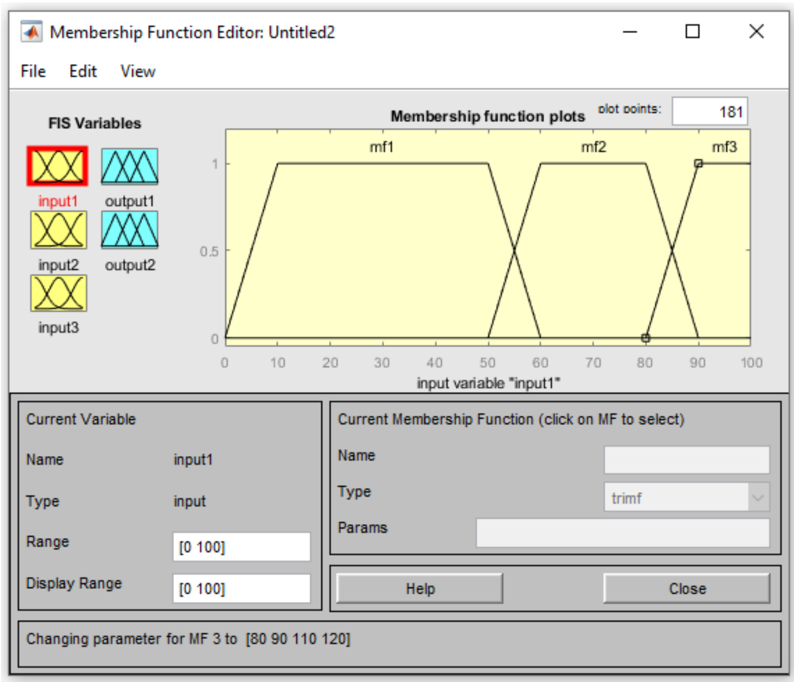

Fig. 8. Membership functions of parameter "temperature" in the window of the editor MATLAB

Causal relationships between parameter values and decision outcomes are formulated as a set of fuzzy logic rules. The format of the base rule of the if-then output is considered a fuzzy implication. For example, if the condition of the rule is “vibration level is medium," "temperature level is medium," and "noise level is medium," the result for this condition can be "long-term use at high rotation frequency is possible." That is, the fuzzy knowledge base of information with the dependence "parameter values" → "decision result" will consist of linguistic rules (Fig. 9): If “the vibration level is high,” “the temperature level is medium,” and “the noise level is medium,” the rotation frequency is low and the operating time should be reduced.

Table 2

Primary knowledge (database)

№	Vibration of bearings	Noise of bearings	Temperature of bearings
1	low	low	low
2	low	medium	low
3	low	high	low
…	………………………………	………………………………	………………………………
9	low	low	medium
10	low	medium	medium
11	low	high	medium
…	………………………………	………………………………	………………………………
25	high	low	high
26	high	medium	high
27	high	high	high

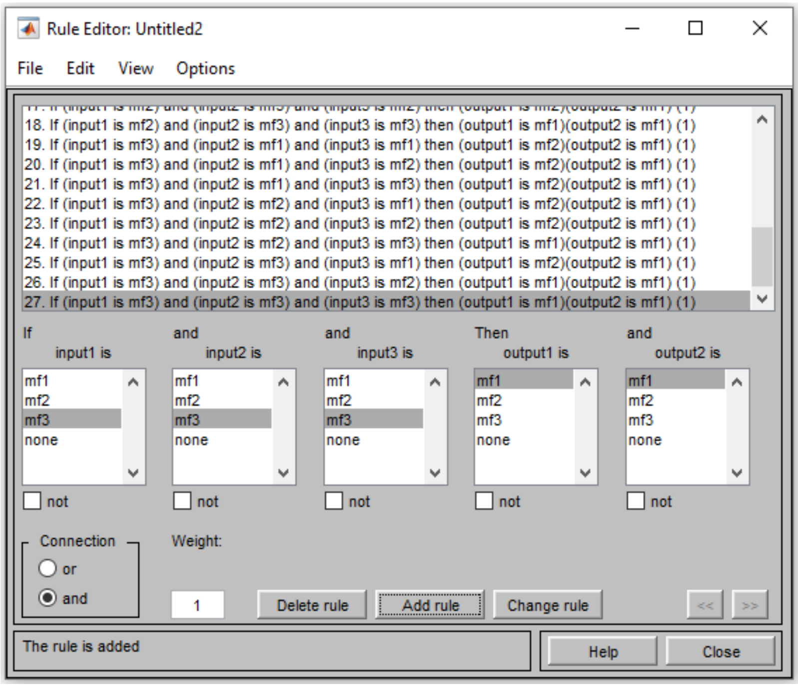

Fig. 9. Window of the editor of rules

Finally, the "2 input - 1 output" surface can be obtained based on the logical decision findings. The surface rotation frequency or operating duration can be calculated based on temperature, vibration, and noise.

Ultimately, according to the results of the logical decision, it is possible to get the “2 input – 1 output” surface. That is, it is possible to obtain the surface of rotation frequency or operating time according to temperature and vibration, according to temperature and noise, and according to noise and vibration.

5. CONCLUSIONS

In order to evaluate the technical state of traction motor bearings, an expert diagnostic system has been developed. Real-time information regarding the traction motor bearings' condition can be obtained by combining diagnostic parameters with the expert system that was built. The system can determine whether the traction motors' bearings are malfunctioning or in good working order based on the vibration, temperature, and noise levels. It can also determine whether the traction motors’ operation should continue.

Fig. 10. Visualisation of fuzzy decision

The system can indicate how long (working duration) and at what rotation frequency the bearings can be used in the event of a problem. Such a multi-parameter system, unlike traditional systems, enables the identification of specific defects at an early stage of development. Analyzing modifications to their operational characteristics is another option. This helps you avoid emergencies while the machine is operating by enabling you to anticipate when maintenance and repairs will be needed. An expert bearing diagnostic system was developed using a model that was implemented using the Fuzzy Logic Toolbox package.

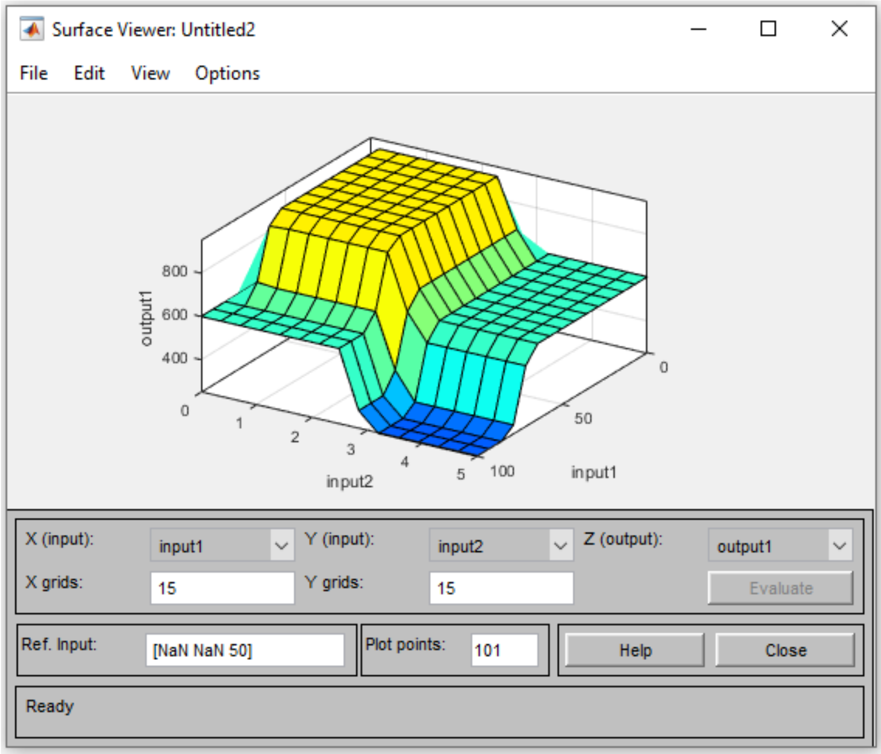

Fig. 11. Surface based on the synthesized “2 input, 1 output” parameter

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