CONTRIBUTION TO DIAGNOSTICS OF ASYNCHRONOUS MOTORS

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Asynchronous motors are a frequent power member of electric drives. In engineering practice their reliability is important. Although the available literature indicates a high reliability of these machines, in many applications reliability needs to be monitored and evaluated. A significant role in this process occupies technical diagnostics. Engineering practice knows a considerable amount of diagnostic methods; for our purposes, the important ones are the following: vibration and noise diagnostics, thermodiagnostics, electrodiagnostics, etc. The results of diagnostics can be evaluated in different ways; the present paper demonstrates the use of fuzzy expert systems, in particular it deals with a partial problem related to the application of vibration diagnostics. Based on the measurement of values of vibrations of the experimental stand, its fault has been clearly identified.

KEYWORDS

diagnostics, asynchronous motor, electric drive, expert system, fuzzy expert system, fuzzy subsystem, angular misalignment

1 INTRODUCTION

Asynchronous motors are the most widely used machines in engineering practice as a drive unit e.g. for pumps, fans, compressors, cranes, elevators, machine tools, transportation equipment or aviation. Therefore, monitoring or possible increasing the reliability of asynchronous motors is an important technical issue.

The available literature describes asynchronous motors as quality, highly reliable technical systems. However, on the other hand, these issues are also subjected to extensive debates, especially in connection with deployment of the above mentioned machines in severe environments (e.g. belt conveyor drives for transporting coal and tailings) or in plants with high demands on reliability (aviation, rail and city traffic) where the elimination of drive operation can have considerable secondary consequences.

Figure 1 shows one of the examples of the use of asynchronous motors in industrial practice.

When discussing the quality of engineering systems, it is important to know what the concept of quality means. The quality is characterized by a degree of compliance of the requirements and a set of inherent features; these are e.g. functional, safety, environmental, ergonomic and also reliability features. For our case, particularly important features are those of reliability, which is a subject of scientific discipline called reliability.

Reliability in a broad sense is understood as the stability of the utility properties of the object over the specified time and under specified conditions of use. In individual cases it is expressed by "sub-properties" such as durability, storability, reliability, maintainability, maintenance assurance, repair ability, diagnostics, and possibly also safety.

Figure 1. The use of asynchronous motors in belt conveyor [Svoboda 2015]

This article is devoted to diagnostics. Diagnosing the fault condition is a set of operations carried out for the purpose of fault detection, localization of defective part and identification of fault; it is an identification of current state of the monitored object.

Using of diagnostics increases the system reliability. The technical diagnostics is based on non-destructive and non-dismantling methods and uses the symptoms of faults, i.e. a change of output parameters of diagnosed objects and accompanying variables. A combination of the output values constitutes a fault symptom [Jaksch 2011].

Currently, the issues of diagnostics are often very complex, not only as for the choice of suitable diagnostic methods, tools, etc. Moreover, it is not any more sufficient when evaluating the application results, e.g. of mathematical statistics, or other similar methods. A choice of new procedures is coming to the forefront. One of them is the use of artificial intelligence, such as artificial neural networks, fuzzy logic and expert systems [Nikitin 2010].

2 USE OF FUZZY SET THEORY IN ENGINEERING DIAGNOSTICS

In engineering diagnostics, it is usually not always possible to unambiguously determine the exact boundary between the fault and operable condition. If we diagnose a more complex object, there is no clear mutual visualisation between diagnostic variables, classes of faults and corresponding diagnoses. Classes of faults can overlap when the same values of diagnostic variables correspond to different diagnoses. In this case, the theory of fuzzy sets can be used to determine the technical condition of diagnosed object [Jaksch 2011].

In practice, fuzzy sets have become the most common way of formalizing the uncertainty of natural language words. In the case of complex diagnosed subjects with a plenty of diagnosed parameters for which it is not possible to accurately determine their interrelations, using the fuzzy theory is necessary [Jamrichová 2011]. For complex multiparametric diagnostics, the use of fuzzy expert systems is appropriate.

Generally, expert systems are computer programs simulating decision-making activities of an expert in solving complex tasks using appropriately coded, explicitly expressed special knowledge, taken from an expert, in order to achieve a quality of decision-making at the expert level in the chosen problem area.

This article addresses only the issues of a fuzzy subsystem as part of a fuzzy expert system as shown in Figure 2. This is used for actual diagnostics, i.e. a module of actual diagnostics is developed.

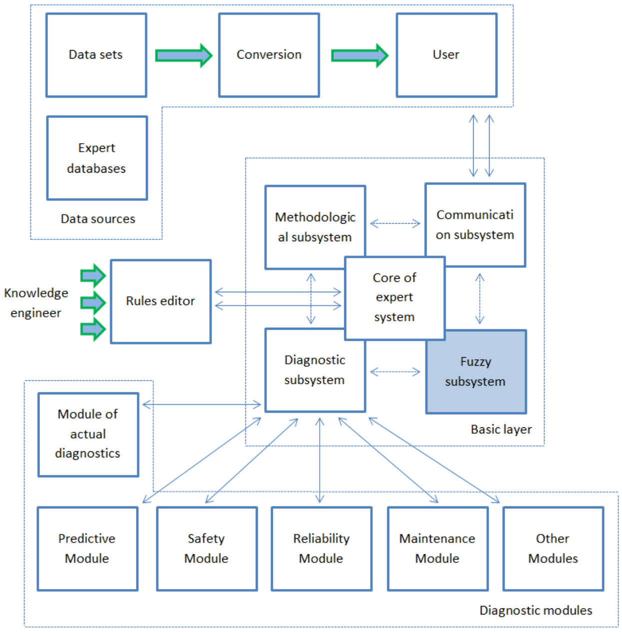


Figure 2. Block diagram of fuzzy expert system

The article uses the fuzzy subsystem, which is composed of blocks of according to Figure 3; these are briefly described below.

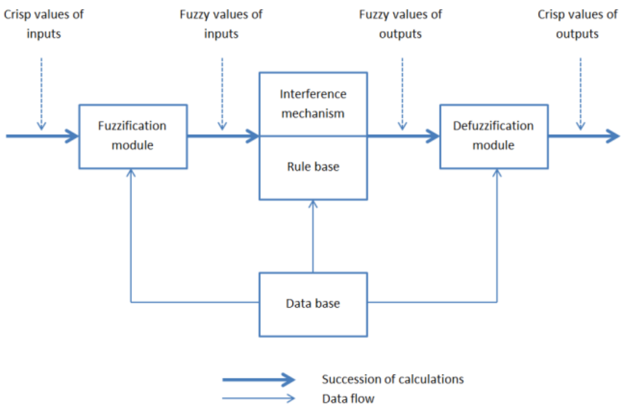


Figure 3. Block diagram of fuzzy subsystem [Hammer 2009]

A fuzzification module provides a conversion of crisp values to fuzzy set. It is a conversion of the input data loaded with uncertainties into fuzzy sets defined by specific features of membership. For specification of fuzzy set, it is necessary to determine its membership function. If it is possible to somehow quantify the values of quantities expressed verbally, it is necessary, as the first step, to transform the specific values into the so-called normalized form (i.e. the closed interval 0-1). The next step is then to assign each crisp value with a degree of membership into one or more fuzzy sets, which correspond to the basic terms. Here it is necessary to completely cover the entire normalised universe with standardized carriers of selected individual fuzzy sets. It is followed by determination of specifically used membership functions

The role of inference mechanism is to gradually evaluate all rules and aggregate their results into a single fuzzy set. For the given fuzzy facts, the assumptions of fuzzy rules of the system, which best correspond to these facts, are searched for and the implications of these facts are derived in the form of fuzzy sets. Generally, the results of inference operation are several fuzzy sets, which represent fuzzy sets of implications of used rules.

A rule base and data base are collectively referred to as the knowledge base of fuzzy system. The data base contains the data on fuzzy sets of all variables in the system. The rule base contains all the rules of the fuzzy system.

The role of defuzzification module is to obtain a crisp value from the given fuzzy set. This is a conversion of the result of decision making, which we receive in the form of fuzzy set, into a specific unambiguous numerical value [Hammer 2009].

To evaluate the technical condition of the drive, a diagnostic fuzzy subsystem was developed using the tool Fuzzy LogicToolbox of MATLAB programming environment.

A fuzzy set theory allows us to mathematically describe vague concepts and work with them. Provided that it is not possible to determine the exact boundaries of the class determined by a vague concept, we can substitute the decision about membership or non-membership of the given member into the class by a degree selected on a defined scale. Then, each member is assigned a degree expressing its position and role in this class on the organized scale.

A linguistic variable is the fundamental unit representing knowledge, whose values are words or phrases of natural or artificial language. The rule base, established by authors, has nine linguistic variables representing the amplitude of mechanical vibration rate at the first, second and third speed frequency of the drive in the direction of axes X, Y, Z. Each linguistic variable has two linguistic values: L - low level, H - high level.

For both linguistic values of L and H, it was necessary to choose the membership function. The s-function and the z-function were selected because these functions are the most often used functions to represent fuzzy sets, which characterize the uncertainties of the "low level", "high level". Membership functions were chosen by the direct method, which is subject to the possibility of measuring the input data in a quantitative scale [Leonenkov 2005].

Linguistic variables are processed using fuzzy statements. The structure of the statement is formed by the linguistic variable and the value of this variable, which is verbal, not numerical. These statements are usually interconnected using logical operators AND, OR, thus forming the resulting fuzzy statement, which is a prerequisite for the following rule:

IF (fuzzy statement) THEN (fuzzy statement).

This rule is an implication, but not crisp; it is a fuzzy implication. Its result is called the consequent (conclusion). The resulting decision represents an aggregation of the results from all the fuzzy rules.

As noted above, diagnostic parameters are the amplitudes of mechanical vibrations rates at multiples of speed frequencies of the drive in the direction of axes X, Y, Z. The most important information on the technical condition of the drive is mainly associated with the amplitudes of vibrations at the first three speed frequencies (nine diagnostic parameters).

The number of rules is defined by the following formula:

$$R = s^n \qquad (1)$$

where R is the number of rules in the base, s is the number of linguistic values, n – the number of diagnostic parameters.

When designing a fuzzy system, it is necessary to expect that an increase in the number of diagnostic parameters will considerably increase the number of rules in the base.

A model of drive diagnostics has been implemented in Matlab software and its toolbox Fuzzy Logic. As a basis of fuzzy system evaluation of drive technical condition, we selected the algorithm of Mamdani fuzzy inference, i.e. the consequent of each rule contains a fuzzy statement:

$$IF\ (p_1 = P^{jr}_1)\ AND \dots AND\ (p_n = P^{jr}_n)\ THEN\ (q_1 = Q^{jr}), \dots ,(q_n = Q^{jr})$$
$$r = 1,2,\dots,R. \qquad (2)$$

where $p_1, p_2, \dots p_n$ – diagnostic parameters, j indexes the fuzzy sets, r is the rule number, $q_1, q_2, \dots q_n$ – output variables, R is a total number of rules in the formula (1).

The input crisp value of p_i is fuzzified; i.e. fuzzy sets P are formed. These input fuzzy sets indicate the output fuzzy sets Q on the output of each fuzzy rule. The results of all rules are aggregated into the resulting fuzzy sets Q that are defuzzified by COG method (Center of Gravity). This method, also often called the method of Center of Area (COA), is one of the most common methods. As the name suggests, the crisp value of variable is determined as coordinates of center of gravity [Leonenkov 2005].

A set of fuzzy rules R approximates the system whose output q defines the condition of diagnosed object depending on the values of input diagnostic parameters.

Determination of a degree of membership of probability of faults to low, medium or high level is shown in Fig. 4.

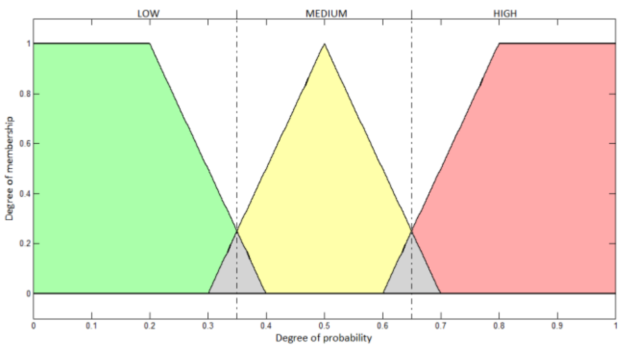


Figure 4. Function of membership of output values.

3 EXPERIMENTAL STAND

To verify the theoretical conclusions from the previous chapter, an experimental stand (Figure 5) was designed and built up, consisting of two three-phase asynchronous motors of company Siemens (power - 4 kW, speed - 2930 rpm, voltage - 400 V, current - 8.1 A), interconnected by a flexible coupling.

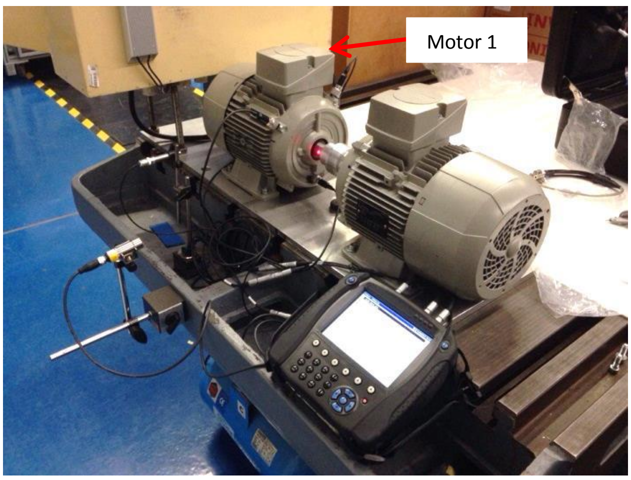
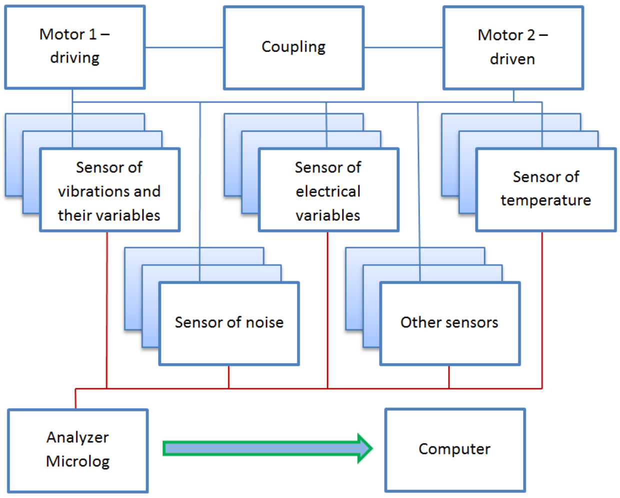


Figure 5. Experimental stand

A block diagram of the stand with a system of sensors is shown in Figure 6.

To evaluate the technical condition of the experimental stand by the methods of vibration diagnostics, we used the instrument



Micrlog CMXA-48 – a four-channel analyzer, allowing you to perform an advanced analysis of measured

Figure 6. Block diagram of experimental stand

data, including their processing in the appropriate software (Figure 7).

Figure 7. Analyser Micrlog CMXA-48 [SKF 2015]

Vibration measurement was performed on non-rotating parts of the motor 1 at speed frequency of 50 Hz.

Measurements were performed only for the described operating mode. Different modes were not considered.

To measure vibrations, we used a set of three accelerometers with a frequency range from 0.5 to 10 000 Hz (Figure 8) [SKF 2015].

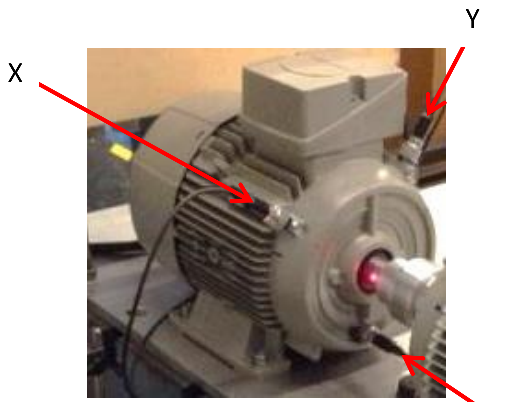


Figure 8. Mounting of accelerometers on the motor 1

Accelerometers were mounted at specially designed measuring points in the directions of axes X, Y and Z by means of magnets (Figure 8).

4. VERIFICATION OF CREATED FUZZY SUBSYSTEM

A fuzzy subsystem was created in the MATLAB program; this subsystem is capable of evaluating the technical condition of the experimental stand to differentiate the following failures:

A - imbalance, soft foot;
B – mechanical looseness, resonance, rotor galling;
C - bent shaft;
D - angular misalignment;
E - parallel misalignment.

When measuring the stand vibrations, the obtained data were subsequently loaded and processed in the created fuzzy subsystem in the form of block diagram in Figure 9.

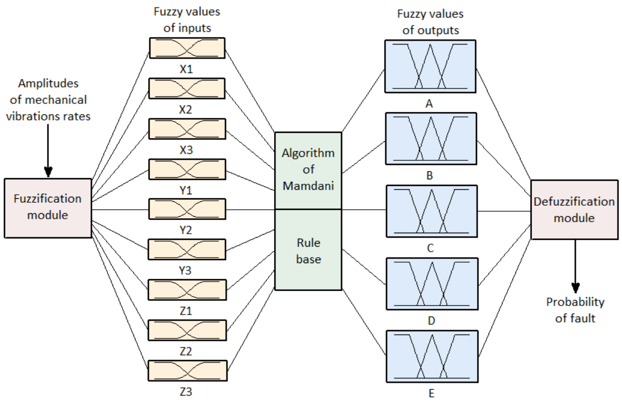


Figure 9. Block diagram of created fuzzy system.

Linguistic variables x_1, x_2, ... z_3 represent input fuzzy values. To use these nine linguistic variables, we created, using the operator AND, 512 rules, which represent a partial evaluation of the technical condition of experimental stand depending on the values of amplitudes of mechanical vibrations rates. As an example of created rules, the rule identifying the angular misalignment is referred to:

If ($x_1$is L) and (x_2 is L) and (x_3 is L) and (y_1 is L) and (y_2 is L) and (y_3 is L) and (z_1 is H) and (z_2 is H) and (z_3 is H) then (A is L) and (B is L) and (C is L) and (D is H) and (E is L).

where: x_1, x_2, x_3 are the amplitudes of mechanical vibrations rates at the first, second and third speed frequency in the direction of X axis;
y_1, y_2, y_3 are the amplitudes of mechanical vibrations rates at the first, second and third speed frequency in the direction of Y axis;
z_1, z_2, z_3 are the amplitudes of mechanical vibrations rates at the first, second and third speed frequency in the direction of Z axis;
A is L – low level of probability of occurrence of fault of type A,
D is H – high level of probability of occurrence of fault of type D.

The above rule is a specific form of summarising the information from the external database for the correct procedure in order to detect the angular misalignment using methods of vibration diagnostics (omitting the information on the measured vibration phase).

Figure 10 shows the frequency spectra of vibration rates in the X, Y and Z axes, which were measured on the experimental stand when creating the angular misalignment of motors. The figure shows that the current technical condition of the experimental stand can be characterized by the presence of significant axial vibrations (which were in the antiphase with a difference of approximately 180 º). Vibration rates in the X and Y axes are much lower.

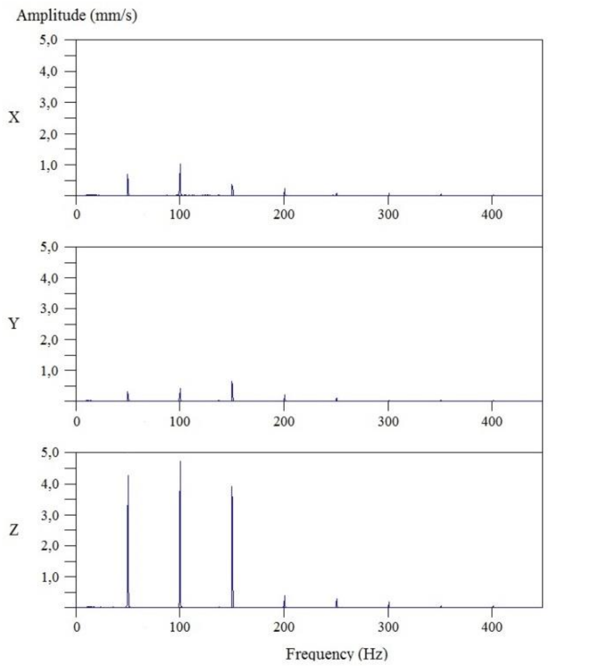


Figure 10. Spectrum of mechanical vibration rate in the X, Y, and Z axes.

Table 1 shows the values of amplitudes of vibration rates from the spectra in Figure 10.

Axis	Amplitude of vibration rate at 1st speed frequency, mm/s	Amplitude of vibration rate at 2nd speed frequency, mm/s	Amplitude of vibration rate at 3rd speed frequency, mm/s
X	0.73	1.16	0.47
Y	0.31	0.34	0.63
Z	4.26	4.79	3.97

Table 1. Values of amplitudes of vibration rates.

After processing the collected data in the created fuzzy subsystem, the technical condition of the experimental stand was evaluated in terms of Figure 11.
Based on Figure 11, we can hypothesize that the examined experimental stand probably has an angular misalignment (probability of fault is high i.e. 0.8469).

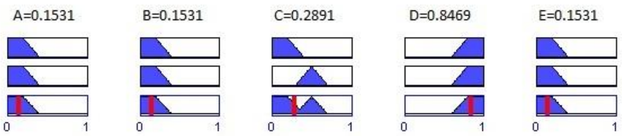


Figure 11. Results of the evaluation of drive technical condition at angular misalignment in the MATLAB product.

As the representation of the result of analysis in MATLAB environment is less illustrative for a less experienced user, a new graphical interface was designed and created - Figure 12.

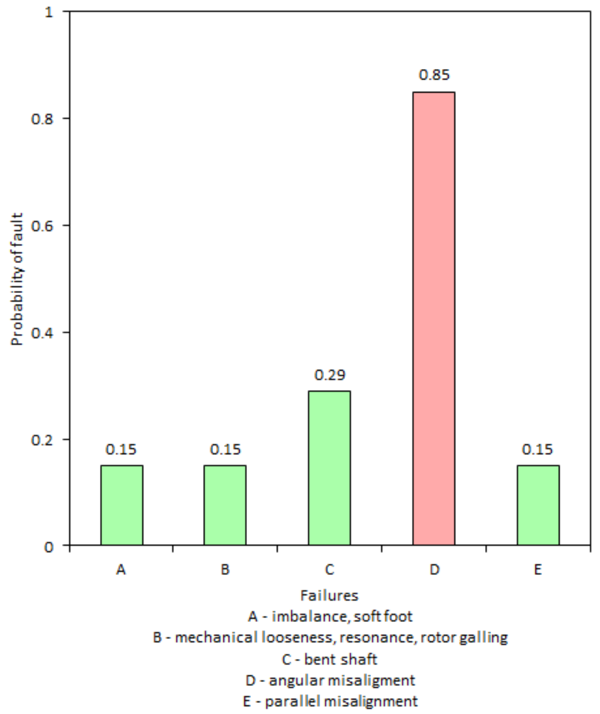


Figure 12. Results of evaluation of technical condition of experimental stand at angular misalignment in graphical form.

According to Figure 12, using Figure 4, we can state the following:

- Probability that the experimental stand is unbalanced, has a soft foot, mechanical looseness, increased resonance, motor galling, a bent shaft or possibly parallel misalignment is relatively low (0.15 to 0.29),
- Probability that the experimental stand has an angular misalignment is high (0.85).

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CONCLUSIONS

The article is a contribution to the diagnostics of asynchronous motors. It describes modern approaches that are based on the theory of fuzzy expert systems; a fuzzy expert system was defined in a novice manner. Within this system, the possibility of practical applications of the created fuzzy subsystem based on the analysis of the results of vibration diagnostics was indicated and verified. This subsystem is capable of evaluating the technical condition of the experimental stand in order to differentiate five types of faults. It was confirmed that a major constraint for its widespread use in practice is a significant increase in the requirements for computing performance related to the growth of the assessed variables. Despite this fact, the proposed solution seems to be beneficial because it shows one of the ways for diagnostics of asynchronous machines. In future, it will be necessary to focus on the use of measurement results of other diagnostic variables and search for the options how to reduce a task scope using the appropriate mathematical or other methods. Similarly, within the use of expert systems, it will be highly recommended to focus on the examination and creation of other modules, such as e.g. a prognostic diagnostic module, a maintenance module, etc. This way of creating the fuzzy expert system could in future allow a proper evaluation of the technical condition of equipment and machines even by less experienced professionals.

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