Noaniq mantiq asosida asinxron motorlardagi asosiy nuqsonlarni aniqlash

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Dolzarblik: noaniq xulosa chiqarish yondashuvining kengaytmasi asenkron mashinalarning nosozliklarini diagnostika qilish uchun taqdim etiladi, ular ommaviy ishlab chiqarish jarayonida sinovdan oʻtkaziladi. Simulyatsiyaga asoslangan uchta yondashuvning samaradorligini qiyosiy oʻrganish ham taqdim etilgan.
Maqsad: qaror modeli parametrlarini moslashtirish uchun funktsional bogʻliqlik va oʻz-oʻzini oʻrganish yondashuvidan foydalangan holda, indüksiyon mashinalarining malaka parametrlari asosida qarorlar qabul qilish orqali jarayonni qoʻllab-quvvatlash usuli muhokama qilinadi. Taqqoslash uchun ishlab chiqilgan noaniq diagnostika tizimi va an'anaviy yondashuv natijalari ham taqdim etiladi.
Usullar: noaniq mantiqdan foydalangan holda asinxron mashinalarda nosozliklarni diagnostika qilishning tegishli yondashuvi bir nechta vazifalarni bajarishni oʻz ichiga oladi: oʻlchov natijalarini (yuksiz va qisqa tutashuv rejimlarida oqim va quvvat) an'anaviy domendan noaniqga aylantirish; ma'lumotlarni qayta ishlash va qaror qabul qilish; va noaniq holatdan noaniq holatga teskari transformatsiya. Ushbu muammoni hal qilish uchun biz elektr motor parametrlarining ikki guruhi oʻrtasida noaniq munosabatlarni ishlab chiqdik. Birinchi guruhga texnologik omillar va oʻlchangan elektr parametrlari kiradi. Boshqa guruh mahsulot sifati parametrlaridan iborat.
Natijalar: Ushbu yondashuv asenkron mashinaning chiqish ma'lumotlaridagi ogʻishlarga ta'sir qilgan dizayn va texnologik omillarni (oʻlchovlar, material) aniqlash imkonini beradi.
Kalit soʻzlar: noaniq mantiq, asinxron motor, oʻlchov natijalari, texnologik omillar, sifat parametrlari, qaror qabul qilish modeli

Определение дефектов асинхронного двигателя на основе нечеткой логики

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Актуальность: представлено расширение подхода нечеткого вывода для диагностики неисправностей асинхронных машин, которые проходят испытания в ходе их массового производства. Также представлено сравнительное исследование эффективности трех подходов на основе моделирования.
Цель: обсуждается метод поддержки процесса путем принятия решений на основе параметров квалификации асинхронных машин, применения функциональных зависимостей и самообучающегося подхода для настройки параметров модели принятия решений. Для сравнения также представлены результаты разработанной нечеткой диагностической системы и традиционного подхода.
Методы: соответствующий подход к диагностике неисправностей асинхронных машин с использованием нечеткой логики предполагает выполнение нескольких задач: преобразование результатов измерений (тока и мощности в режимах холостого хода и короткого замыкания) из традиционной области в нечеткую; обработка данных и принятие решений; и обратное преобразование из нечеткого состояния в нечеткое. Для решения этой задачи нами разработаны нечеткие соотношения между двумя группами параметров электродвигателя. Первая группа включает технологические факторы и измеряемые электрические параметры. Другая группа состоит из параметров качества продукции.
Результаты: данный подход позволяет определить конструктивные и технологические факторы (размеры, материал), повлиявшие на отклонения выходных данных асинхронной машины.
Ключевые слова: нечеткая логика, асинхронный двигатель, результаты измерений, технологические факторы, параметры качества, модель принятия решений

Definition of asynchronous motor defects based on fuzzy logic

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Relevance: there is an extension of the fuzzy inference approach for troubleshooting asynchronous machines that are being tested during their mass production. A comparative study of the effectiveness of the three approaches based on simulation is also presented
Aim: a method of supporting the process by making decisions based on the qualification parameters of asynchronous machines, the application of functional dependencies and a self-learning approach to configure the parame-

ters of the decision-making model is discussed. For comparison purposes, the results of the developed fuzzy diagnostic system and the traditional approach are also presented.
Methods: an appropriate approach to asynchronous machines fault diagnosis using fuzzy logic involves performing several tasks: converting measurement results (current and power in idle and short-circuit modes) from the traditional domain to the fuzzy one; data processing and decision making; and reverse transformation from the fuzzy state to the non-fuzzy one. To solve this problem, we have developed fuzzy relations between two groups of electric motor parameters. The first group includes technological factors and measured electrical parameters. The other group consists of product quality parameters.
Results: this approach allows you to determine the design and technological factors (dimensions, material) that influenced the deviations of the asynchronous machines output data.
Keywords: fuzzy logic, asynchronous motor, measurement results, technological factors, quality parameters, decision-making model.

1. Introduction

Trends in energy development are reduced to increasing the level of intellectualization, i.e. the use of active adaptive control and monitoring. Active adaptive control allows automation to generate and issue control actions based on current circuit conditions. It is implemented through digitalization, which involves the transition from analog measuring equipment to digital, continuous updating of the array of data on the operating parameters and the composition of the consumer's equipment. Intellectualization allows obtaining energy systems formed according to the Smart Grid concept, which makes it possible to solve a number of problems related to restrictions on their operating modes [1]. In particular, the tasks of monitoring start and stable operation of powerful asynchronous motors. To determine the critical states of an asynchronous motor, up-to-date information on its electrical parameters is required. It should be noted that its use allows taking into account the change in electrical parameters both during operation and during production, associated with the phenomenon of magnetic circuit saturation, temperature change, insulation aging, equipment repair, and also to avoid the use of passport data, which most often indicate the average parameters of the entire series, and not a specific unit of equipment. Currently, to determine the electrical parameters of an asynchronous motor, no-load and short-circuit tests are used, as they have the greatest accuracy. These methods are not suitable for systems formed according to the Smart Grid concept, because require complete decommissioning of the equipment, as well as: the presence of a diagnostic platform, specialized equipment and competent personnel. The use of identification methods will allow obtaining up-to-date information on the electrical parameters of the asynchronous motor without disrupting the operation process, as well as the production process. Thus, it becomes possible to obtain universal approaches that can be used both at the manufacturing stage and at the operation stage.

Identification methods based on the use of the G-shaped equivalent circuit of an asynchronous machine have become widespread. The use of a simplified equivalent circuit of an asynchronous motor leads to [2,3]:

- roughening of the obtained resultsю;
- possibility of determining only static characteristics of the load;
- inability to track trends in changes in a specific electrical parameter of the equipment;
- an important feature of the system is that the behavior of the load in them is described by dynamic characteristics.

These characteristics can be obtained by using the T-shaped equivalent circuit of an asynchronous machine in the calculations. It is worth noting that this equivalent circuit allows tracking the trend of changes in electrical parameters, making it possible to solve the problem of diagnosing an asynchronous machine during operation, but does not make it possible to solve the problem of diagnosing at the stage of the production process. As a result, an identification method is needed that allows determining the electrical parameters of an asynchronous machine in operating modes with an acceptable error. To achieve this goal, the following tasks were formulated:

- development of a method for parametric identification of an asynchronous machine;
- selecting a numerical method for solving over determined systems of equations;
- creating a mathematical model in the Matlab Simulink software package;
- identifying the electrical parameters of an asynchronous machine using signals from the mathematical model;
- evaluation of the results obtained.

To identify the electrical parameters, it is necessary to create a transient mode of the machine operation. It should be noted that the greater the multiplicity of the disturbing effect in relation to the initial mode, the more accurately the electrical parameters of the asynchronous machine will be determined [4,5]. These modes can occur when the mechanical moment of resistance on the motor shaft changes or the network operating mode changes. In this case, the start of the asynchronous machine is used as a transient mode.

Results of parametric identification of the asynchronous machine .

The system of equations can be written for each moment in time of the transient process. For two moments in time, there will be eight equations of the form and five unknowns, which is more than enough to find a solution, but real measurements have an error, as a result of which the resulting over determined system of equations will not have an exact solution.

Using the least squares method, it is possible to determine the parameters of the equation system, and increasing the number of moments in time for which the equations are written will reduce the identification error.

The resulting system of equations is divided into smaller ones, the solutions of which are the desired electrical parameters of the asynchronous machine. The obtained electrical parameters are averaged, and a system of equations is identified that gives the most reliable result.

As is known, the least squares method has a significant drawback, such as the sensitivity of estimates to sharp outliers that occur in the original data. For the unbiasedness of estimates in the least squares method, it is necessary and sufficient to fulfill the most important condition of regression analysis: the conditional mathematical expectation of a random error by factors must be equal to zero. This condition, in particular, is fulfilled if the mathematical expectation of random errors is equal to zero, and the factors and random errors are independent random variables. Based on the above, the most optimal way to solve the tasks is to use artificial intelligence methods, in particular the fuzzy logic method.

AM's are widely used electric machines and, due to their performance, simplicity and relatively high efficiency, they cover almost all electrical and electromechanical drives. The smooth operation of most electromechanical drives depends on the quality characteristics of AM, which is the main element of such drives .In mass production of AMS, a large number of parameters must be monitored and tested. Among the parameters to be monitored, the most important are power factor, efficiency, maximum speed, inrush current, and initial speed, as these parameters reflect a variety of AM faults and defects. It is also important that proper monitoring of the above parameters can detect all types of AM faults.

Because they are difficult to correctly diagnose directly by measuring the output parameters. Non-traditional approaches are required to effectively detect AM faults when testing them in a mass production environment. The main attractive features of the fuzzy approach, such as flexibility, resistance to in accurate data, and expert experience, allow you to create systems that can solve much more complex diagnostic problems at a low solution cost. The application of artificial intelligence procedures based on fuzzy logic to develop a method for monitoring the state and diagnosing faults of asynchronous motors is investigated using a higher-order static analysis [6]. This vibration-based diagnostic system can detect a limited number of defects: rod breakage, rotor eccentricity, and stator short circuit.

Some well-known testing methods [7] are based on a set of inequalities that include interdependencies between measured and standardized (normalized) parameters and are quite complex due to the fact that they include many design and technological parameters. Even more importantly, the above parameters are not stable and change over time, although these parameters are taken into account as constant coefficients. In addition, the measured parameters, such as average power and current, which are estimated for each tested AM, contain certain errors. Consequently, the instability of many design and technological parameters, on the one hand, and measurement errors of control parameters, on the other hand, lead to significant in accuracies in the decision-making process during tests in mass production. Another disadvantage of the traditional approach to AI testing is related to the in adequacy of mathematical models, which is presented as a set of inequalities [8]. Thus, the traditional approach to testing AAI in mass production involves more uncertainty rather than precise mathematical or functional dependencies. The assumed uncertainty of traditional algorithms was confirmed both by analyzing mathematical errors and by experimental studies, including computer modeling, which took into account the influence of all three components (inaccuracy of mathematical models and measurement input data and instability of the so-called constant coefficients). These short comings of the traditional approach have become the main reason for the use of fuzzy algorithms for testing AM in mass production.

2. Methods and materials

An appropriate approach to AM fault diagnosis using fuzzy logic involves performing several tasks: converting measurement results (current and power in idle and short-circuit modes) from the traditional domain to the fuzzy one; data processing and decision making; and reverse transformation from the fuzzy state to the non-fuzzy one. To solve this problem, we have developed fuzzy relations between two groups of electric motor parameters. The first group includes technological factors and measured electrical parameters. The other group consists of product quality parameters.

The fuzzy system includes sensors of measured parameters, a data transmission channel, and data processing units. During the operation of the system, data from the sensor outputs are fuzzified and then sent to the measurement channel. This allows you to use a relatively cheap channel with minimal band width (compared to a traditional channel that transmits a lot of fuzzy data). This is the advantage of a fuzzy approach to data collection. When processing input data, in addition to fuzzy algorithms, an artificial neural network is also used. The use of neural networks allows us to take into account many complex relationships between the groups of parameters mentioned above and predict the technological process of electric motor production.

Another difficult problem when testing an asynchronous machine (s) is its rather low testability. The low testability of AM is due to the difficulties of direct measurement of parameters. There are several ways to improve the testability of AM [3]. One of them is based on the use of built-in additional equipment (for example, sensors) both inside and outside the AM. This method has certain limitations due to the fact that, on the one hand, AM having moving parts, and on the other handй-, in most cases they are operated in difficult conditions. A more promising direction is the developments of algorithms that provide high testability of AM. Advances in information technology provide countless technological improvements in the performance and functionality of test and control systems. They are mainly supported by the rapid development of microcontrollers, which are currently used for electronic control of asynchronous motors in mass production. In addition, there is still a significant increase the functionality and complexity of the system, due the constant demand for increase deficiency and power factor, as well as for reduced energy efficiency and mechanical losses.

3. Results

The main goal of using the neuro-fuzzy adaptive inference (ANFIS) approach is to simplify the process of estimating the parameters of membership functions (MFS). A full description of ANFIS fault diagnosis for AM is given in [9].The approach under discussion allows us to define a decision-making model without having a pre-defined model structure based on the characteristics of system variables. These fuzzy methods provide a fuzzy modeling method for obtaining information about a data set in order to calculate the MFS parameters that best allow the corresponding fuzzy inference system to track the specified input/output data. This training method works similarly to neural networks. Using a given set of input / output data, the MF parameters of the system are adjusted (adjusted) either using the inverse correlation algorithm or in combination with the least squares method.

A diagnostic system of this type is based on mapping input data through input MF and related parameters, and then converting it to output data through input MFs and related parameters. The parameters associated with MFs will change during training. This approach to modeling will work if the training data provided for estimatingпараметров MF parameters fully reflects the features of the training system that is supposed to be modeled.

Due to the fact that in some cases data is collected using noisy dimensions, and the training data may not be representative of all the characteristics of the data that will be presented in the model, the process of changing the model was also carried out. During model validation, input vectors from input/output data sets are passed to the trained model to see how well the system model predicts the output values of the corresponding data set. This verification procedure was performed using both the so-called test data set and the, verification data set. In the proposed approach, the output of the tested AM is measured and compared with the expected output.

The AM measured electrical parameters-currents (I0, Is) and powers (Po, Ps) for the no-load and short-circuit test modes-are used as the AM output. Expected results represent the response of the decision-making model to the measured parameters of the AM being tested. The mathematical model describing the decision-making process duplicates the behavior of AM at the learning stage (Figure).

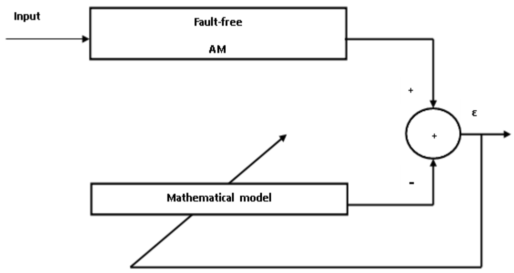

Fig.1. Learning face structure

By the end of the training stage, a decision-making model is created. The decision model is based on a set of inequalities, including the relationships between measurable (I0, Is, P, P0, Ps) Ps and standardized AM parameters. These decision-making models include many design and technological parameters for AM. The mathematical model for the training stage is described as follows [10]:

$$\begin{cases} I_S - k_1 \le 0 \\ I_s - k_2 I_0 - \sqrt{k_3 - (k_4 + k_5 I_0)^2} - k_6 \ge 0 \\ I_0 - \frac{k_7 I_S^2 - k_8}{k_9 I_S - k_{10}} + \sqrt{(\frac{k_7 I_S^2 - k_8}{k_9 I_S - k_{10}} - k_{11})^2 + k_{12}} \le 0 \\ P_S - k_{13} - k_{14} I_S^2 \ge 0 \\ P_0 - k_{15} + k_{16} P_S \le 0 \end{cases} ; \quad (1)$$

where k_1+k_{16}, which are constants in this inequality, reflect the influence of design and technological parameters on the mathematical model, and also include standardized параметры AM parameters.

The training phase, these coefficients (k_1-k_{16}) are adjusted to minimize the error (E). After this training phase, a comparison is made during the testing phase, where decision models are used as reference models and the error signal is measured (Fig.2).

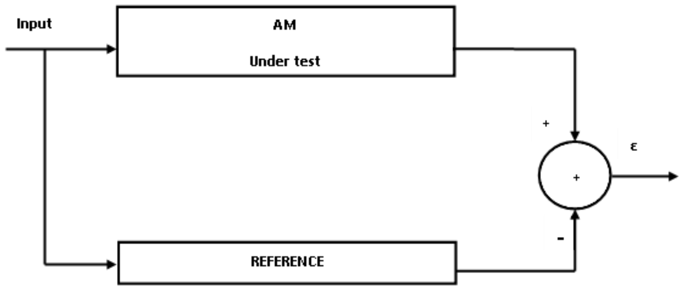

Fig.2. Structure of the testing phase

This error signal increases if the test and reference AM are different. As an adaptive system, the threshold value can determine the permissible discrepancy, as in analog circuit testing systems [11]. At the first stage (training phase), the reference decision model is trained for large permissible deviations for all measured electrical parameters (Io, Po, Is, Ps). Since this type of measurement deviation is used, it is possible to diagnose all types of faults in the AM. Similar to the design sequence of neural systems, the next stage of the AM diagnostic procedure also includes the functioning stage (Fig.3).

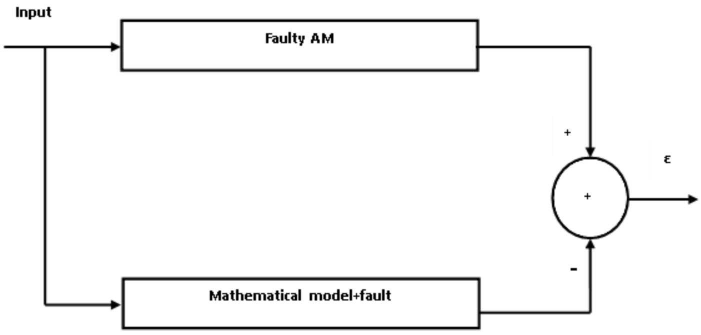

Fig.3. Structure of the functioning phase

This stage is characterized by the introduction of some known errors in the mathematical model of making decisions about reliability. The mechanism of introducing errors is achieved by adding a soft deviation A_k; to the i_{th} coefficient k_i. After introducing a known error into the reference mathematical decision model, its output is compared with the output of the faulty AM model (Figure 3).

If a match is found, a defect is identified that may have caused the failure. Therefore, if the error introduced in the decision-making model is the same error as the one introduced in the decision-making model.

If it affects the tested AM, then both the mathematical model and the tested AM will represent very similar behavior. Thus, when the error output is minimal, the possible location of the error is determined, since the algorithm tracks the components of the above inequalities in which errors are introduced (Ak;). Due to the fact that a combination of sixteen different deviations results in countless output signals, this diagnostic method is able to detect countless faults in the AM under test. Given the complexity of creating an error-based decision model for Ak; deviations, it is preferable to use artificial neural networks in this case.

To identify the electrical parameters, it is necessary to create a transient mode of the machine operation. It should be noted that the greater the multiplicity of the disturbing effect in relation to the initial mode, the more accurately the electrical parameters of the asynchronous machine will be determined [12,13]. These modes can occur when the mechanical moment of resistance on the motor shaft changes or the network operating mode changes. In this case, the start of the asynchronous machine is used as a transient mode.

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4. Discussion

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5. Conclusion

This article presents an approach to the diagnosis of AM, experienced in production and operation. This approach allows you to determine the design and technological factors (dimensions, material) that influenced the deviations of the AM output data. The measured electrical parameters - currents (I0, Is) and powers (Po,Ps) - are used as output data).Modeling of a fuzzy system for diagnostics was carried out using Math Works software products Math Works (Matlab and Simulink), where some parts of the system were modeled and analyzed.

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