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Research article

A fuzzy set theory-based fast fault diagnosis approach for rotators of induction motors

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Abstract: Induction motors have been widely used in industry, agriculture, transportation, national defense engineering, etc. Defects of the motors will not only cause the abnormal operation of production equipment but also cause the motor to run in a state of low energy efficiency before evolving into a fault shutdown. The former may lead to the suspension of the production process, while the latter may lead to additional energy loss. This paper studies a fuzzy rule-based expert system for this purpose and focuses on the analysis of many knowledge representation methods and reasoning techniques. The rotator fault of induction motors is analyzed and diagnosed by using this knowledge, and the diagnosis result is displayed. The simulation model can effectively simulate the broken rotator fault by changing the resistance value of the equivalent rotor winding. And the influence of the broken rotor bar fault on the motors is described, which provides a basis for the fault characteristics analysis. The simulation results show that the proposed method can realize fast fault diagnosis for rotators of induction motors.

Keywords: fuzzy set; fault diagnosis; rotators; induction motors

1. Introduction

With the rapid development of modern science and technology, many intelligent equipment systems have been constantly created and produced, bringing convenience to all aspects of people's lives [1]. In order to provide faster and more convenient service modes, the structure of intelligent systems is becoming more and more complex. The parts that make up the system are becoming more and more interconnected, and the failure of the whole system can be caused by a single subtle event [2]. However, the connection between events is generally random, fuzzy, incomplete and gray, which can be collectively referred to as uncertain [3]. So how to analyze and deal with this uncertain causal knowledge has become a very important issue [4]. As power equipment, the normal operation of an induction motor is an important part of ensuring the safety, high efficiency and low consumption of the production process [5]. Under normal circumstances, the induction motor structure is relatively firm, the service life is relatively long, but under the action of its own and external factors [6]. This will make the motor defects and evolve into faults, shorten the life of the motor, such as the motor itself has some unreasonable structure, causing defects in the manufacturing process [7]. If the fault of the motor can be found in time and the motor can be maintained at the early stage of the fault, the service life of the motor can be extended [8]. For large-scale production systems with continuous processes, it can timely adjust the production planning and motor maintenance, to avoid economic losses caused by motor failure shutdown [9].

The artificial intelligence methods of induction motor rotor fault diagnosis include fuzzy logic, neural network, pattern recognition, expert system, data fusion, etc [10,11]. Based on a large number of historical fault data, the corresponding input/output mapping relationship is established to realize the judgment and classification of motor faults [12,13]. Fuzzy logic reasoning is a process of deducing new fuzzy propositions from known fuzzy propositions according to people's uncertain reasoning mode [14]. It is a kind of uncertain reasoning, which analyzes and solves the uncertain problems in logic by introducing a membership function [15]. The diagnosis method based on fuzzy logic reasoning does not need to establish accurate mathematical model but is realized by establishing an accurate fuzzy programming and membership function [16]. However, for complex systems, due to uncertainty and nonlinearity, accurate fuzzy programming and membership function are also difficult to establish [17]. The method based on fuzzy reasoning can approximate the natural language in fuzzy form. Its approximate reasoning ability has made great progress in application, but the fuzzy logic system lacks self-learning ability and is prone to random and unreliable results [18].

For technical problems and economic concerns, at first, people only focus on large induction motor fault, all kinds of serious measures are to introduce mature reliable relay protection device. However, this method can only be used to prevent the further expansion of accidents and economic losses, because the relay can only operate when the motor has serious faults [19,20]. Instead, it cannot be known and controllable for the production process and motor state. Later, people began to adopt the method of artificial maintenance, through periodic plans to conduct comprehensive maintenance and cleaning work of motor, and the method to discover the motor defects, and prevent serious faults has a certain positive role [21]. Then, people began to study its running state by monitoring the motor running data, and based on the current status to predict the trend of further development, so as to determine the content of the motor repair work and time, which is based on the state of the thought of maintenance and predictive maintenance, implementation method of this kind of thought known as motor fault diagnosis technology [22]. Motor fault diagnosis technology aims to study a variety of intelligent online monitoring, and diagnosis system, to prevent the occurrence of motor faults and timely detection and elimination of faults, ensure the reliable operation of motor, reduce excess maintenance, reduce maintenance costs, improve production efficiency, has very important economic and social significance.

This paper discusses how to use fuzzy theory to represent the uncertainty of uncertain information, analyzes the selection of knowledge representation and fuzzy reasoning methods, and analyzes the advantages and disadvantages of production representation, frame representation and other methods in representing knowledge. Specifically, the technical contributions of this paper can be summarized as follows:

1) A reasoning method suitable for a fault diagnosis system is obtained through analysis. Knowledge matching refers to the similarity between the evidence set and the preconditions of a certain item or several rules in the knowledge base.

2) Based on the dynamic mathematical model of the induction motor, the rotor failure simulation model is established by changing the resistance value of the equivalent rotor three-phase winding. The stator phase current, electromagnetic torque and rotor speed under normal rotor winding and abnormal rotor winding are compared and discussed respectively, and the simulation current signal under the two modes is simply analyzed, and the feasibility and shortcomings of the simulation model are also discussed.

3) From the perspective of multi-dimension, we discuss the dimensionality reduction of a three-phase current signal and convert it into two signals, and extract the characteristic components of rotor broken bars fault through the form of synthetic modulus, which not only makes full use of the stator three-phase current signal but also breaks the contingency of single-phase current signal in the diagnosis algorithm. Finally, the validity of these two diagnosis algorithms for the fault detection of broken rotor bar is verified by simulation and experiment.

The remainder of this paper is organized as follows. In the next section, the related works will be shown in detail. In Section 3, the proposed method will be described comprehensively. In Section 4, the simulation and experiments are carried out. Finally, some conclusions are drawn in Section 5.

2. Related work

It is common to combine multiple AI methods to achieve better diagnostic results than a single method [23]. The researchers built an adaptive neural fuzzy inference system based on BP neural network, and the experiment proved that the fuzzy neural network can obtain a better diagnostic effect than the standard BP neural network. The method based on the analytical model is the earliest developed, which requires the establishment of a more accurate mathematical model of the diagnosed object [24]. Scholars put forward the multi-loop theory of AC motors with a single coil as the unit of analysis [25]. The multi-loop model of the induction motor can accurately model the fault state of the motor, especially rotor bar breaking and air gap eccentricity faults, which provides convenience for the application of the analytical model method for motor fault diagnosis.

The stator current analysis method carries on the spectrum analysis of the stator current under the air gap eccentricity of the motor, and the obtained spectrum diagram will have the component of specific frequency. On the basis of the traditional magnetomotive force and magnetometric wave method, scholars used the stator current analysis method to explore the variation law of the characteristic frequency value in the stator current spectrum under different eccentricities and different loads [26]. After that, under the same eccentricity, the larger the load, the larger the amplitude of the characteristic frequency current. Under the same load, the larger the eccentricity is, the larger the amplitude of the characteristic frequency current is. The proposed multi-loop model of the AC motor provides convenience for the current calculation of eccentric motor and becomes a powerful tool for the subsequent research on the characteristic components of stator current of the eccentric motor. Scholars use multi-loop modeling, using the finite element method to analyze the three-phase induction motor under static eccentricity, combined with the stator three-phase current spectrum diagram, study the relationship between the amplitude of the current component at a specific frequency and the eccentricity, compared with the traditional method of magnetomotive force and magnetometric wave, the results obtained by this method are closer to the measured value [27,28]. With the progress of research, scholars found that static eccentricity could not fully explain the eccentricity of the actual motor, so it was necessary to study the characteristic frequency components of the stator current under the mixed eccentricity of the motor [29].

Information processing technology is the key of motor fault diagnosis technology, and it is also one of the hot spots of theoretical research. The traditional signal analysis methods are the filtering technique and the Fourier spectrum analysis technique [30]. With the development of researchers, other signal analysis methods that are superior to Fourier spectrum analysis appear, such as the short-time Fourier transform method, quadratic time-frequency analysis methods such as Wigner distribution and Choi-William distribution, wavelet decomposition method, adaptive time-frequency analysis method, high-order spectral statistics, etc.

The instantaneous power is the product of the line voltage between two terminals of the motor stator and the corresponding line current. Compared with the spectrum analysis of the stator current, the spectrum analysis of the instantaneous power can effectively avoid the influence of the fundamental current on the fault characteristic components, and better highlight the fault characteristics of the motor [31]. Rotor bar breaking fault occurs in a motor, which will lead to the increase of motor vibration. By obtaining a motor vibration signal and analyzing its characteristics, it can be used to diagnose whether a motor bar breaking fault occurs [32]. Scholars compared the application of stator current and vibration signals to rotor bar breaking faults and bearing faults of motor, and pointed out that current signals are more conducive to the analysis of rotor bar breaking faults and vibration signals are more conducive to the analysis of bearing faults [33–35].

3. Methodology

3.1. Correlation measure of intuitionistic fuzzy sets

Compared with fuzzy sets, intuitionistic fuzzy sets can more accurately describe the fuzziness of fuzzy concepts [36]. It extends the membership degree of traditional fuzzy sets to the other two information, the non-membership degree and the hesitancy degree, and describes fuzzy concepts more accurately. Compared with traditional fuzzy sets, it is more flexible and practical to represent fuzzy concepts. Let X be a non-empty domain. An intuitionistic fuzzy set on X is defined as:

$$A = \{(x^{-1}, v_A^{-1}(u), \mu_A^{-1}(x)) | x \in X\} \tag{1}$$

When the domain X is continuous, the intuitionistic fuzzy set A is:

$$A = \int_x ln\, x \cdot (v_A^{-1}(x), \mu_A^{-1}(x)) \,, x \in X \tag{2}$$

When the domain X is discrete, the intuitionistic fuzzy set A is:

$$A = \prod_{i=1}^{n} ln\, x_i \cdot (v_A^{-1}(x_i), \mu_A^{-1}(x_i)),\, x \in X \quad (3)$$

The intuition index represents the degree of uncertainty that element x belongs to set A, also known as the degree of hesitation. If the degree of hesitation is small, it means that the value of μ can be confirmed to a large extent. If the degree of hesitation is large, it means that the value of μ is not known accurately or definitely, that is, we know very little. To sum up, (0, 1) means that the degree of membership is 0, the degree of non-membership is 1, and the degree of hesitation is 0. (1, 0) means that the degree of membership is 1, the degree of non-membership is 0, and the degree of hesitation is 0. (0, 0) means that the degree of membership and non-membership are both 0, and the degree of hesitation is 1. The results of intuitionistic fuzzy set intersection, union and complement are consistent with the voting model. The meaning of [0.4, 0.3] is 4 for those in favor, 3 for those opposed or disapproved, and 3 for those who hold a neutral attitude; [0.5, 0.2] indicates that the evidence for support is 5, the evidence against is 2, and the evidence for abstention is 3. The number of supports of [0.4, 0.3] is less than the number of supports of [0.5, 0.2], and the number of objections of [0.5, 0.2] is less than [0.4, 0.2]. Other operations on intuitionistic fuzzy sets can be similarly interpreted.

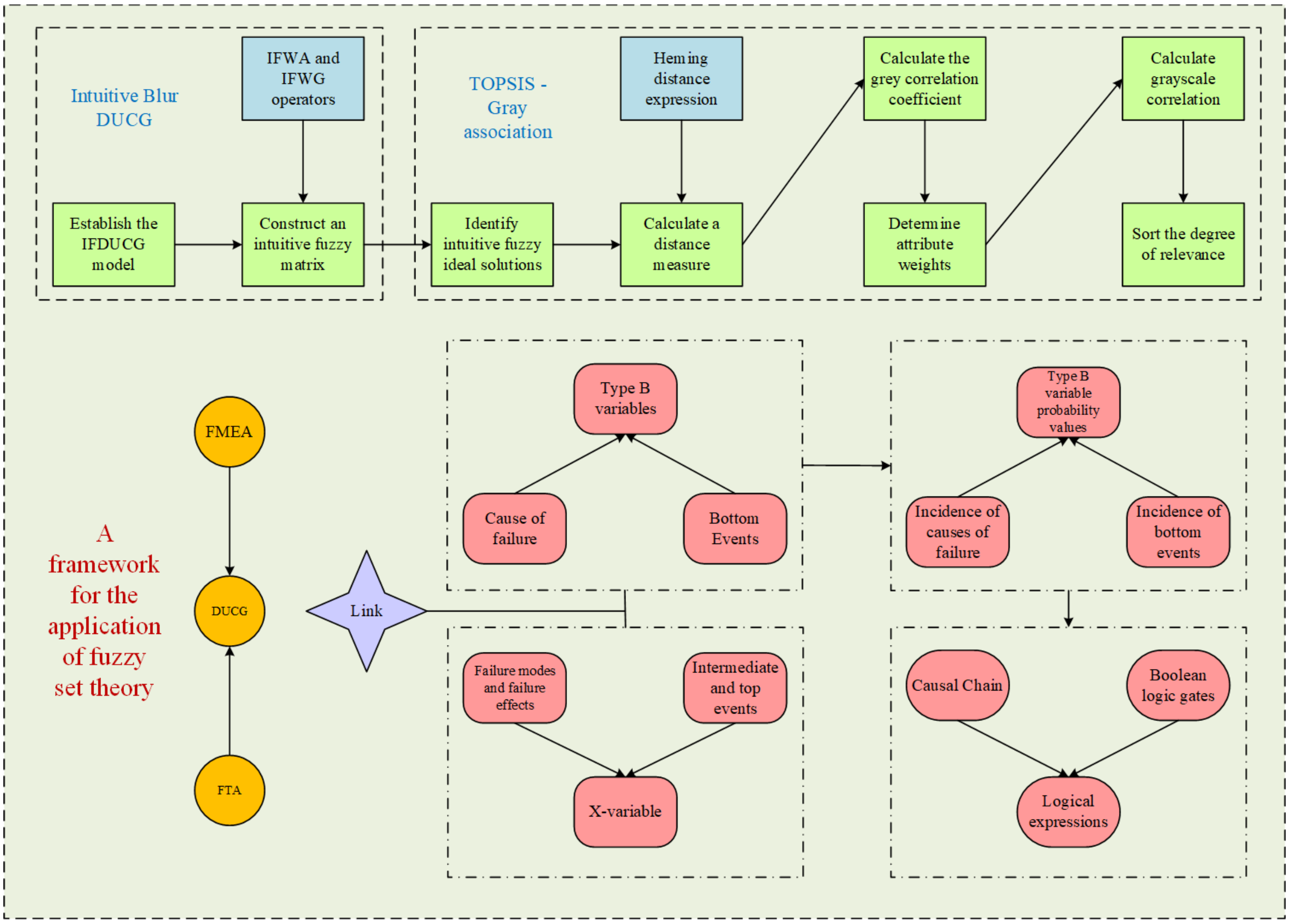

Figure 1. Application framework of fuzzy set theory.

Let X be a finite set, and both A_1 and A_2 be intuitionistic fuzzy sets.

$$\rho_1(A_1, A_2) = \frac{\left(c_1(A_1,A_1)+c_1(A_2,A_2)\right)^2}{2c_1(A_1,A_2)} \tag{4}$$

$$c_1(A_1, A_2) = \prod_{i=1}^{n} \frac{\mu_{A_1}(x_i)+\mu_{A_2}(x_i)}{v_{A_1}(x_i)+v_{A_2}(x_i)} \tag{5}$$

The correlation coefficient reflects the correlation degree of two intuitionistic fuzzy sets. The larger the correlation coefficient is, the more correlated it is; the smaller the correlation coefficient is, the less correlated it is. The application framework of fuzzy set theory is shown in Figure 1.

3.2. Determination of membership function in fuzzy reasoning

Whether in theory or practice, the determination of membership function is the first step, the selection of whether membership function is appropriate or not will involve the calculation of the membership degree, membership degree will participate in the subsequent fuzzy reasoning process, so it will be very important to solve the practical application of fuzzy theory [37]. Different people have different criteria for choosing membership functions. In the process of the practical application of fuzzy theory, it will be found that there are many kinds of fuzzy reasons involved in different problems, and they are not related to each other, which leads to complex and changeable fuzzy classification [38]. There is a basic principle to comply with that is:

1) The shape of the membership function is unimodal, and the multi-modal function cannot be used, that is, the set represented by the membership function is a convex set similar to the unimodal mountain.

2) The number of sets represented by the membership function is generally odd, and the membership function can be represented symmetrically, with the same number on both sides of the symmetry.

3) The fuzzy quantifier should be given according to the degree of semantic meaning, without illogical overlap. In general, it means that a certain point on the domain can participate in the membership calculation of at most two membership function regions, and this point can participate in the membership calculation of only one membership function, but not more than two. When two membership functions have overlapping points, these points will also comply with two principles: first, the point cannot be expressed as the maximum membership degree in both functions, and second, the membership function of the overlapping points cannot add up to more than 1. Two membership functions with the same input will not have two maximum memberships.

For theory and practical application of choosing a membership function are all need careful seriously, the choice of membership function is directly related to the stand or fall of subsequent research results, however, the uncertainty of knowledge is not due to one, thus causing the fuzzy sets on the classification of difficulties, appear different classification, the result of fuzzy uncertainty. In most cases, when the human brain conducts fuzziness analysis, it is also a qualitative reflection of knowledge subjectively to things [39]. This psychological reflection of the human brain is uncertain and fuzzy, so the membership function selected is also a subjective selection and judgment process. The determination of membership function is the basis of the whole subsequent reasoning, but different forms will get different membership functions. In the actual application process, the membership degree calculated by different membership functions can achieve relatively satisfactory results in fuzzy reasoning, but they are different in some details and system reaction time.

This kind of function is more suitable for fuzzy sets when words representing small fuzziness are described. The general form of its membership degree is:

$$A(x) = \begin{cases} \text{-1} & x < -a \\ 0 & \text{-}a \leq x < a \\ 1 & x = a \\ f(x) & x > a \end{cases} \tag{6}$$

where *a* is a constant and *f(*)* is a non-increasing function. Different partial small fuzzy distributions can be obtained by choosing *f(*)*. The sigmoid function is as follows:

$$f_s(x;\alpha,\beta,\gamma) = \begin{cases} \text{-1} & x < \alpha \\ 0 & x = \alpha \\ 2\sqrt{(\alpha+x)(\alpha-\gamma)} & \alpha < x < \beta \\ \sqrt{\left(\frac{\alpha+x}{2}\right)\left(\frac{\alpha-\gamma}{\alpha+\beta}\right)} & \beta \leq x < \gamma \\ 1 & x = \gamma \\ 2\sqrt{\frac{(\alpha+x)(\alpha-\gamma)}{3}} & x > \gamma \end{cases} \tag{7}$$

3.3. Representation of knowledge

The representation of knowledge in another way is the description of knowledge in the computer, its advantages and disadvantages will affect the performance of the fuzzy expert system, so a reliable, simple and effective representation of knowledge is very important to the fuzzy expert system [40]. With the in-depth study of expert systems, more and more fields are involved, and the types of knowledge are more and more complex. However, there are still rules to sum up knowledge, and knowledge can be divided into many types according to the characteristics of knowledge. Different types of knowledge will be processed by fuzzy expert systems according to different forms of processing. To establish a reasonable form of knowledge, it is necessary to know the types of knowledge in the field. Knowledge is not an objective reflection of the real world, but an attribute that describes the connections and differences between things. Different connections create different knowledge. Knowledge itself has different properties can be described in the following aspects:

1) Relative correctness: Knowledge is a reflection of the phenomenon of objective reality it is not without foundation generation, is in some regularity or logic of science, knowledge can discriminatephenomenon is true or false, can be validated through science and through strict logic reasoning, that is knowledge production is accord with certain conditions. Therefore, to verify the correctness of knowledge, knowledge needs to be placed in a suitable condition and environment. In addition, there will be no unconditional absolute truth or absolute fallacy in the world, and the so-called absolute phenomena are not correct.

2) Ambiguity and imprecision: In the process of gradual understanding, there will inevitably be misunderstandings in cognition. It is possible to know something and think it is correct at this time. However, after a period of time, with the change of the development environment of things, this seemingly true knowledge will become less accurate. Therefore, people are accustomed to using the uncertainty of knowledge to represent knowledge, which leads to the existence of knowledge ambiguity. Many facts and concepts are expressed in terms of less accurate knowledge, which often has an ambiguous intermediate state. This property is called knowledge ambiguity and imprecision. The appearance of a thing is not obvious to people, so the ambiguity of knowledge is quite reasonable.

3) Representability: To be used in a fuzzy expert system, knowledge must be transformed into a form that can be understood by people. Knowledge can be expressed in a fixed form and stored in the system to participate in subsequent reasoning. In addition, knowledge can be transplanted to other systems after being stored in the system.

4) Correlation: Knowledge is a form of relationship that reflects different things or concepts, and this relationship is called correlation. The relation of things can be either static or dynamic. Besides the relation, it also reflects the difference between the thing and other things.

There are many kinds of knowledge representation methods, mainly including first-order predicate logic representation, production representation (or rule representation), semantic network representation, frame representation, script representation and so on. By comparing their characteristics and application scope, the appropriate knowledge representation method is selected for the design of a fuzzy inference expert system.

1) Production representation: Production representation is very intuitive for expressing common causal relations, and is convenient for reasoning and modular management. Moreover, its format is fixed, and it is easy to detect the consistency and integrity of knowledge, and it is easy to realize the interpretation function. Its inference engine is also closer to human thinking. Therefore, this paper uses production notation to put the rule knowledge into the Sql Server database. A set of production can be graphically represented by a so-called "and/or tree". The process of proving or solving a problem using "and/or tree" can be regarded as a search or matching process on a tree. Its regular form can usually be in the following form:

If < premise 1, premise 2, premise n >, then < conclusion >.

IF E then H(CF, λ) or E→H, CF, λ

where E is the premise. In a fuzzy proposition, it means either a simple premise (condition 1, no other conditions) or a combination of premises (with multiple conditions), which can be composed in various forms. H represents the fuzzy conclusion of the fuzzy proposition (also the conclusion that follows). Its credibility is represented by a value in the interval [0, 1], which also represents the credibility of the conclusion, and the default value is 1. CF represents the credibility of the knowledge expressed in this form, which represents a definite real value or a fuzzy number (or fuzzy language value), also known as the credibility factor. The value of CF is determined by the corresponding domain experts in the process of giving domain knowledge according to the actual situation. λ represents when the rule knowledge can be selected under what conditions, known as the threshold. You can see that the production representation is similar to a top-down search and matching process.

In addition, production representation can not meet the requirements of high efficiency of the system, because in the process of reasoning, it needs to be solved by one rule after another, which will take a long time. Therefore, when the rule base is relatively large, that is, there are too many rules, it cannot meet the requirements of high efficiency when the system deals with problems.

2) Frame representation: Frame notation is, as its name suggests, a structured representation that stores experience in the form of data structures. A frame consists of two parts: the first part is the frame name, and the second part is the slot, which is the information used to describe the various aspects of the thing. A slot represents the different properties of the thing, and below it is made up of many values.

3) First-order predicate logic representation: The first-order predicate logic representation can satisfy systems with high formal requirements. It has high accuracy in the process of expressing human thinking and reasoning, and its form is the form of a predicate formula.

4) Semantic network representation: It is a structured graphical representation of knowledge,

composed of arcs and nodes, a structured graphical representation of knowledge, in which the entities and concepts of things are represented by nodes, and the relationships between nodes are represented by arcs.

The way semantic network representation presents problems is relatively intuitive and easy to understand. Knowledge acquisition experts can acquire knowledge more easily than other representations. The two nodes can be represented in different forms such as tree form, linear form, etc. In addition, this representation is more simple and more clear in expressing the relationship of things, which can be derived through nodes and arcs, and is also easy to explain. Concepts are easy to interview and learn because their related connections and portraits are organized by a corresponding node.

The bad side of semantic network representation is that it has a limited range of expression compared to others. If more nodes are used, the network structure will be cumbersome and complex, which will be more complicated to deal with.

3.4. Selection of fuzzy inference method

Reasoning, in simple terms, is the process of reasoning from known facts to conclusions. Fuzzy reasoning is a form of reasoning that deals with fuzzy concepts. Classical logic is based on the deduction, which is essentially different from each other. The definition of deductive reasoning is the process of specialization of abstract information, which is universal to special reasoning.

However, problems arise in practical applications, and deductive reasoning cannot solve all problems. Since deductive reasoning does not apply to fuzzy concepts or uncertain information, deductive reasoning and inference machines based on it are powerless to deal with such problems. But in this case, one can still think and reason.

The fuzzy reasoning method is a process of deriving a new proposition from one or more known propositions according to certain principles. Generally speaking, reasoning consists of two parts, one is the known proposition, which is the starting point of reasoning, called the premises (or antecedent) from the proposition the new proposition is called the conclusion (or antecedent). Forward reasoning and inverse reasoning are two forms of fuzzy reasoning. The fuzzy expert system designed in this paper uses the form of forward reasoning, which is also the form of the general expert system. Mamdani's fuzzy inference method is to take small operators to establish the relation "and" between fuzzy sets A and B, denoted as:

$$R_c = A \times B = \int_{X\times Y} ln(x,y) \cdot (\mu_A^{-1}(x) \vee \mu_B^{-1}(y)) \tag{8}$$

There are two basic forms of intuitionistic Fuzzy reasoning: one is intuitionistic Fuzzy Modus Ponens, which is simply denoted as IFMP, and its basic models such as fuzzy sets in the domain of knowledge are replaced by intuitionistic fuzzy sets. Then, for the corresponding IFMP problem, predecessors gave the ICRI algorithm:

$$B^*(y) = sup\, T\left(B(x), B(y), I\left(A^*(y), \frac{A^*(x)}{B(x)}\right)\right), y \in Y \tag{9}$$

where, T is the intuitionistic fuzzy t-norm, and I is the intuitionistic fuzzy entrainment operator. The key problem in the ICRI algorithm is to determine the intuitionistic fuzzy entrainment operator. It has different choices and can choose different intuitionistic fuzzy entrainment operators according to different needs.

The reason why this algorithm is not selected in this paper is that both CRI algorithm and ICRI algorithm only use one implication, namely A × B, and fuzzy implication operator is needed to transform it into the form of fuzzy relation. However, when A* is given to find B*, it does not consider the relation between A→B and A*→B*. CRI algorithm lacks a logical basis and does not have reducibility, that is, when A→B is known and A = A* is given, the conclusion drawn should be strictly in accordance with B* = B, but the conclusion deviates from the actual conclusion. CRI algorithm focuses on the simplicity of operation, so it neglects the rationality analysis of logic semantics. In artificial intelligence systems often need to put two knowledge by reasoning model (e.g., two fuzzy predicates, two segments of framework or predicate formula), which checks whether or not they are the same, this is the matching of knowledge, knowledge matching refers to the evidence in a set and knowledge base or the premise condition that some rules of similarity degree. In the fuzzy theory, approximate reasoning based on similarity measure is mainly to compare the degree of similarity between fuzzy sets, and the distance measure based on intuitionistic fuzzy sets is more commonly used. Several distance formulas between intuitionistic fuzzy sets are listed here.

The standard Hamming distance is:

$$d_1(A_1, A_2) = \frac{(1+n)n}{2} \sum_{j=1}^{n} \frac{\left|\mu_{A_1}^2(x_j)+\mu_{A_2}^2(x_j)\right|}{\left|v_{A_1}^2(x_j)+v_{A_2}^2(x_j)\right|} \tag{10}$$

The standard Euclidean distance is:

$$d_2(A_1, A_2) = \left(\frac{(1+n)n}{2} \sum_{j=1}^{n} \frac{\left|\mu_{A_1}^2(x_j)+\mu_{A_2}^2(x_j)\right|}{\left|v_{A_1}^2(x_j)+v_{A_2}^2(x_j)\right|}\right)^{\frac{1}{2}} \tag{11}$$

In order to solve the problem that Hamming distance measure is sometimes not suitable in practical application, the following distance measure is defined to overcome this defect:

$$d_5(A_1, A_2) = \sum_{j=1}^{n} \frac{\omega_j}{2} \left(\frac{\left|\mu_{A_1}^2(x_j)+\mu_{A_2}^2(x_j)\right|}{\left|v_{A_1}^2(x_j)+v_{A_2}^2(x_j)\right|} - \frac{\left|\mu_{A_1}^2(x_j)-\mu_{A_2}^2(x_j)\right|}{\left|v_{A_1}^2(x_j)-v_{A_2}^2(x_j)\right|}\right) \tag{12}$$

And the matching function based on distance measure is:

$$M_d(R, P) = \frac{d^2(R,P)-1}{2} \tag{13}$$

Knowledge matching refers to the degree of similarity between the evidence set and the preconditions of an item or several rules in the knowledge base. This system uses distance measure to calculate knowledge matching. The basic idea is based on the most common understanding of "matching": two matches are the same; the degree of matching between the two is good, that is, the degree of proximity between the two is high.

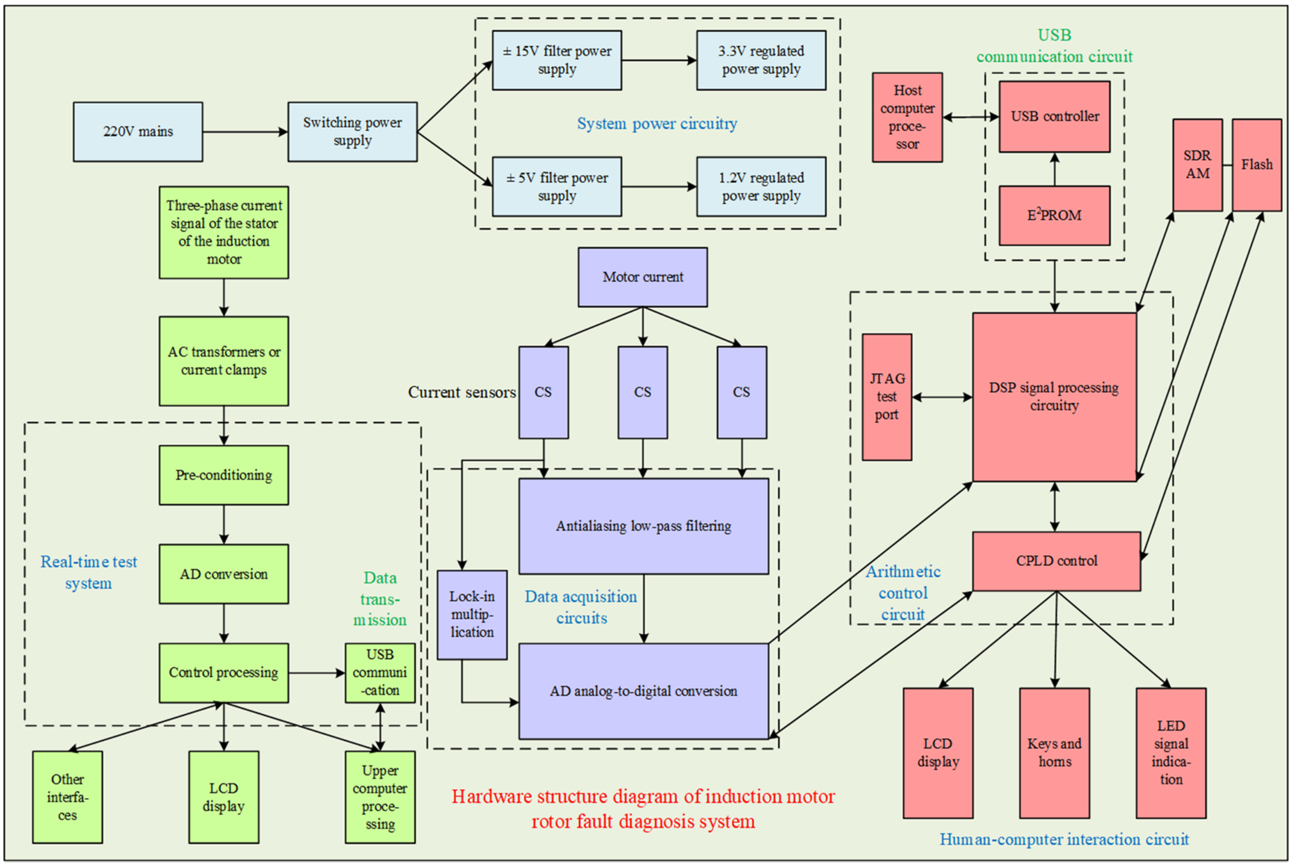

Figure 2. Hardware structure diagram of induction motor rotor fault diagnosis system.

P represents the anatomic element of the production rule, *R* represents the assertion of the matching fact, and its membership degree is $s = (s_1, s_2)$. Their meanings are the same as those of assertion *P* and its corresponding membership degree in the anatomic element of the rule. *d(R, P)* is the distance between *P* and *R*. If the value is greater than a threshold value ζ preset by a domain expert, the system will start and execute the rule, so as to obtain a corresponding value, the size of which is the "quantity product" of the value of the intuitionistic fuzzy matching function and the value of the deterministic factor *CF* is (mx1, 1-m(1-x2)), and its meaning means that after the rule is executed. If the value of the intuitionistic fuzzy matching function calculated is less than ζ, the system does not execute this rule. The hardware structure diagram of the induction motor rotor fault diagnosis system is shown in Figure 2.

4. Results and analysis

4.1. Rotor fault simulation analysis of induction motor

In the simulation process, the default fourth-order Runge-Kuta solver with fixed a step size in the Simulink system was used to avoid the interference of nonlinear factors in the simulation model, and the simulation step size was fixed to 0.05 ms, and the simulation time was 2 s. In addition, for the sake of comparison, the external resistance R'r of the rotor A-phase winding is set as 0 Ω and 2 Ω respectively, which correspond to the two cases of a normal and asymmetric rotor winding in turn.

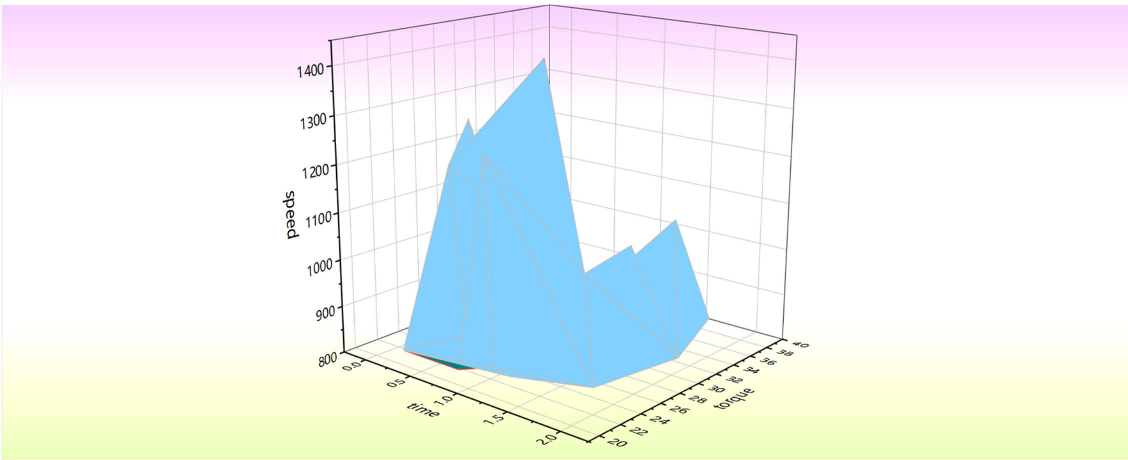

Figure 3. Simulation results of induction motor model speed when rotor windings are normal.

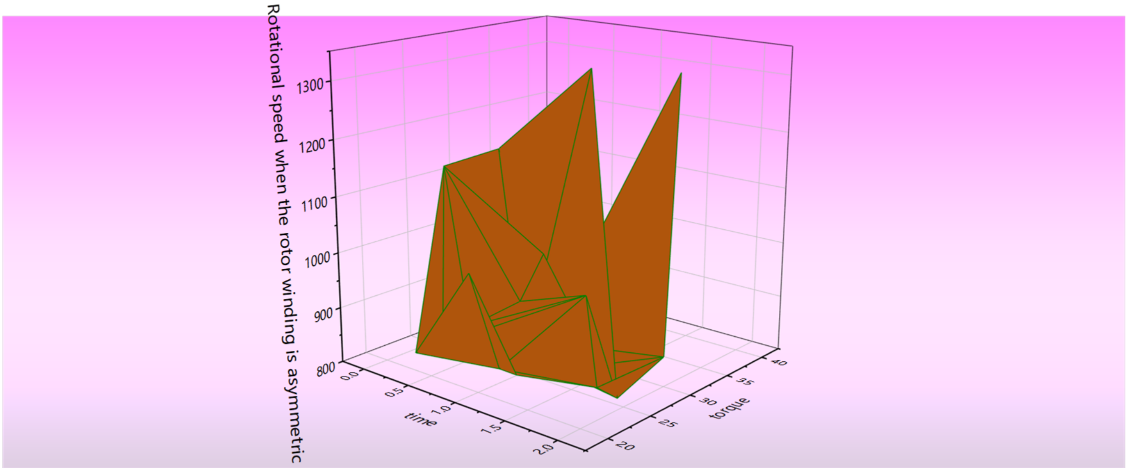

Figure 4. Simulation results of induction motor model speed when rotor windings are asymmetric.

The induction motor has a certain starting process during operation, and the starting current fluctuates greatly, reaching a steady state of about 0.2 s. At this time, the stator three-phase current amplitude is about 3.16 A, the torque is about 8.81 N m, the rotor speed is about 1465.8 r/min, and the rated speed of the motor is n0 = 60 f/P = 1500 r/min. Considering the influence of friction and damping, the output results of the simulation model are consistent with the actual motor operation, and the simulation model can also approximate the simple operation of the motor. When the A-phase winding of the rotor is externally connected with 3 Ω resistance, the three-phase winding of the rotor is asymmetrical, and the stator phase current, torque and rotor speed of the simulation model all show certain fluctuations, but the fluctuation amplitude is small and difficult to observe. Simulation results of induction motor model speed when rotor windings are normal are shown in Figure 3. Simulation results of induction motor model speed when rotor windings are asymmetric are shown in Figure 4.

At the same time, FFT is directly carried out on the stator A-phase currents of the motor under the above two simulation states, respectively, and the spectrum analysis results are shown in Figures 5 and 6.

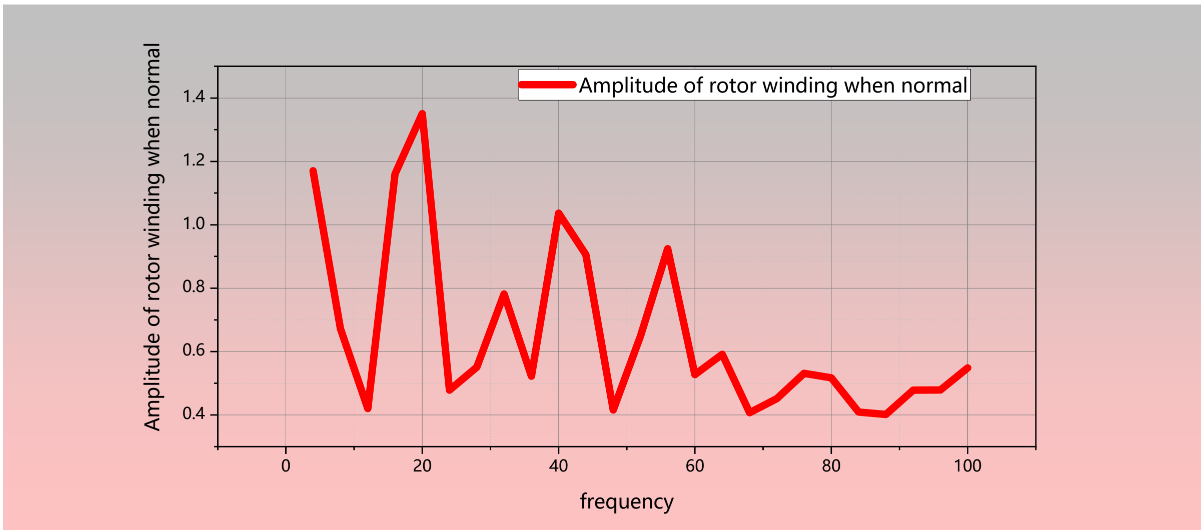

Figure 5. Stator A-phase current spectrum when the rotor winding is normal.

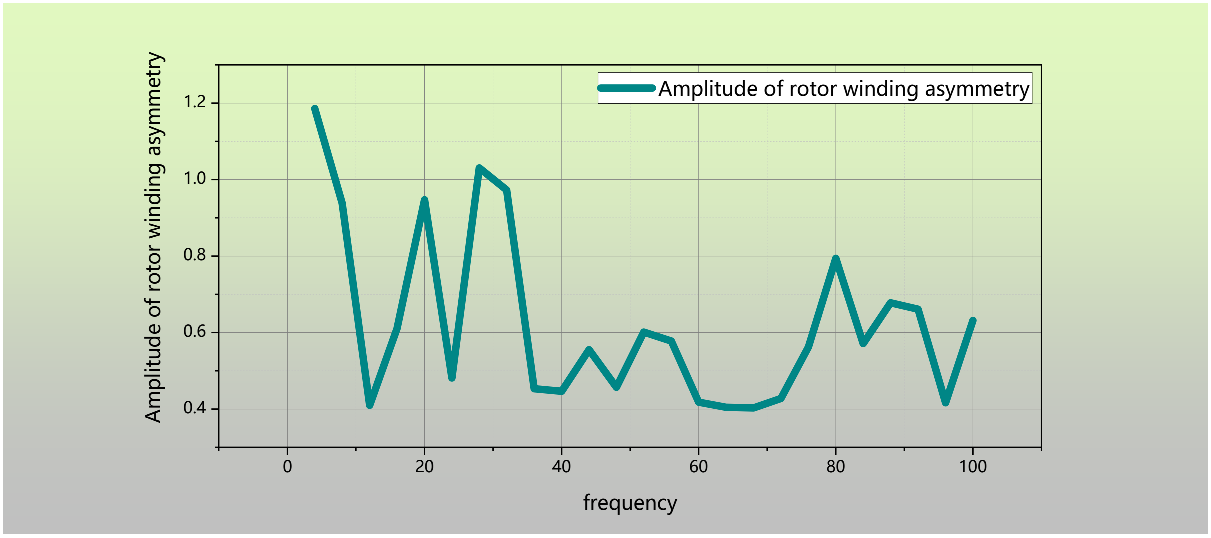

Figure 6. Stator A-phase current spectrum with asymmetric rotor windings.

It can be seen from the spectrum diagram that when the rotor winding of the induction motor is normal, FFT analysis of the stator A-phase current in a steady state is carried out directly, and there is no obvious edge component on both sides of the power frequency component.

When the rotor winding of the induction motor is asymmetrical, FFT analysis of stator A-phase current in a steady state is carried out directly. Besides the obvious power frequency component, there are also a few edge components on both sides of the power frequency component in the spectrum diagram. However, strictly speaking, the rotor winding asymmetry model cannot completely replace the rotor broken bar model, so there are fewer differences in simulation waveform output and spectrum analysis, and it can only be used as an approximate rotor broken bar fault simulation model.

In addition, based on the construction of the whole simulation model and the analysis of model results, it can be found that the fault simulation model is directly established under the ABC coordinate system on the basis of the physical model of the three-phase induction motor, and the whole system is intuitive and clear. At the same time, compared with the motor simulation under the two-phase stationary or two-phase rotating coordinates, the model can set the resistance and inductance values of the stationary and rotor three-phase windings separately to simulate the fault simulation under various situations. Moreover, the product differentiation form is adopted in the model to avoid the instability of system simulation. However, the fault simulation model established directly in ABC coordinates also has some defects.

First of all, the fault simulation model established under the multi-loop theory can not directly simulate the number and position of rotor broken bar roots. Some modules are simplified, and the simulation results of the model will have a small amount of deviation. Secondly, many Simulink modules nested need to call MATLAB function solver, resulting in a relatively long simulation time. In a word, compared with other models, the simulation model is simple and intuitive, and the simulation effect is relatively ideal. It is suitable for qualitative analysis of stator and rotor faults of induction motor and the simulation time is not high.

4.2. Simulation signal verification

In order to verify the effectiveness of the proposed principal component modulus spectrum analysis method for rotor bar breaking fault detection, it is assumed that a set of stator three-phase current signals which can represent rotor bar breaking characteristics are generated by a certain type of motor under ideal conditions. At the same time, combined with the characteristics of fault characteristic components induced in stator three-phase winding with the frequency of $(1 \pm 2\ s)f_0$ when the rotor bar is broken, the voltage fundamental frequency is 50 Hz, the motor slip rate s is 0.025, the sampling frequency of the current signal is 1 kHz, and the sampling time is 4 s. White noise with mean value 0 exists in the stator phase current and acts as random interference. In addition, the stator current signal of the motor rotor without guide strip breakage is also assumed for comparison. The time-domain waveform of the stator three-phase current signal is shown in Figure 7.

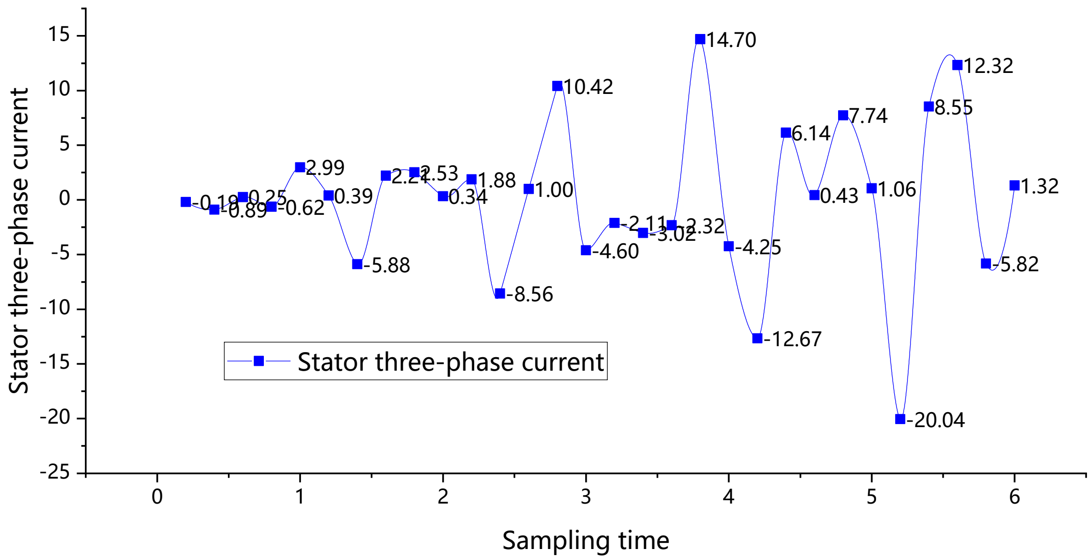

Figure 7. Time-domain waveform of stator three-phase current signal.

When the rotor guide strip is normal, there is no obvious change in the time-domain waveform of the stator phase current, and there is no obvious edge characteristics on both sides of the stator A-phase current fundamental wave (50 Hz). However, this is not enough to constitute an effective basis for the normal rotor. Therefore, the rotor of the motor can be judged normal by analyzing the principal component modulus spectrum of the stator three-phase current signal and filtering out its DC component. The time-domain waveform of the stator three-phase current signal when the rotor guide bar is broken is shown in Figure 8.

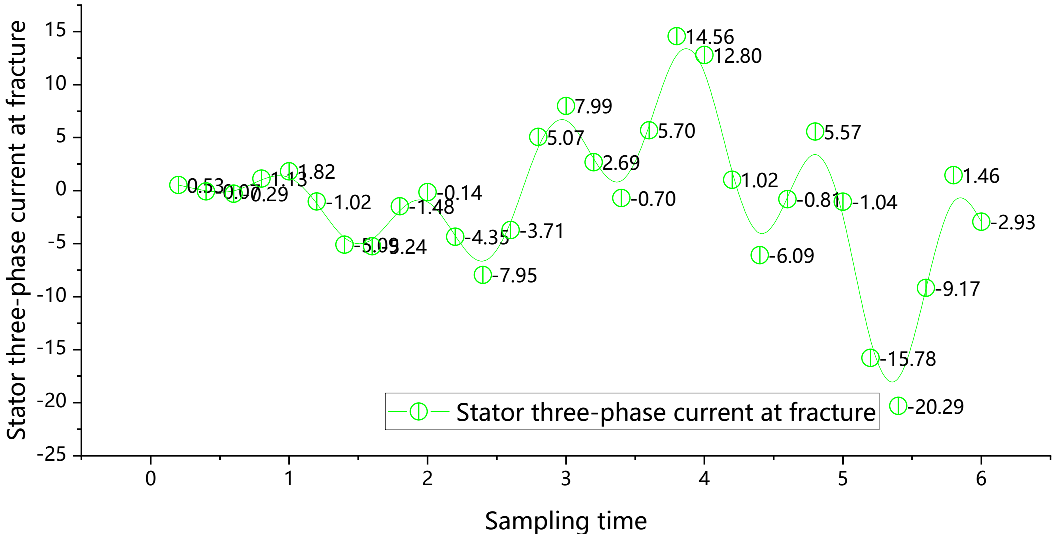

Figure 8. Time domain waveform of stator three-phase current signal when rotor guide bar is broken.

When the rotor of the induction motor is broken, the amplitude of the stator three-phase current signal fluctuates to a certain extent, and the edge components on both sides of the fundamental wave of the stator A-phase current do exist. Through the principal component modulus analysis of the stator three-phase current signal, the frequency values of two obvious spikes (2.5 Hz and 5 Hz) are exactly consistent with 2 sf0 and 4 sf0 given by the simulation conditions, but the amplitude at 4 sf0 is very small compared with that at 2 sf0.

4.3. Simulation experiment analysis of motor rotor bar breaking fault

In order to further analyze the rationality of this fault detection method, the measured rotor bar broken data of variable frequency motor is used to study. Among them, the data used are quoted from MARATHON56T34F5301 squirrel cage motor of mechanical fault comprehensive simulation experiment platform produced by Spectra Quest, USA, which has stator three-phase current signals with three broken strips.

For the squirrel-cage induction motor installed on the fault test platform, there are the following characteristic parameters: three-phase one-pole, frequency 50 Hz, rated power 1/3 H.P., rated voltage 380 V, speed 2855 r/min, and rotor guide number 34. During the experiment, a perforated AC current sensor with a power supply of ± 12 V and a 4-channel synchronous analog input 16-bit NI USB-9162 data acquisition card were also used. At the same time, in order to facilitate the comparative study, the stator three-phase current signals of the rotor normal motor at 10 Hz and half-load and the rotor broken-strip fault motor at 10 Hz no-load, 20 Hz half-load and 30 Hz full load are collected and analyzed respectively. The driving load is regulated by the gearbox. In the experiment, the sampling frequency of current signal is 1 kHz, and 8192 signal points are selected for verification. The time-domain waveform of the stator three-phase current (30 Hz full load) tested for the rotor broken-bar motor is shown in Figure 9.

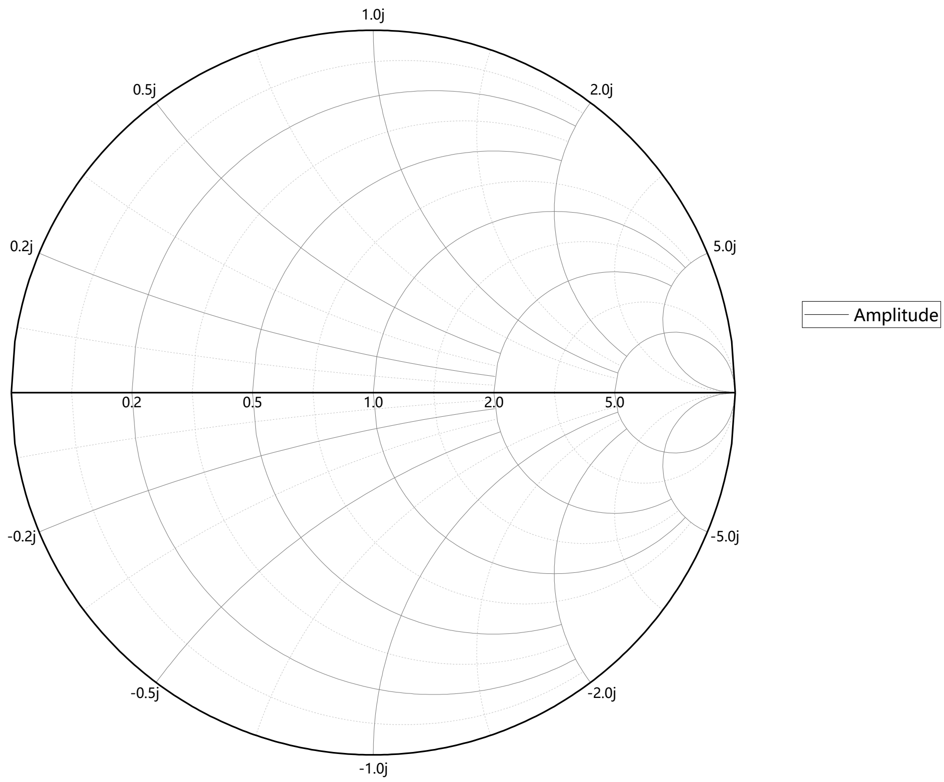

Figure 9. Time-domain waveform of stator three-phase current tested by rotor broken-bar motor (30 Hz full load).

When the load is zero at the same rotation frequency, the slip frequency is very low and the fault characteristic frequency is not easy to be extracted. For the normal motor, the stator three-phase current is sinusoidal, and there is almost no fault characteristic component 2 sf0 and its double frequency in the principal component modulus spectrum diagram. There is an obvious fault characteristic component 2 sf0 and its double frequency in the principal component modulus spectrum of the stator three-phase current, and the characteristic component which can characterize the broken rotor bar fault becomes more and more obvious with the increase of the rotational frequency and the load.

5. Conclusions

According to the motor rotor broken bar, after its stator current signal is an amplitude modulation signal this characteristic, this paper briefly introduces the commonly used mechanical signal amplitude demodulation method, and summarizes their adaptation range. The applied energy operator only needs single-phase current and three adjacent current sampling values, which removes the interference of the fundamental frequency component and weakens spectrum leakage. Moreover, it has a low utilization rate of computer storage resources and is easy to be applied to DSP processors. The application of principal component modulus fully considers the influence of the three-phase current phase sequence of the stator, and combines with the characteristics of dimensionality reduction of principal component analysis, the stator three-phase current signal is processed to obtain two principal component components which can characterize the rotor breaking bar fault, and then the principal component modulus is constructed to propose the characteristic frequency of breaking bar fault. In addition, the fault detection method is analyzed and verified from the perspective of simulation and experiment, which highlights its effective application in rotor broken bar fault detection, and also provides a broader research idea for rotor broken bar fault diagnosis of induction motors. The next step is to discuss and analyze the situation of multiple guide bar fractures and multiple faults compound in the experimental process, and to complete the diagnosis research of compound faults by seeking a more suitable fault separation algorithm.

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Conflict of interest

The authors declare there is no conflict of interest.

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