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Research article

A fuzzy neural network-based automatic fault diagnosis method for permanent magnet synchronous generators

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Abstract: In recent years, automatic fault diagnosis for various machines has been a hot topic in the industry. This paper focuses on permanent magnet synchronous generators and combines fuzzy decision theory with deep learning for this purpose. Thus, a fuzzy neural network-based automatic fault diagnosis method for permanent magnet synchronous generators is proposed in this paper. The particle swarm algorithm optimizes the smoothing factor of the network for the effect of probabilistic neural network classification, as affected by the complexity of the structure and parameters. And on this basis, the fuzzy C means algorithm is used to obtain the clustering centers of the fault data, and the network model is reconstructed by selecting the samples closest to the clustering centers as the neurons in the probabilistic neural network. The mathematical analysis and derivation of the T-S (Tkagi-Sugneo) fuzzy neural network-based diagnosis strategy are carried out; the T-S fuzzy neural network-based generator fault diagnosis system is designed. The model is implemented on the MATLAB/Simulink platform for simulation and verification, the experiments show that the T-S fuzzy diagnosis strategy is significantly improved, and the design purpose is achieved. The fuzzy neural network has a parallel structure and can perform parallel data processing. This parallel mechanism can solve the problem of large-scale real-time computation in control systems, and the redundancy in parallel computation can make the control system highly fault-tolerant and robust. The fault diagnosis model based on an improved probabilistic neural network is applied to the fault data to verify the effectiveness and accuracy of the model.

Keywords: fuzzy neural network; automatic fault diagnosis; intelligent analysis; permanent magnet synchronous generators

1. Introduction

As a bridge between electrical and kinetic energy, the safe and stable operation of the motor is a prerequisite for the continuous operation of the entire electrical system. As engines often work in very harsh environments, overloading and insulation aging, which bring high ambient temperature and excessive demagnetization current, as well as long-term violent physical vibration and collision, will cause permanent magnet failure, thus leading to demagnetization failure [1]. The demagnetization failure will bring a series of chain reactions, further aggravating the temperature rise and increasing the current during motor operation, which may damage the whole motor in severe cases [2]. Therefore, the identification, classification, and location of demagnetization faults can help the maintenance personnel to find the spots early and reduce the maintenance cost, and they can also play a role in guiding the motor design [3]. This year, the research and development of permanent magnet synchronous motors worldwide have yielded fruitful results and practical experience, which provides many options for the future development of permanent magnet synchronous motors. Meanwhile, the permanent magnet synchronous motor does not readily dissipate heat due to its small size and compact structure, and it is easy to operate in high-temperature environments. Fault diagnosis is a technique to understand and grasp the operational status of a machine, determine the normal or abnormal status of the machine as a whole or locally, detect faults early, determine the cause of faults, and predict the occurrence of faults. Electric motors provide a constant source of power to the production equipment of a factory to ensure normal production. However, when the machine is overloaded, the long operation will cause the motor to be overloaded and stressed, and it will be easily affected by the external environment, which will lead to failure. If it is not judged and handled in time, the motor will not operate normally and even cause damage to the motor, bringing unforeseen economic losses to the enterprise. Therefore, motor fault diagnosis technology is very important, as it is the basis to ensure the normal and reliable operation of the motor.

The design of permanent magnet synchronous motor (PMSM) controllers in areas with high control performance requirements, such as wind turbines and motors for electric vehicles, is subject to stringent requirements. The design process also requires the use of various parameters during the engine’s operation [4]. For example, in the PMSM magnetic field-oriented vector control system, the speed and current loops of the dual closed-loop system are controlled by PID regulators, and the parameters of the PID regulators are often related to the parameters of the permanent magnet synchronous motor. However, the actual motor operating parameters are susceptible to flux saturation, stator current, and temperature. For example, when the engine is operated for a long time and the temperature rises, the stator winding resistance becomes more extensive, and the magnetism of the permanent magnets decreases [5]. In this case, the torque performance of the motor deteriorates, further affecting the engine's efficiency. In addition, the fluctuation of the d-q axis inductance will also affect the output performance of the electromagnetic torque. These factors can lead to inaccurate motor controller design and reduce the reliability of the system operation [6]. As with other motors, the PMSM is subject to a high probability of failure due to the high external environmental impact and load shock. Regular operation of the PMSM is essential to monitor the health status of the motor, which is closely related to the motor parameters. However, in the long-term process of the engine, various failures are bound to occur due to its load, losses, surrounding environment, etc. Once it happens, it will usually lead to the whole system not working. More seriously, it may lead to the destruction of the entire production chain, causing a significant impact on production life and causing certain property losses [7]. Therefore, regarding the problem of the motor being prone to failure, we should vigorously develop the research of motor fault diagnosis technology to take timely measures to minimize the impact caused by the loss when the motor fails. At the same time, studying the causes of failure and understanding the changes in motor parameters at the time of loss is also conducive to improving motors in the motor development process and accelerating the motor field's rapid growth. Also, motor fault parameters are essential in motor fault location, decision-making, and maintenance [8]. Therefore, by studying the parameter changes of the PMSM, we can determine the operational status of the motor, and by monitoring the parameter changes of the PMSM, we can detect the fault early and eliminate the hidden trouble.

Fault diagnosis is a technique to understand and grasp the operational status of a machine, determine the normal or abnormal status of the device as a whole or locally, detect faults early, determine the cause of defects, and predict the occurrence of spots [9]. Electric motors provide a constant source of power to the production equipment of a factory to ensure average production. However, when the machine is overloaded, it may bring unforeseen economic losses to the enterprise [10]. Therefore, the motor fault diagnosis technology is critical as it is the basis to ensure the normal and reliable operation of the motor. Due to the continuous development of deep learning technology and its successful application in image, video, and natural language processing, a wave of learning deep learning techniques has been initiated in the academic and industrial areas [11]. First, the deep learning problem is a machine learning problem, which involves algorithms that summarizes general laws from a limited number of samples and can be applied to unknown data. Secondly, the model used in deep learning is generally complex. The complexity mainly refers to the data flow between the original input of the sample and the output through multiple linear or nonlinear components. Each component will process the information, and then affect the subsequent components. Therefore, when we get to the final output, we don't know how much each component contributes. This problem is called the contribution degree allocation problem, which is a very critical problem in deep learning, it is related to how to learn the parameters in each component. The parameters of a neural network can be learned from the data by using machine learning. Because neural network models are generally complex and the information transfer path from input to output is generally long, the learning of complex neural networks can be viewed as deep learning. Because the back propagation neural network achieves a better recognition effect in recognition, the limitations of motor fault diagnosis are based on feature engineering theory. The disadvantage of permanent magnet motor turn-to-turn short circuit fault data is that it cannot support deep neural network learning. Using fuzzy neural networks, fault detection can be performed on modelled systems. The recursive operation of the fuzzy neural network is used for long-time forecasting, without reference to the actual output, to provide external inputs to the system within the training data. The compensated neural network model can forecast the normal operating behaviour of the system. If a fault occurs, the measured output of the system is compared with the predicted output to generate a residual, which will give the actual sensor measurement deviation. The residual signal is analyzed and fault detection can be performed by applying fault decision rules. The sensor output information can also be used to identify faults. This paper combines fuzzy neural networks and generative adversarial neural networks to propose a fuzzy neural network based on residual connectivity for permanent magnet motor fault diagnosis, using stator current and vibration of the permanent magnet motor as feature data. The fuzzy neural network method with residual connections eliminates the artificially selected feature steps of the PM motor fault diagnosis algorithm, and the adversarial neural network is used to expand the feature data to provide sufficient data for the learning of the fuzzy neural network with residual connections. The study of motor fault diagnosis has important research significance for information acquisition technology, deep learning, and information processing technology, and it has important economic value for social production and life. According to the gradual change of the stator current and vibration of permanent magnet motor in the fault state, the stator current and vibration act as a feature of permanent magnet motor failure.

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 fault types of permanent magnet motors and the formation mechanism of permanent magnet motor faults are introduced, and the application of artificial intelligence technology in the field of fault diagnosis is studied. In Section 4, the permanent magnet synchronous generator fault diagnosis method is simulated. Finally, some conclusions are drawn in Section 5.

2. Related works

In the middle of the 20th century, with the rapid development of computers, artificial intelligence control methods emerged and attracted more and more scholars to research intelligent control. Intelligent control refers to the ability to independently control the control object and achieve the desired control objectives with little human intervention and belongs to the advanced stage of control theory [12]. Intelligent control does not require a rigorous mathematical model of the controlled object but can simultaneously take into account the uncertainty and imprecision of the system when maintaining the system. PID control has the advantages of simple structure and easy parameter adjustment, so it is often used in PMSM servo control systems [13]. However, the PMSM is strongly nonlinear, and it isn't easy to obtain the desired control effect by simply using PID control as linear control. The problem is that the traditional PID control parameters can not be changed with the change of the motor system, which improves the dynamic response performance and anti-interference ability of the motor [14]. It is usually proposed to combine intelligent control with PID control to realize the real-time self-regulation of PID control parameters. The emergence of intelligent control is mainly used to deal with complex controlled objects, environments, or tasks [15]. So, when controlling extraordinary things with uncertain disturbance factors, intelligent control has become the preferred control method because of its nonlinear and self-correcting characteristics. It can achieve the purpose of improving the robustness of the system. The commonly used intelligent control methods are fuzzy control, neural network control, etc., and the combination of these intelligent control methods with each other or with advanced algorithms such as genetic algorithms and differential evolutionary algorithms can eliminate the influence of parameter changes and perturbations on the system, thus achieving better control results [16].

In general, traditional machine learning models need to extract features artificially, and then specific model algorithms will classify or predict the extracted features. In other words, traditional machine learning models rely heavily on feature extraction, and how well the features are extracted by humans will greatly affect the final results of the model. However, the process of feature extraction often takes a lot of time, and feature extraction also requires specialized knowledge, and different extraction methods are needed for different problems, which undoubtedly increases the difficulty of algorithm model design. Deep learning is a type of representation learning that does not require much human involvement and can automatically extract features from the data, simplifying the model design process. Motor fault diagnosis technology is based on the mechanism of the motor fault. Collecting the vibration signal, temperature rise change, electrical characteristics, and other states during the motor's operation can help to determine whether the operation of the engine is regular or not. With the joint efforts of researchers and scholars from various countries in the past decade, the motor fault diagnosis method has been realized in theory and achieved great success [17]. Although the motor fault diagnosis technology started late, many achievements have been obtained based on continuous development. The adaptive morphological method based on variational mode decomposition provides theoretical support for removing the characteristic frequency of rolling stretch signal [18]. The selection of a particle swarm algorithm can optimize the filter and facilitate the completion of adaptive filtering. Simulation experiments can be conducted to extract the characteristic fault signal of merit. The causes of rolling bearing faults can be analyzed and compared with adaptive morphology and other regulation methods. Zhang proposed a new way to diagnose motor inter-turn short circuit faults, the expansion of sample data, robust establishment, and training ensemble diversity are all taken care of by generative adversarial neural networks [19]. Then sparse self-coding deep learning networks are used to accomplish efficient and accurate fault diagnosis and classification. The combination of both can make this new method more precise and efficient.

Using the finite element method, Zhang et al. [20] conducted an in-depth study of the internal magnetic field, branch current and counter potential variation patterns of a permanent magnet synchronous motor under different degrees of demagnetization and during regular operation and verified the reliability of the finite element method through experiments. Raj et al. [21] analyzed the stator current spectrum, wavelet variation processed the current signal, fused the sample information entropy, and compared them to extract the fault characteristic frequency and determine the appropriate fault characteristic quantity to detect the demagnetization fault of a permanent magnet synchronous motor. Saeed et al. [22] combined the methods of fundamental adaptive waveform and empirical modal decomposition to propose a form capable of diagnosing local demagnetization. Lu et al. [23] conducted a finite element analysis of the magnetic field distribution of a permanent magnet synchronous linear motor. They used a probabilistic neural network algorithm to identify and accurately classify its local demagnetization faults. The experimental results showed that the method has relatively high identification accuracy. Due to the characteristics of wind resource utilization, the operating conditions of wind turbines are variable [24]. There are many phases of current and speed sensor faults and common marks such as output gain variation, DC bias and output jamming. The complex operating conditions and multiple types of sensor faults lead to the imbalance of managing data and multi-sensor fault samples, which brings difficulties to the machine learning-based fault diagnosis methods regarding learner training and generalization performance [25]. The permanent magnet synchronous wind turbine operation control and fault diagnosis methods are designed in two-phase stationary or rotating reference coordinates. In symmetric three-phase systems, because the phase currents satisfy the constraint that the vector sum is zero, which leads to the system output measurement matrix row is not full of rank, the fault estimation observer built based on the traditional model can only realize the residual generation or fault estimation in two-phase stationary or rotating coordinates. It is challenging to locate and estimate the phase current sensor fault.

3. Fuzzy neural network-based fault diagnosis model design for permanent magnet synchronous generator

3.1. Fuzzy neural network model construction

Fuzzy reasoning is performed based on expert experience, and finally, a defuzzification operation is applied to the obtained undefined variables, thus getting the exact control amount of the controlled object. However, to use fuzzy control, it is necessary to add human experience, which can make a lot of time spent be on adjusting fuzzy rules. Neural networks have strong self-learning and self-adaptive capabilities. The feed-forward neural network is the structure of layer-by-layer "propagation" from front to back [26]. It has the advantages of simple design, easy implementation, and strong approximation ability. However, the neural network lacks the guidance of artificial knowledge and experience, and the initial values of the network parameters can only be zero or random numbers, leading to a long response time. If the fuzzy control and neural network are correctly combined, not only can the advantages of each part be reflected, but the disadvantages of each can also be compensated. In this chapter, a fuzzy neural network PI controller is designed and used to achieve real-time PI parameter self-adjust to enhance the system's immunity and robustness.

Compared with other neuro-fuzzy systems, the T-S (Tkagi-Sugneo) model fuzzy neural network has convenient and efficient features. Take the rule r^i as an example, the fuzzy inference is as follows: the inference rule represents the output as a linear combination of the inputs, where a_j^i is the fuzzy set of the fuzzy system; P_j^i is the undefined system parameters; y^i is the work obtained according to the rule.

Let the input be $X = [X_1, X_2, \cdots, X_k]$, and the affiliation of each input variable X_j is obtained according to the fuzzy rule as:

$$U_a = \sum \exp \frac{\left(x_j + C_j^i\right)}{\sqrt{B_j^i - k}} j = 1, 2, \mathrm{L} \;\; \mathrm{k},\ \mathrm{i}=1, 2, \mathrm{L} \;\; \mathrm{n} \tag{1}$$

- B_j^i——Width of the affiliation function
- C_j^i——The center of the affiliation function
- n——Fuzzy sub set number
- k——Input parameters

The affiliation degrees are fuzzily calculated using the fuzzy operator as a concatenated multiplicative operator.

$$w = \frac{\sum\left(k_i - x_1\right) * \left(k_i - x_2\right)}{\sqrt{k_i^n + x_k}} \tag{2}$$

Calculate the output value of the fuzzy model based on the unclear calculation results y^i:

$$y^i = \frac{\sum_{n=1}(w^i + p_0^i x_1)}{\sum (w^i + n)} + p_k x_k \tag{3}$$

The fuzzy neural network of the T-S model consists of five layers: input layer, fuzzy layer, fuzzy rule layer, normalization layer, and output layer. The structure is shown in Figure 1.

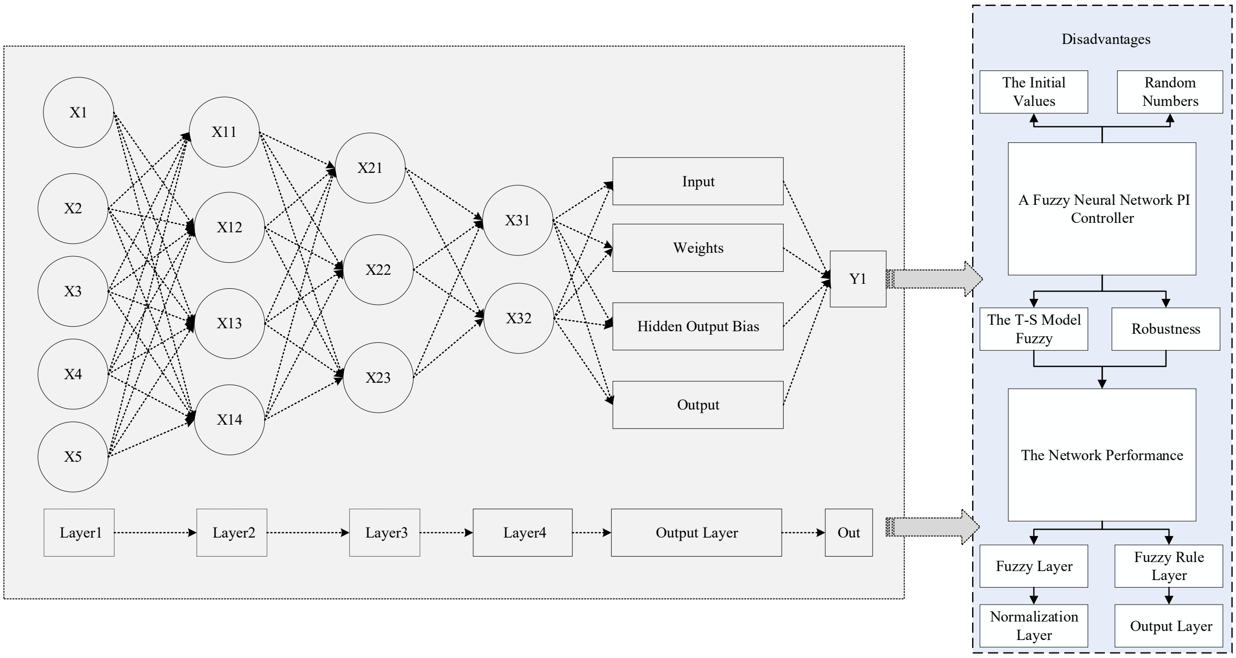

Figure 1. Network structure diagram.

The affiliation function and the weights of each layer of the fuzzy neural network greatly influence the network performance. The centroid and width in the Gaussian function and the network weights used in this paper are the main parameters of the whole fuzzy neural network, so specific learning algorithms need to be selected to correct the control parameters in the fuzzy neural network to make the control system achieve a good control effect. The error gradient method has been widely used with its mature theoretical research basis and the advantage of rigorous computational derivation. This paper uses the gradient descent method to adjust the network control parameters of the recurrent fuzzy neural network online. Similarly, the error function is defined as:

$$e = \sum \frac{\sqrt{n-2}}{y_o(n) + y_o(n)^2} \tag{4}$$

3.2. Permanent magnet synchronous generator failure characteristics analysis

When the PMSM is in operation, physical quantities such as the current and voltage change with the motor, so the cause of motor failure can be analyzed by using these physical quantities, and the changes in physical quantities can be summarized as a basis for determining the loss [27]. In this paper, the fault diagnosis of the PMSM is performed by using the method based on signal analysis, where the physical quantity selected is the current. This section focuses on the changes in the harmonic components of the current that occur after a fault. When a PMSM experiences a turn-to-turn short-circuit fault in the winding, the symmetry of the magnetic field in the stator winding is broken. The current in the motor changes, where the wind in the fault phase is larger than the current in the other two phases, and the current in the further two phases increases compared to the average current under the influence of the fault phase. And the frequency of these increased harmonic components is summarized as follows:

$$f_{(s-c)} = \sum \frac{(z \times p) - 1}{\sqrt{f_s - v}} \tag{5}$$

where f_S is the frequency of the motor, v shows a positive integer, z suggests the number of slots in the engine, and p is the number of pole pairs. When the air gap distance in the PMSM changes, the internal magnetic field also becomes uneven, resulting in a difference in the motor current, which is expressed as

$$f_s = \sum_{s=1} (2k+1) \times (p-1) \tag{6}$$

The electromagnetic force, an essential parameter in the operation of permanent magnet synchronous motors, is influenced by several physical quantities simultaneously. During the engine's rotation, the rotor is subjected to electromagnetic forces in two directions: the tangential electromagnetic force, also known as the electromagnetic torque, which drives the rotor's rotation, and the radial electromagnetic energy, which is perpendicular to the shaft.

The permanent magnet synchronous motor is a nonlinear, strongly coupled controlled system, and the electromagnetic coupling relationship between the stator and rotor parameters during the motor operation is complex and time-varying. To facilitate the analysis and design of better control algorithms for PMSM, it is necessary to simplify the PM synchronous motor to a certain extent and establish a simple and suitable mathematical model to idealize the PM synchronous motor, assuming, for example, (1) disregarding the magnetic circuit saturation, hysteresis, eddy currents, etc.; (2) disregarding the harmonic effects and considering the magnetic field generated between the motor stator winding and rotor permanent magnet as completely symmetrical and sinusoidally distributed; (3) does not consider the losses generated by temperature and frequency changes during motor operation; (4) no damping on the rotor and no damping effect on the permanent magnets. To downscale and decouple the complex PMSM mathematical model, the stationary coordinate transformation Clark transformation and synchronous rotating coordinate transformation and Park transformation are required to transform the mathematical model of the motor from the abc three-phase coordinate system to under the d-q two-phase synchronous rotating coordinate system. Since the motion of each pair of poles of the PMSM is the same, the analytical model of the motor is drawn with one pair of poles as an example.

The three stator windings of a permanent magnet synchronous motor are spatially symmetrical and differ from each other by a 120° electrical angle. The three-phase stationary coordinate systems a, b, and c coincide with the center axis of the three stator windings. The a-axis is used as the stator reference axis. The dq coordinate system is rotated synchronously with the rotor, and the angle between the d-axis and the a-axis is defined as the rotor position angle. The stator voltage equation of the permanent magnet synchronous motor is:

$$\begin{bmatrix} U_{a-1} \\ U_{b-1} \\ U_{c-1} \end{bmatrix} = \begin{bmatrix} r_s & I_a & 0 \\ I_b & r_s & 0 \\ r_s & 0 & I_c \end{bmatrix} - p \tag{7}$$

Vector control has the advantages of simple operation, good torque performance, and wide speed range, and it can achieve high control performance when controlling PMSM systems. Vector control technology converts the stator current of a permanent magnet synchronous motor into currents in the dq coordinate system, which are the stator current excitation component i_d and the stator current torque component i_q, and it controls these two present components separately to give the AC motor control performance that is similar to that of a DC motor. The proposed vector control makes a big step forward in developing motor control technology, and the block diagram of the PMSM vector control system is shown in Figure 2.

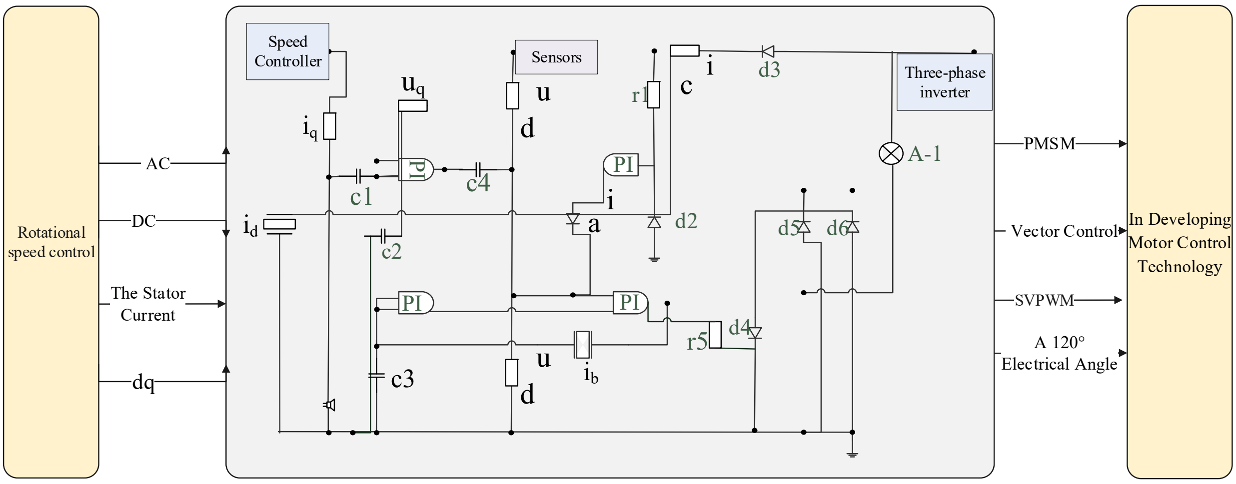

Figure 2. PMSM vector control system block diagram.

3.3. Fuzzy neural network-based fault diagnosis system design for a permanent magnet synchronous generator

Ambiguous natural language is often used to characterize states in condition monitoring and fault diagnosis. To determine states with fuzzy signs more accurately and efficiently, the concept of fuzzy sets must be used to describe the reasons for whether they belong to a state or not. It is described in terms of the degree of attribution, and affiliation. Especially for monitoring and diagnosing motor faults, the causal relationship between the causes and signs of the states is complex, and it is impossible to establish an accurate mathematical model between fault signs and states. A neural network can store the correlation between input and output in the form of weights by learning method and make associations based on them to realize the nonlinear mapping of information to production.

Therefore, fuzzy logic systems and neural networks complement each other, and since both are processed in numerical form, they can be combined to form fuzzy neural networks. On the one hand, fuzzy neural networks can use linguistic descriptions to collect knowledge, which can quickly introduce enlightening expertise and track the inference process; on the other hand, they can have learning functions like neural networks to improve the accuracy of judgments [28]. Based on the traditional multilayer perceptron, it cannot handle expert linguistic descriptions, and can only deal with the ideal case of data, which is that the failure mode corresponding to specific data can only belong to a particular state but not to several states at the same time [29]. Therefore, this paper combines the fuzzy concept in the neural network so that both its input and output are semantic subordination, which can handle input in the form of language and the output has a fuzzy nature in the fault mode recognition.

In this paper, a fuzzy neural network with a biased recurrent neural network is used, whose learning algorithm and modification of weights that are consistent; the concept of fuzziness is fused on the input and output expressions. First, the input is fuzzified, and for each input feature S`, it can be expressed as a fuzzy set formed by short and intermediate-length, and significant linguistic expressions with the help of the affiliation function in fuzzy logic. Second, the output is fuzzified, as the samples are often pathological, their boundaries are unclear, and the patterns used for training often have non-zero values at more than one output, the corresponding pattern output cannot be made to be 1 and the rest to be 0. Therefore, in the training phase, the work should be made to reach the desired affiliation degree as much as possible. The backpropagation algorithm continuously checks the weighted values so that the output can give the corresponding pattern affiliation degree at any input. The backpropagation algorithm is used to alter the weighting values so that the work can provide the affiliation of the connected node at any information so that the fault diagnosis module can judge the state of the data with fuzzy boundaries more effectively.

For the model problem with i output nodes of class l, the mean and standard deviation of the numerical training data, k is denoted by the n-dimensional vectors λ_k and σ_k respectively, then the weighted distance formula of the training model S for the class k is expressed as

$$z_{(i-k)} = \sum_{j=1} \left(f_j - \lambda_{(k-j)} \right)^2 + \sigma_{(k-j)} \tag{8}$$

where f_j is the j element of the i pattern. The weighted value $1/\sigma_{k-j}$ is used to consider the variance of the class, the feature values with significant variance have smaller weights in the classification. The affiliation function of the i pattern to the k course is defined as

$$w_k + s_i = \sum_{g=1} \left[z_{(i-k)} + f \right] - 1 \tag{9}$$

where f and g are two positive constants that control the fuzziness of the affiliation set of the class. Equation (9) represents the distance of a pattern to a class; the greater the distance, the smaller the affiliation degree. In the case of the maximum fuzzy degree, the distance has l non-zero elements. Then the fuzzy corrector can be used to increase the size of each type of affiliation:

$$\varphi_k + s_i = \sum \frac{\left[w_k(s_i) + w_{k-1} \right]}{\sqrt{s_i - 1}} \tag{10}$$

The most crucial task of synchronous generator fault diagnosis is to extract the correct information reflecting the status of the generator equipment by analyzing and identifying the various external signs and information during operation and corresponding to its status pattern. This system is based on the analysis of possible abnormalities in the stator of synchronous generators in the case of rotor winding short-circuit faults and establishes a corresponding condition and fault diagnosis system.

Synchronous generator rotor winding short circuit fault diagnosis is purposed to determine whether the rotor winding is working correctly according to the information change pattern generated during the generator operation; if it is not working correctly, the type of fault and the trend of the responsibility should be determined [30–32]. Therefore, the diagnosis process includes acquiring and processing characteristic quantities, diagnosis decisions, and fault handling. The flow chart of synchronous generator fault diagnosis is shown in Figure 3.

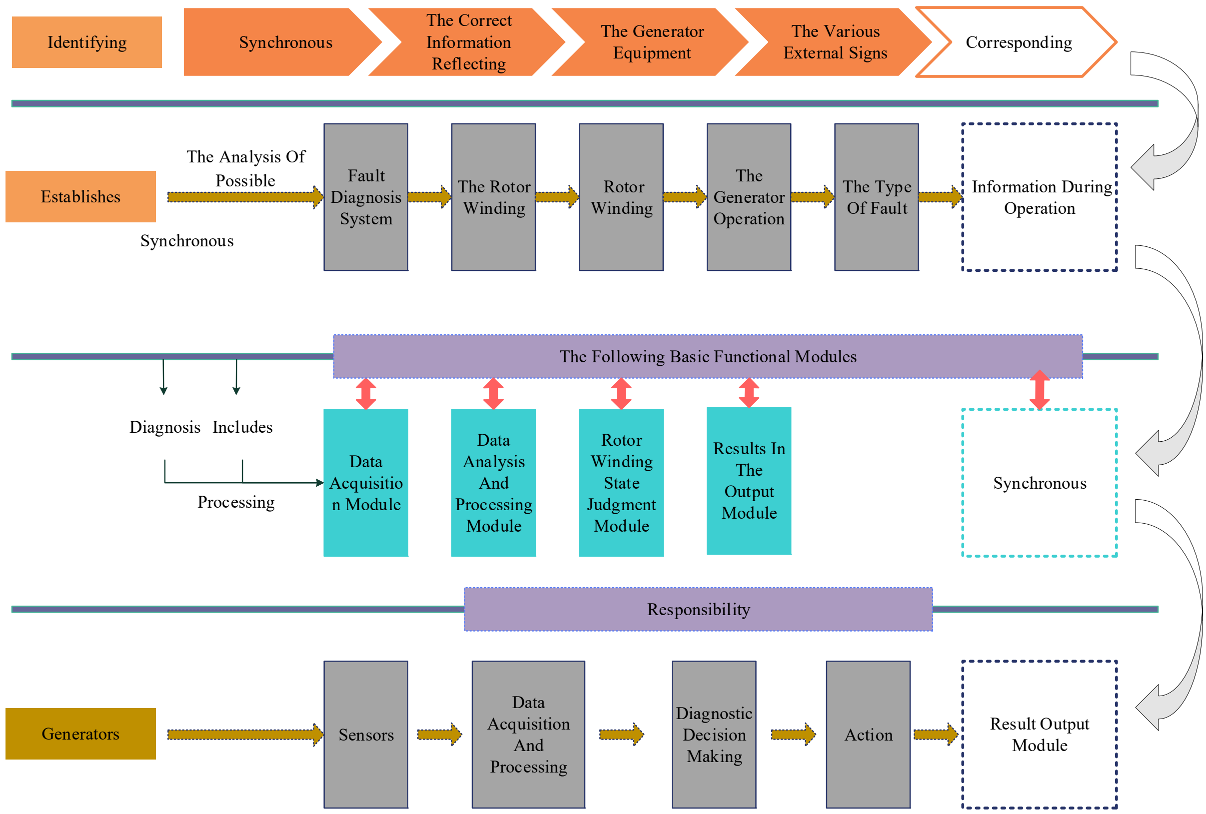

Figure 3. Synchronous generator fault diagnosis flow chart.

The two-pole synchronous generator fault diagnosis system studied in this paper mainly consists of the following basic functional modules: (l) data acquisition module: acquisition of various parameters, A/D conversion; (2) data analysis and processing module: analysis and processing of the sampled data, this paper is mainly to achieve harmonic voltage analysis and rotor excitation current prediction; (3) rotor winding state judgment module: through the analysis, determine what the rotor winding; (4) results in the output module. This paper uses a fuzzy neural network fault diagnosis method for permanent magnet synchronous generators to improve the recognition rate of one fault, which has practical value. It assembles a fuzzy neural network, which can learn complex data, has the advantages of strong adaptivity, fast operation and a good understanding of the fuzzy mechanism, and it can solve the irreversible relationship of the fuzzy system [33–35]. In the field of machine learning, the evaluation of models is very important, and only by choosing the evaluation method that matches the problem can we quickly find the problems of the algorithm model or the training process, and iteratively optimize the model. Model evaluation is mainly divided into two stages: offline evaluation and online evaluation [36]. And the evaluation metrics are chosen differently for different types of machine learning problems such as classification, regression, ranking, and sequence prediction. In this paper, the generator fault evaluation method based on fuzzy neural network modeling is used to pay more attention to the application in fault evaluation.

4. Analysis of results

4.1. Fuzzy neural network model analysis

Since the fuzzy neural network model adversarial neural network replaces all of the implicit layers of the generative adversarial neural network with convolutional layers, uses batch normalization in the generator and discriminator, and removes the fully connected layers. A relative comparison is applied to evaluate the effectiveness of the proposed fuzzy neural network-based adversarial neural network to expand the sample data and the generative adversarial neural network to expand the sample data and to verify the effectiveness of the generative adversarial neural network. The characteristics and demagnetization mechanism of the rotor permanent magnets of the permanent magnet synchronous motor were studied and analyzed. In this paper, the test set data is packaged and transferred to the training project file after the calibration of the dataset is completed. In the project folder, the author creates the init_weight file to assign the initial weights to the fuzzy neural network model and the weight_out folder to store the output weights after training. Then, the author creates the Traindata.cfg training file, import the config file, define the input layer, output layer, hidden layer, and activation function, and then call the Scikit-fuzzy algorithm API to determine the fuzzy layer. The training status is displayed every 10 iterations to view the gradient descent of the model loss function, and the systematic error is set to $E = 1e - 2$. The gradient of e_k decreases with the number of iterations as shown in Figure 4, and finally Matlibplot is called to plot the gradient of the error e_k during training of the fuzzy neural network.

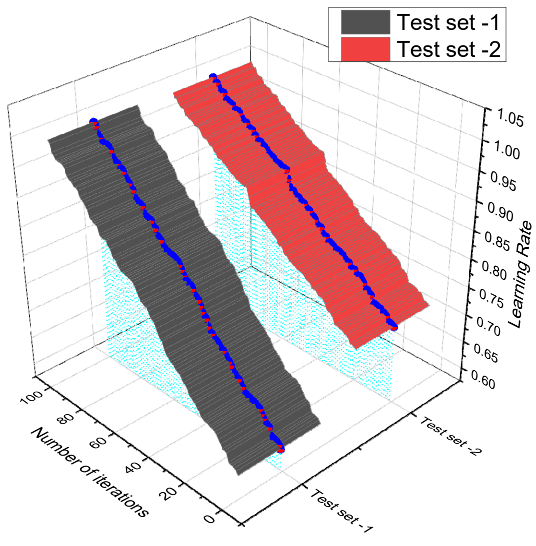

Figure 4. Gradient decreases with the number of iterations.

In this experiment, because the experimental sample data used is not particularly large, there is no need to use a large computer for the experiment, and the machine performance of a personal computer is sufficient to complete the entire experimental process. The main configurations of the machines used in this experiment are shown in Table 1.

Table 1. Instrument configuration.

Configuration Category	Specific parameters
Operating system	Windows 10 operating system
CPU	Intel core i7-8750H
Operating Memory	32.00 GB DDR4
Video card	NVIDIA RTX2060 6G GDDR6 discrete graphics card
Hard disk	512 GB SSD
Development Platform	ANSYS Maxwell
Development Framework	Tensorflow

This paper analyzes the demagnetization mechanism of permanent magnets from the characteristics of permanent magnets, then theoretically analyzes the variation of torque and current signal under demagnetization fault. Finally, a finite element simulation model of the local demagnetization fault of the motor is built based on Maxwell software. In this paper, the trained weigh_out file path is imported into the test file, and the file uses the trained weights saved in weigh_out to build the input layer, output layer, hidden layer, and fuzzy layer. In turn, then the trained fuzzy neural network model is created. Finally, we import the test set to test the classification effect of the model. There are 200 calibrated samples in the test set, which are input into the fuzzy neural network model to obtain the input results.

Table 2. Energy entropy of various types of faults.

Failure	Energy entropy				
Normal	0.005226	0.004584	0.004353	0.000726	0.005085
Short circuit between turns	0.001281	0.006790	0.002736	0.004741	0.008752
Demagnetization 10%	0.006472	0.006851	0.004716	0.002793	0.009262
Demagnetization 20%	0.009090	0.008633	0.002316	0.006074	0.008170
Demagnetization 30%	0.001623	0.009116	0.001359	0.000776	0.006982
Demagnetization 40%	0.000166	0.003745	0.003484	0.008410	0.004476
Demagnetization 50%	0.009139	0.008525	0.005160	0.005842	0.006051
Demagnetization 60%	0.005972	0.005848	0.009768	0.005234	0.008451

In this paper, we take the permanent magnet synchronous motor demagnetization fault and winding turn-to-turn short circuit fault as the research object and extract the current data of the motor in the normal state, 10%, 20%, 30% uniform demagnetization state and turn-to-turn short circuit state respectively through the experimental platform, and get the IMF (intrinsic mode function) components by VMD (virtual machine disk) decomposition based on the collected data. The energy entropy of each piece is eventually merged as the feature vector. The energy entropy of each type of fault designed in this paper is shown in Table 2. Each category includes 500 samples, and there are 5 categories in total, so there are 2500 samples in the data set, and the sample labels have experts to give evaluation results. Since it is necessary to set up training data and test data for fault diagnosis by using the fuzzy network, 400 samples from each category are selected as the training set. The total number of samples constituting the training set is 2000. The remaining 100 samples of each class, 500 samples in total, are used as the test set to test the accuracy of the PNN (probabilistic neural network) model, PSO (particle swarm optimization) -PNN model and FCM (fuzzy clustering mean) -PSO-PNN model. The fuzzy neural network is trained based on the historical fault data records of the generator. When the input exceeds the training set, the trained fuzzy neural network can adjust itself online and generalize. The unsupervised training of the depth model using data from the normal operation of the equipment allows the trained self-encoder model to extract the features of the data in normal operation; then the test data is fed into the trained depth model, so that the reconstruction error will be smaller if the test data is normal, and larger if it is faulty data.

This paper is compared with the conventional fuzzy fault diagnosis to verify the designed unspecific neural network generator for fault diagnosis. Matlab/Simulink is used to build the unclear fault diagnosis and fuzzy neural network fault diagnosis models, respectively. These two controllers are used as speed regulators for the vector diagnosis system of permanent magnet synchronous motors. The PMSM parameters used in the simulation are pole log p = 1, R_s = 0.901N, stator inductance $l_d = l_q$ = 6.553 mH, and rotational inertia J = 1.2 × $10^{-4}kgm^2$. The learning rate η = 0.33 and momentum factor $\alpha = 0.01$, $k_p = 0.9$, $k_i = 0.1$ are obtained by reviewing the data and performing simulation debugging. The no-load speed curve for fault diagnosis is shown in Figure 5, given a speed of 1000 r/min, and the no-load start of the motor system with fuzzy PI control, and fuzzy neural network fault diagnosis, respectively.

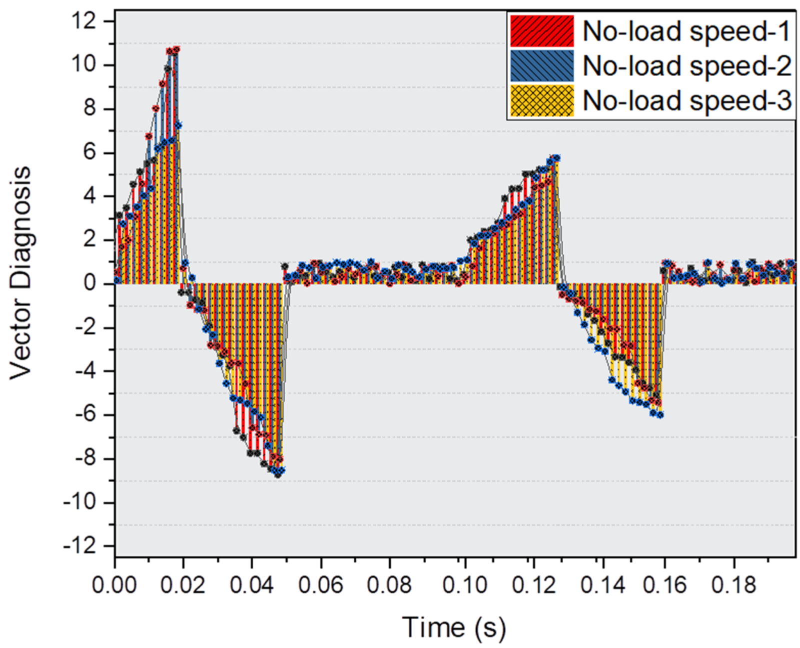

Figure 5. No-load speed curve for fault diagnosis.

The training results of the fuzzy neural network with residual connections are shown in Figure 6. The number of convolutional layers is 48 for both down-sampling (average pooling) and overlapping pooling, and the loss rate of the deep convolutional neural network with residual connections is 0% after 3000 iterations of the diagnostic model. The trained neural network is used to perform error-free fault diagnosis of permanent magnet motors on 200,000 test samples. The recursive fuzzy neural network controller is used in the PMSM vector control system. The sensor obtains the PM motor's speed information, and the error is received by the difference between the feedback speed information and the given speed. Then the speed error variation is obtained by its derivation. The speed error and the error variation are used as two inputs to the recursive fuzzy neural network controller.

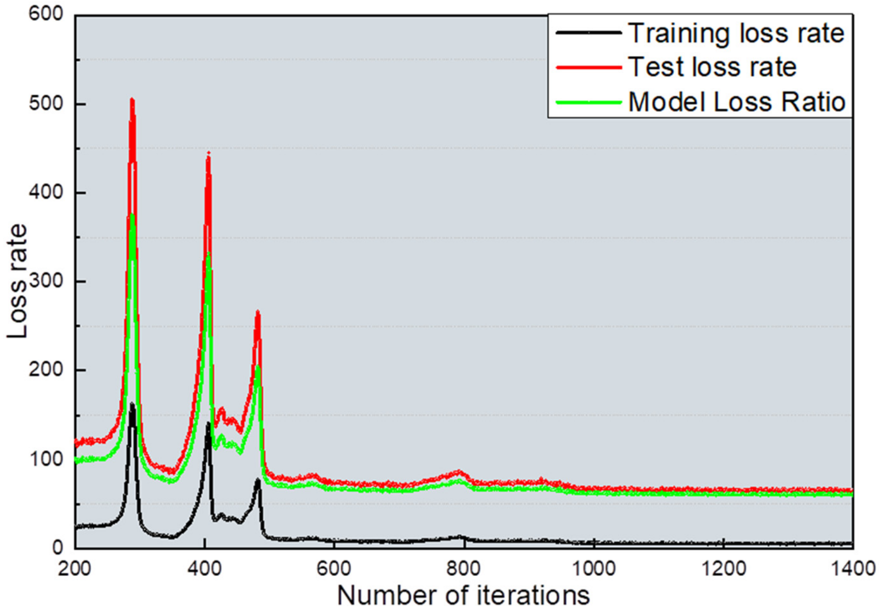

Figure 6. Training results of fuzzy neural network with residual connections.

Sample data capacity is essential for the learning efficiency and accuracy of deep neural networks. Therefore, to verify the effect of expanding the sample data capacity by deep convolution generative adversarial networks (DCGAN) on the accuracy of inter-turn short-circuit fault diagnosis of the permanent magnet motor. The original average and inter-turn short-circuit fault data are used in the ratio of 2:1 to build the training set, and the number of samples in the training set is 2400. After the sample data expansion by the DCGAN, the sample size increases from 2400 to 3200, and the ratio of "normal" data to "inter-turn short-circuit fault" in the training set is about 1.7. Also, 400 sets of data are randomly selected from the inter-turn short-circuit fault sample data as the test set to test the effect of inter-turn short-circuit fault diagnosis.

4.2. Permanent magnet synchronous generator fault diagnosis method implementation

In machine learning and data mining applications, Scikit-Learn is a powerful Python package that we can use for classification, feature selection, feature extraction, and aggregation. In this paper, a fault in a two-pole synchronous generator generates a second harmonic voltage on the stator side of the synchronous generator. It causes a change in the rotor current. Therefore, the input variables are determined as the percentage of the stator's second harmonic voltage relative to the total rated voltage and the percentage deviation of the rotor current from the standard condition. The fault type is used as the output variable.

For the linguistic value fields of the input and output variables and the corresponding affiliation functions, the number of linguistic values is often chosen as 3, 5 and 7. Then the defined fuzzy set defines its affiliation function, and the affiliation function should cover the whole range of values. If a range of values needs to be sensitive, then the corresponding affiliation function can be "dense". In addition, there should be an overlap between the affiliation function, the general overlap of 25% to 50%, to improve its robustness.

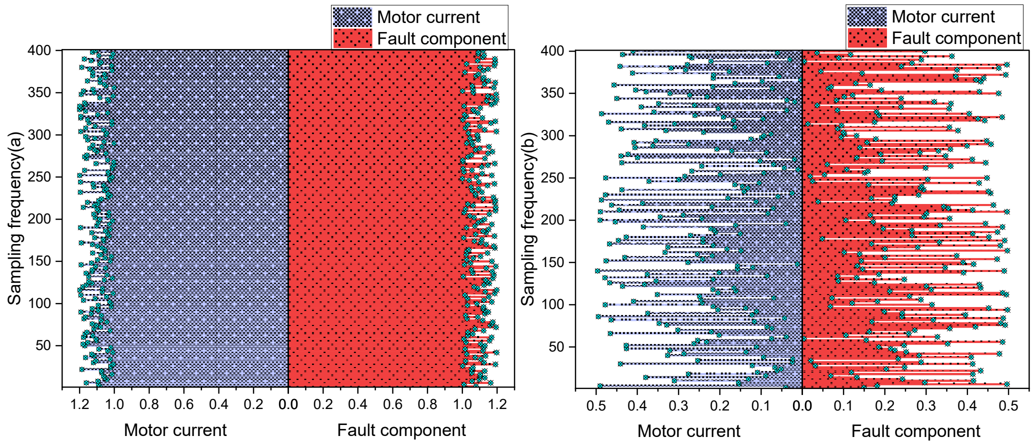

Figure 7. Transformation of motor current and fault components.

For the generator, rotor winding turn-to-turn short circuits, one-point grounding, and two-point grounding faults, any fault that the Fourier transform can detect can also be seen by the wavelet transform, and the wavelet transform has less volatility. The transformation of motor current and fault components is shown in Figure 7. Therefore, this paper uses the wavelet transform to analyse the simulated excitation current signal and extract the higher harmonics that reflect the fault components.

By solving the formal equations and performing ANOVA for each transition equation with a significance test, the multifactor regression method was used to find out that the factors that have more influence on the rotor current from the stator side of the synchronous generator are: stator current, active power, reactive power, and power factor, and their regression coefficients are 0.0075, –0.0018, –0.3902, –0.13930. The regression coefficients are 0.0075, –0.0018, 1.3902, and –0.13930, and other factors are not significant to the rotor current, so they are not considered. Thus, the above four factors are used as the input to the rotor's current prediction system.

To verify the correctness and accuracy of the analytical model of the direct drive permanent magnet synchronous motor (DDPMSM) no-load back EMF (electromotive force) with different degrees of demagnetization of any number of permanent magnets, the irreversible demagnetization of 75%, 50%, 25% of the permanent magnets with number 1 at rated speed and 100 r/min, and the irreversible demagnetization of 75%, 50%, 25% of the permanent magnets with number 1 and number 2 at the same time was compared with the finite element results. The analytical calculations of the single coil no-load back potential and the narrow element results are compared and analyzed, as shown in Figure 8. It can be seen that the analytical results of the DDPMSM single coil no-load counter potential and the finite element calculation results agree. Still, there is a specific error caused by the neglect of the harmonic component in the analytical model. Simultaneously, with the increase of the demagnetization degree, the error between the analytical calculation results and the finite element calculation results becomes larger and larger. This is because the harmonic content of the potential increases with the increase of demagnetization, so the error caused by ignoring the harmonics also increases. Therefore, the developed analytical model of DDPMSM no-load reactive potential can analyze the single-coil no-load reactive potential when different degrees of demagnetization faults occur in arbitrary numbered permanent magnets.

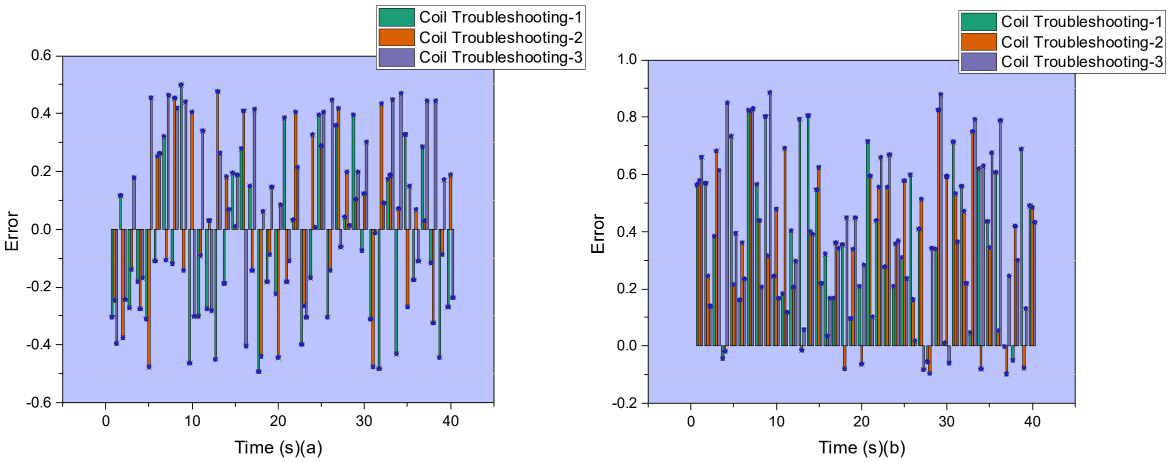

Figure 8. Fuzzy neural network for permanent magnet synchronous generator fault diagnosis before and after comparison analysis.

In the actual operation of PM motors, due to the compact structure of PM motors, when a particular fault occurs in PM motors, failure to deal with it in time can cause damage to other parts of PM motors, resulting in multiple defects or concurrent faults in PM motors. Many scholars currently use a specific PM motor signal as a characteristic quantity for PM motor fault diagnosis. When a single fault occurs in a PM motor, a single signal as a distinct quantity can correctly diagnose the type of PM motor fault. When multiple defects or concurrent faults occur in a PMM (pulse mode multiplex), a single signal is not used as the characteristic quantity to correctly diagnose the type of PMM faults. Since the stator current signal and vibration signal contain the fault characteristics of the PM motor in different states, the stator current signal and vibration signal are used as the fault characteristics of the PM motor in this paper when multiple faults or concurrent faults occur in PM motors. The correct rate of PM motor fault diagnosis results using a single feature signal as PM motor fault diagnosis feature quantity is lower than the correct rate of PM motor fault diagnosis results using a composite feature signal as PM motor fault diagnosis feature quantity. To better validate the effectiveness of fuzzy neural networks in generator fault diagnosis. Using the same experimental environment, another fault data sample is used to train the fuzzy neural net. The analysis of the diagnosis results shows that the degradation fault degree prediction results obtained by using the fuzzy neural network-based local degradation fault diagnosis method proposed in this paper are more accurate than the degradation fault degree prediction results obtained based on the single domain feature parameters.

5. Conclusions

A permanent magnet motor is important driving equipment that is widely used in various industries, whether the normal operation of a permanent magnet motor directly affects the operation status of production equipment, the study of permanent magnet motor fault diagnosis has a high economic and academic significance. Through reading a lot of literature about motor fault diagnosis and neural networks. Learn various fault diagnosis methods, and understand the advantages of each method and the differences between each method. In the era of big data, the learning ability of shallow neural networks seriously affects the accuracy of their fault diagnosis due to their weak generalization ability. In this paper, based on the summary of previous research, we propose a permanent magnet motor based on stator current characteristics and vibration characteristics by combining the powerful learning ability of deep neural networks in the context of big data. A fault diagnosis method of fuzzy neural network based on residual connection is proposed. As the generator fault phenomenon and the fault, cause have a close relationship, each fault phenomenon may be caused by one or more fault causes, and each spot will cause some corresponding sensation. The complexity and ambiguity of the fault phenomena, causes, and mechanisms of large generators are difficult to be described by accurate mathematical models, and it is difficult to rely on deterministic criteria to determine the nature of the fault. Currently, the fuzzy method is used for status monitoring and diagnosis based on obtaining the comprehensive effect of system status, accumulating maintenance experience, and concentrating expert opinions. Artificial intelligence technology and fault diagnosis technology can achieve more accurate fault diagnosis. This paper studies the mathematical model of a short circuit between turns of a permanent magnet synchronous motor. The analysis of the mathematical model reveals that the effect of an inter-turn short course on the engine can be expressed as a voltage component related to the number of shorted turns and fault resistance added to the fault-free motor mathematical model. A finite element simulation model was developed based on the equivalent circuit model. The FEM (finite element modeling) simulation shows that the current amplitude of the stator fault phase increases in the turn-to-turn short-circuits fault condition, the phase difference of the stator three-phase current is no longer 120°, the negative sequence current component of the stator recently increases as the number of turns increases and the fault resistance decreases, and the frequency-dependent member of the stator current spectrum changes. The simulation shows that the fuzzy neural network model with residual connections has faster learning efficiency and accuracy in PM motor fault diagnosis. When multiple faults or concurrent faults occur in PM motors, the accuracy of PM motor fault diagnosis results using composite feature signals as feature quantities is higher than that using single feature signals as feature quantities.

The fuzzy neural network has a variety of cross-connected modules, and the residual connection module used in this paper is only one of them. If different diagnostic methods have different diagnostic results for the same feature quantity, it may be possible to analyze various cross-connected modules separately and integrate various cross-connected modules to achieve an online diagnosis of permanent magnet motors. The selection of optimal hyperparameters for neural networks is selected by experience and continuous repetition of trials regardless of whether it is a shallow neural network or a deep neural network. However, this method of selecting the optimal hyperparameters is not only time-consuming but also consumes the researchers' efforts. Therefore, there is a need to design an optimization algorithm that can automatically delete the optimal hyperparameters of neural networks to improve the efficiency of researchers.

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Conflict of interest

The author declares there is no conflict of interest.

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