Fault Diagnosis of Permanent Magnet Synchronous Motor Inter Turn Short Circuit Based on Deep Reinforcement Learning

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Abstract. With the increasing market share of Permanent Magnet Synchronous Motor(PMSM), the fault diagnosis and prediction technology for PMSM is becoming increasingly important. Firstly, in order to solve the problem of insufficient fault sample data consisting of negative sequence current, electromagnetic torque and other inter turn short circuit fault feature terms, the Conditional Generation Adversarial Network(CGAN) is used to expand the data set. Then, with sufficient data, Dueling_DQN algorithm of deep reinforcement learning is used to train and optimize the extended data set. Finally, the effectiveness of the algorithm in the field of PMSM fault diagnosis is verified by simulation training. The results show that the fault diagnosis accuracy of the algorithm can be reached 97.5%, while improved the convergence speed and saved the time cost of fault diagnosis.

1. Introduction

Recently, as a driving element of environmental protection and green energy, the motor is widely used in economic life. However, due to the narrow working environment, high temperature oscillation, frequent startup and shutdown and other adverse factors, overvoltage or overcurrent is very easy to occur in the motor. These will result in inter turn short circuit, open circuit and other faults of the motor, which affecting the normal operation of the motor.

The failure of PMSM seriously affects the safety, stability and the service life of the equipment. Therefore, in order to effectively extend the service life and ensure the safe and stable operation of the equipment, effective fault diagnosis of PMSM is of great significance. Circuit fault and power fault are two types of fault with high frequency in motor fault. Among them, stator winding fault is a very serious AC motor fault, including circuit open circuit and short circuit. Inter turn short circuit is a very common short circuit fault. The causes of inter turn short circuit are mostly due to humid equipment environment, partial discharge or mechanical stress, resulting in large circulating current in the winding. If it is not found in time, it will lead to serious phase to phase short circuit and induce serious production accidents[1].

The development phase of PMSM fault diagnosis method can be divided into three stages: manual diagnosis stage, modern automatic diagnosis stage and artificial intelligence diagnosis stage[2-3]. Among them, artificial intelligence methods combined with the experience and logical reasoning to
judgment motor state, which have more advantages in terms of fault diagnosis. Deep learning and reinforcement learning are important branches in the field of artificial intelligence. Deep reinforcement learning (DRL) combines deep learning and reinforcement learning, which not only has the strong perception ability of deep learning, but also combines the strategy selection and decision-making ability of reinforcement learning[4]. Since the deep mind team of Google succeeded in using DQN in high latitude and large state space games such as Atari 2600, DRL has gradually become a research hotspot in the field of artificial intelligence. Since 2013, great progress has been made in the research of DRL algorithm. Silver and others have successfully applied DQN algorithm to video games[5]. Guo, Van and Hausknecht have optimized and improved DQN algorithm, and successively proposed the algorithm combining DQN with Monte Carlo tree search[6], double_DQN algorithm[7], DRQN algorithm combining LSTM and DQN[8]. The training effect of DRL algorithm is excellent. However, the DQN application in PMSM fault diagnosis is still in its infancy and has a lot of research space.

It is worth noting that the DRL algorithm has certain requirements on the number of samples in the data set. When the data amount is small, effective training cannot be achieved. However, the insufficiency problem of sample data exists in the fault diagnosis of PMSM. Therefore, CGAN were used in this paper to effectively train and expand sample data of fault features, including negative sequence current and electromagnetic torque, so as to meet the data requirements of DRL training. Meanwhile, in order to reduce the training time cost of DQN algorithm, the optimization algorithm Dueling_DQN algorithm is proposed to train and learn the data set, adjust the optimization algorithm parameters, improve the training process, and increase the convergence speed. Finally, the practicability and superiority of this method in PMSM fault diagnosis are verified.

2. Characteristics analysis of PMSM

PMSM is a synchronous motor that uses rare earth permanent magnet as rotor to provide excitation and generate synchronous rotating magnetic field. It is mainly composed of rotor, stator, bearing, end cover and other components. When the A-phase short circuit of PMSM occurs, the three-phase flux of the motor is asymmetric, and the short circuit current increases. The relationship between positive sequence current, negative sequence current, zero sequence current and three-phase current is shown as follows:

\[
\begin{bmatrix}
    i_0 \\
    i_a \\
    i_c
\end{bmatrix} = \frac{1}{3} \begin{bmatrix}
    1 & 1 & 1 \\
    a & a^2 & 1 \\
    a^2 & a & 1
\end{bmatrix} \begin{bmatrix}
    i_a \\
    i_b \\
    i_c
\end{bmatrix}
\]

\[i_0 = \frac{1}{3} (i_a + a^2 i_b + a i_c)
\]

Where \(a = e^{\frac{2\pi}{3}}\); \(i_a, i_b, i_c\) denote three phase current vector; \(i_0, i_+, i_-\) represent the zero sequence current, positive sequence current and negative sequence current.

Negative sequence current is an important indicator to measure motor phase imbalance[9]. Since there are many factors affecting the current, such as the imbalance of power supply, which will affect the negative sequence current. Therefore, it is difficult to achieve effective and accurate diagnosis simply using the negative sequence current as the basis for judging the state of the motor. When the motor short circuit fault occurring, the phase current will increase. Meanwhile, the more short circuit turns, the higher the peak value of the phase current, and finally the electromagnetic torque rises and the obvious fluctuation changes occur. Therefore, combined the electromagnetic torque with the negative sequence current as the judgment basis of the motor state, which can improve the diagnosis accuracy. In the normal state of the motor, its air gap magnetic potential is expressed as follows[10] :

\[f(a, t) = F_s + F_i = F_s \cos(\omega t - p\alpha) + F_i \cos(\omega t - p\alpha + \varphi + \frac{\pi}{2})\]
Where $F_F$ is the main magnetic potential, $F_s$ is the three-phase synthetic magnetic potential of stator windings; $p$ denote the number of pole-pairs; $\omega, \alpha, \varphi$ represent the angular frequency, mechanical angle and the sum of the power angle. Tangential magnetic density of PMSM is:

$$f = \frac{1}{\mu} B_n B_n$$ (4)

PMSM generates electromagnetic torque under the action of tangential force, which is expressed as[11]:

$$T = \frac{2\pi R^2 L}{N\mu} \sum_{i=1}^{\infty} (B_{ni} * B_{ni})$$ (5)

When inter turn short circuit fault occurs in PMSM, it will cause distortion of circular air gap magnetic field and increase of ellipticity, resulting in reduction of electromagnetic torque. Therefore, the combination of electromagnetic torque and negative sequence current as the judgment basis of motor state can effectively improve the accuracy of PMSM fault diagnosis.

3. Deep reinforcement learning

In DRL, deep neural network is used to identify spatial or data states and extract features, and reinforcement learning explores the optimal strategy for learning to achieve goals. DQN algorithm is a typical DRL algorithm, consisted of deep neural network and Q-learning algorithm. DQN algorithm uses deep neural network to fit Q value, replacing Q-table, to obtain the corresponding Q value of each action. Then, according to the principle of Q-learning, the action with the largest reward is selected as the output, so as to obtain the optimal strategy to achieve the goal through training and learning. However, DQN algorithm has the disadvantages of long training learning time cost and slow convergence speed. Therefore, this paper proposes an optimization algorithm Dueling_DQN for training diagnosis.

The Dueling_DQN algorithm mainly improves the output part of the neural network, which is divided into two parts: one is value function, which represents the value of the static state itself and is only affected by the state without action; the other is advantage function, represents the added value of state-dependent actions that are affected by both the state and the action. The Q value of Dueling_DQN algorithm can be expressed as:

$$Q(s, a; \alpha, \beta) = V(s; \theta, \alpha) + A(s, a; \theta, \beta)$$ (6)

Where $\theta$ is the network parameters of public part, $\alpha$ is the network parameters of value function, $\beta$ is the network parameters of advantage function.

In practice, the network agent cannot obtain the unique solution of $V(s; \theta, \alpha)$ and $A(s, a; \theta, \beta)$ from Equation (6), and cannot accurately distinguish the value function from the advantage function. Therefore, the Q value of Dueling_DQN algorithm can be expressed as following Equation (7), where $|A|$ is the total number of all actions in the action space.

$$Q(s, a; \alpha, \beta) = V(s; \theta, \alpha) + \left[ A(s, a; \theta, \beta) - \frac{1}{|A|} \sum_{a'} A(s, a'; \theta, \beta) \right]$$ (7)

Dueling_DQN algorithm improves the intermediate network structure of DQN algorithm, and its loss function and external Q value update mode are consistent with DQN, as shown in following:

$$L_i(\theta_i) = \left[ r_i^2 + \gamma \max_{a_i, \alpha_i} \hat{Q}(s_{i+1}, a_{i+1}; \theta', \alpha', \beta') - Q(s, a; \theta, \alpha, \beta) \right]^2$$ (8)

The network structure and model of Dueling_DQN algorithm are shown in Figure 1[12]:
The existence of the dominant function in the Dueling_DQN algorithm makes the neural network not need to know the influence of each action on the state during training, and can more intuitively reflect the valuable state. This makes the Dueling_DQN algorithm especially advantageous when the action does not affect the environment in any relevant way. Compared with the DQN algorithm, it can also converge faster and effectively save the time cost of training. However, because the Dueling_DQN algorithm has certain requirements on the amount of data, it is difficult to achieve effective training and learning when the amount of data is too small. Therefore, in this paper, CGAN is introduced to train and expand the data set, increase the number of samples, and effectively improve the diagnostic accuracy of the algorithm.

4. Experiment and analysis

In this paper, the data set of interturn short circuit fault of PMSM is built, and the motor parameters are shown in Table 1:

| Parameter                  | Value  |
|----------------------------|--------|
| Rated power /W             | 550    |
| Rated voltage/V            | 220    |
| Slot number                | 24     |
| Number of pole-pairs       | 4      |
| Number of turns of parallel winding | 257 |
| Rated speed/rpm            | 1500   |

The DRL algorithm has a certain demand for the amount of data, the more data, the better the training effect. However, the PMSM has the problem of insufficient samples. Therefore, this paper proposes CGAN to carry out data expansion training for the sample data set composed of interturn short circuit fault characteristic items such as negative sequence current and electromagnetic torque. With CGAN, random samples as network input, output expansion data after training. Comparing the distribution of original data and expanded data, the data distribution of different iterations is shown in Figure 2, 3 and 4. It can be seen from the figures that, in the training process of CGAN, the expansion data gradually converges from the initial random data to the real data, and finally basically approaches the distribution of the real data, which proves the effective expansion and derivation ability of CGAN.
Figure 2. 10000 iterations.

Figure 3. 60000 iterations.

Figure 4. 100000 iterations.
The sample data set of inter turn short circuit fault is composed of original data and extended data. The label is shown in Table 2. Dueling DQN algorithm is used for training and learning of the data set. The feature items of fault samples such as negative sequence current and electromagnetic torque are taken as the state, that is the input of the neural network, and the output is the Q value of the possible action $Q(s_t,a_t)$. The network agent adopts the $\epsilon$-greedy strategy to randomly select an action with the probability of $\epsilon$, and selects the action with the maximum $Q(s_t,a_t)$ with the probability of $1-\epsilon$, so as to avoid falling into the local optimal solution. The network parameters after several iterations and adjustments are shown in Table 3. The training effect is shown in Figure 5. It can be seen that the network model converges rapidly and the motor state of the PMSM is effectively judged. Meanwhile, the fault diagnosis accuracy of the sample data of the inter turn short circuit fault of the PMSM has reached 97.5%.

| Table 2. Sample labels. |
|-------------------------|
| Label                   | Value |
| Healthy state           | 0     |
| Minor inter turn short circuit fault status | 1     |
| Severe inter turn short circuit, voltage tolerance | 2     |
| Severe inter turn short circuit, voltage out of range | 3     |
| Damaged state           | 4     |

| Table 3. Network parameters. |
|-----------------------------|
| Parameter                  | Value |
| Learning rate              | 0.001 |
| Reward decay               | 0.9   |
| Replace target inter       | 200   |
| Memory size                | 500   |
| Batch size                 | 26    |

Figure 5. Diagnosis accuracy of Dueling_DQN.
Figure 6. Diagnosis accuracy of DQN.

In order to compare with the traditional DQN algorithm, the training effect of DQN algorithm is shown in Figure 6. Compared with Figure 5, the early training and learning time of DQN algorithm is longer. DQN algorithm gradually converges after 1000 iterations, and training becomes stable after 1500 iterations, while Dueling_DQN algorithm begins to converge and rapidly becomes stable after 250 iterations, and also can achieve good training effects. Therefore, Dueling_DQN algorithm significantly improves the shortcoming of DQN algorithm with too long training time, and can realize fast convergence and effectively save the time cost of fault diagnosis, which also proves the validity of the application of Dueling_DQN algorithm in the field of PMSM fault diagnosis.

5. Conclusion
Aiming at the problem of inter turn short circuit faults in PMSM and the defects of small samples, this paper proposes a fault diagnosis method based on deep reinforcement learning. Firstly, CGAN is used to expand the sample data set to meet the training requirements of DRL and improve training efficiency. Then, Dueling_DQN algorithm is used to train and learn the expanded sample data set, which obviously improves the problem of long training time cost of traditional DQN algorithm. Finally, through the simulation training of the fault data set, the effective fault diagnosis accuracy of 97.5% is obtained, which verifies the practicability and effectiveness of the proposed method in the field of inter turn short circuit fault diagnosis of PMSM. However, this method mainly focuses on the diagnosis training of single fault, and has not verified its effectiveness in the superposition of multiple compound faults. How to collect compound fault data, establish compound fault data set, and carry out effective diagnosis remains to be further studied and solved.

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References
[1] Prasad, B.J.C., Ram, B.V.S. (2013) Inter turn fault analysis of synchronous generator using finite element method. International Journal of Recent Technology and Engineering, 2: 150-156.
[2] Espinosa, A.G., Rosero, J.A., et al. (2010) Fault detection by means of Hilbert-Huang transform of the stator current in a PMSM with demagnetization. IEEE Transactions on Energy Conversion, 25: 312-318.
[3] Akin, B., Ozturk, S.B., Toliyat, H.A., Rayner, M. (2009) DSP based sensorless electric motor fault diagnosis tools for electric and hybrid electric vehicle power train applications. IEEE Transactions on Vehicular Technology, 58: 2679-2688.

[4] Kai, Y., Lei, J., et al. (2013) Deep Learning: Yesterday, Today, Tomorrow. Journal of Computer Research and Development, 50: 1799-1804.

[5] Mnih, V., Kavukcuoglu, K., Silver, D., et al. (2013) Playing atari with deep reinforcement learning. Computer Science.

[6] Guo, X., Singh, S.P., Lee, H., et al. (2014) Deep learning for real-time Atari game play using offline Monte-Carlo tree search planning. Advances in Neural Information Processing Systems. Montreal. pp. 3338-3346.

[7] Van, H.H., Guez, A., Silver, D. (2016) Deep reinforcement learning with Double Q-learning. Proceedings of the 30th AAAI Conference on Artificial Intelligence. Phoenix. pp. 1813-1819.

[8] Hausknecht, M., Stone, P. (2015) Deep recurrent Q-learning for partially observable MDPs. Proceedings of the AAAI Fall Symposium on Sequential Decision Making for Intelligent Agents. Arlington. pp. 29-37.

[9] Çira, F., Arkan, M., Gümüş, B., Goktas, T. (2016) Analysis of stator inter turn short circuit fault signatures for inverter-fed permanent magnet synchronous motors. IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society. Florence. pp. 1453-1457.

[10] He, Y.L., Ke, M.Q, et al. (2015) Effect of static eccentricity and stator inter turn short circuit composite fault on rotor vibration characteristics of generator. Transactions of the Canadian Society for Mechanical Engineering, 39: 767-781.

[11] Li, Y., Wang, Y., et al. (2021) Diagnosis of inter turn short circuit of permanent magnet synchronous motor based on deep learning and small fault samples. Neurocomputing, 442: 348-358.

[12] Jiang, F., Ma, R., Sun, C., Gu, Z. (2020) Dueling deep Q-Network learning based computing offloading scheme for F-RAN. 2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications. London.