

Demagnetization fault detection of PMSM based on induced voltage and multi-attention fusion residual convolutional neural network

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The issue of low demagnetization fault diagnosis accuracy and the over-reliance on prior knowledge and human expertise in diagnostic methods for permanent magnet synchronous motor(PMSM) used in electric drive systems., this paper adopts a two-seat permanent magnet synchronous motor(PMSM) for 22-pole 24-slot electric aircraft as an example to study the dynamic identification method for demagnetization faults. The finite element method is used to simulate the motor's electromagnetic field and calculate its no-load back electromotive force, and an advantage in feature learning by combining residual network (ResNet) and convolutional neural network (CNN) is proposed. A multi-attention fusion residual convolutional neural network (MAFResCNN) with a squeeze-excitation module (SEM) and a convolution block attention module (CBAM) is constructed to classify the motor's no-load back electromotive force using wavelet transform (WPT). Experiments show that the method can not only intelligently detect the motor's demagnetization fault but also estimate the degree of demagnetization with high accuracy, with judgment error within an acceptable range.

Index Terms—Permanent magnet synchronous motor(PMSM), Demagnetizing, Residual convolutional neural networks(ResCNN), Multiple attention mechanism

I. INTRODUCTION

During the operation of new energy aircraft, issues such as high starting currents and elevated temperatures due to the sealed environment can lead to permanent magnet demagnetization faults. When the permanent magnet fails, it causes a reduction in torque, increased temperatures at various locations, and diffusion of the fault, which results in the loss of precise control over the electric drive system, thereby posing safety risks to the aircraft [1]. Demagnetization detection largely relies on manual expertise, and research on deep learning-based demagnetization detection is limited. This paper presents a multi-attention fusion residual convolutional neural network (MAFResCNN) with a squeeze-excitation module and convolutional block attention module for classifying the wavelet energy map of no-load induced voltage. Finite element analysis is conducted on a 22-pole, 24-slot permanent magnet synchronous motor used in a dual-seat electric aircraft under various demagnetization states. The simulation results are used to test the diagnostic model, verifying its accuracy and feasibility.

II. DEMAGNETIZATION ANALYSIS OF MOTOR

After the permanent magnet synchronous motor undergoes demagnetization, the magnetomotive force provided by the permanent magnet decrease. According to the magnetic circuit equation (Equation 1), under the condition that other magnetic circuit parameters remain unchanged, the magnetic flux provided by the rotor permanent magnets will decrease [2].

$$\Phi = \frac{F_m}{R_m} \quad (1)$$

Where, Φ denotes the magnetic flux in the magnetic circuit; R_m denotes the magnetic reluctance of the magnetic circuit; F_m denotes the magnetomotive force of the magnetic circuit.

Under no-load conditions, according to Equation (2), demagnetization will cause a decrease in the no-load induced

voltage of the motor at the same speed. From Equation (3), it is observed that the loss rate of the no-load induced voltage is only related to the magnetic flux Φ provided by the rotor's permanent magnet. Therefore, the calculation method for the induced voltage under no-load condition is as follows:

$$E = 4.44 f N k_w \Phi = \frac{4.44 n p N k_w \Phi}{60} \quad (2)$$

$$\Delta E = \frac{E - E'}{E} = \frac{\Phi - \Phi'}{\Phi} \quad (3)$$

Where, f denotes the frequency; N denotes the number of winding turns; k_w denotes the winding factor; p denotes the number of pole pairs of the motor rotor; E' and Φ' denotes the induced voltage and magnetic flux after the motor has undergone demagnetization, respectively.

The discrete wavelet transform is applied, and the wavelet energy map is used as feature input for the multi-attention fusion residual convolutional neural network. For simplicity in analysis and comparison, the classical soft thresholding transformation formula is directly applied [3]:

$$W_k = \begin{cases} \left[\text{sgn}(|W_k| - T), |W_k| \geq T \right] \\ 0, |W_k| < T \end{cases} \quad (4)$$

Where, W_k denotes the wavelet coefficients after thresholding, and T denotes the threshold.

III. MULTI-ATTENTION FUSION RESIDUAL CONVOLUTIONAL NEURAL NETWORKS

A. Method of Feature Enhancement

Due to the high similarity in wavelet time-frequency representations of samples under different demagnetization levels, direct training on the original data may degrade performance. To resolve this, finite element analysis (FEA) is used to identify regions with significant variations due to demagnetization. Time-frequency images from each phase are then concatenated based on these regions, resulting in an enhanced feature representation. The process is shown below:

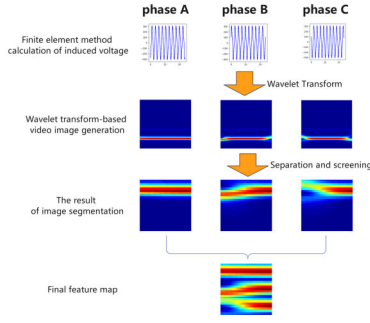


Fig. 1. Workflow of Feature Enhancement

B. Squeeze-excitation module

The core idea of the SE (Squeeze-and-Excitation) module is to apply global average pooling to the input feature maps, compressing each feature map into a single real value with a global receptive field. This operation can be formulated as shown in Equation (6):

$$Y = X \cdot \sigma(W_2 \delta(W_1 GAP(X))) \quad (5)$$

Where, $X \in R^{C \times H \times W}$ denotes the input feature map, C is the number of channels, H and W represent the spatial dimensions of the feature map. GAP denotes the global average pooling operation, W_1 and W_2 are the weights of the fully connected layers, and σ and δ correspond to the activation functions.

C. CBAM module

The Convolutional Block Attention Module (CBAM) is a lightweight attention mechanism that simultaneously considers both spatial and channel information. The two components are formulated in Equations (8) and (9), respectively.

$$M_c(F) = \sigma(MLP(Avgpool(F))) + MLP(Maxpool(F)) \quad (6)$$

$$M_s(F) = \sigma(f^{7 \times 7}([AvgPool(F); MaxPool(F)])) \quad (7)$$

Where, F denotes the input feature map, σ represents the Sigmoid activation function, $MLP(\cdot)$ refers to the multilayer perceptron (MLP) operation, $Avgpool(\cdot)$ and $Maxpool(\cdot)$ indicate the average pooling and max pooling operations, respectively, and $f^{7 \times 7}$ denotes a convolutional kernel with a size of 7.

D. Coordinate attention module

Coordinate Attention captures both channel interdependencies and long-range spatial information by employing a factorized coordinate encoding scheme. This mechanism is formulated in Equation (10):

$$Y = X \odot \sigma(Y)$$

$$Y = Conv_{1 \times 1}(Contact[GAP_h(X), GAP_w(X)])$$

$$GAP_h(X)_c = \frac{1}{W} \sum_{w=1}^W X_{c,h,w} \quad (8)$$

$$GAP_w(X)_c = \frac{1}{H} \sum_{h=1}^H X_{c,h,w}$$

Where, $\odot$ denotes the element-wise multiplication along the channel and spatial dimensions, $Contact$ represents the

concatenation along the spatial position direction, h and w are the row and column indices, respectively, and c represents the channel index.

E. MAFResCNN

The MAFResCNN [4] fuses three attention modules—SEM, CBAM, and CA—to capture highly discriminative fault features and improve feature learning; its architecture is shown in Figure 2.

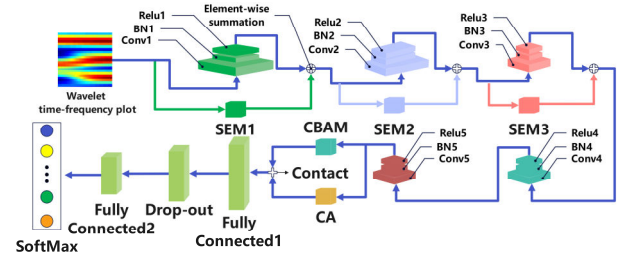


Fig. 2. MAFResCNN network structure

MAFResCNN uses stacked SE-Residual layers to extract multi-scale channel features, then applies CBAM and CA in parallel to refine local details and global spatial cues; their outputs are concatenated and fed through two fully connected layers, drop-out, and softmax for classification.

F. Experimental Verification

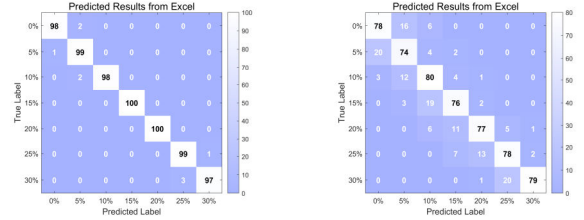


Fig. 3. MAFResCNN classification results (left) and CNN decomposition results (right)

The detection was performed using 200 sets of data from finite element calculations at different demagnetization levels, with 100 sets used for training and 100 sets for testing. The test results are shown in Figure 3. MAFResCNN achieved an accuracy of 98.71%, while the CNN with the same convolutional layers and parameters achieved an accuracy of only 77.42%.

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