Research on Demagnetization Fault Diagnosis of Permanent Magnet Linear Synchronous Motor Based on SqueezeNet Neural Network

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Abstract. This paper studies the demagnetization fault diagnosis method of Permanent Magnet Linear Synchronous Motor based on SqueezeNet neural network. A new demagnetization fault signal acquisition method is proposed to adapt to the spatial topological structure constraints of the double-stator coreless motor, and to obtain effective demagnetization fault signals without invasive measurement, so as to improve the accuracy of the fault signal source. At the same time, a simple linear motor demagnetization fault diagnosis device is designed. The one-dimensional demagnetization fault signal is converted into a two-dimensional image through the Recurrence Plot, and fault feature information is effectively extracted. In addition, this paper innovatively uses the lightweight SqueezeNet model for training. After continuous adjustment of the SqueezeNet network model, it can efficiently complete the classification of permanent magnet linear synchronous motor demagnetization faults.

Keywords: Permanent Magnet Linear Synchronous Motor, Demagnetization Fault Diagnosis, SqueezeNet Neural Network, Recurrence Plot Algorithm

1 Introduction

The field of fault diagnosis for permanent magnet synchronous linear motors (PMSLM) has undergone significant development over the past several decades, forming a systematic and comprehensive knowledge framework. Since the 1960s, researchers have been exploring various on-site testing methods to address the inevitable fault challenges in industrial applications [1]. By the 1980s, online fault diagnosis technology for PMSLM began to demonstrate its unique advantages, marking an important milestone in the field. Particularly since the 1990s, with the rapid advancement of modern signal processing and testing technologies, fault diagnosis has experienced unprecedented growth, attracting significant attention from researchers worldwide. Through continuous innovation, fault diagnosis technology has evolved, gradually moving towards intelligent and automated systems.

In recent years, the vigorous development of artificial intelligence algorithms has injected new vitality into traditional fault diagnosis methods. These emerging algorithms have not only broken the limitations of past expert systems but have also increasingly applied intelligent techniques such as artificial neural networks, genetic algorithms, and fuzzy logic to the fault diagnosis of PMSLM. These methods are now recognized as cutting-edge technologies with immense potential in the industry [2].

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However, when traditional fault detection methods are applied to complex electronic and mechanical systems, the complexity of the diagnostic objects often necessitates the use of multiple detection techniques. While this approach can improve the accuracy of fault identification, it also increases the computational burden and prolongs the time required for diagnosis, thereby affecting the feasibility of real-time fault detection [3]. Additionally, the introduction of expert systems into fault diagnosis has made subsequent software adjustments and optimizations challenging. Moreover, the lack of effective utilization of expert knowledge and experience in relevant fields has further limited the practical application of these traditional methods, making it difficult to meet the increasingly high reliability and real-time requirements of modern industry [4].

In the study of demagnetization faults in PMSLM, signal acquisition is considered a fundamental task, as its effectiveness directly determines the quality of fault information and the complexity of subsequent signal processing algorithms. The signals commonly used for fault diagnosis are mainly divided into three categories: electrical signals generated by the motor coil winding (e.g., current, voltage, and back electromotive force), vibration and sound signals, and magnetic field signals in the air gap of the motor. Researchers have conducted extensive studies in this area. For example, Zhang Dan's team [5] used a Gaussian meter to accurately measure the air gap magnetic flux signal of an iron-free PMSLM, successfully identifying and classifying demagnetization faults. Similarly, Wang Xudong's team [6] focused on the study of local demagnetization fault characteristics in high-thrust PMSLM for vertical lifting applications, demonstrating that the harmonic content of the motor's no-load back electromotive force and air gap flux can serve as a theoretical basis for diagnosis. Other researchers, such as Kim H.K. [7] and Song Juncai [8], have also made significant contributions to understanding the impact of demagnetization on motor performance and the development of fault detection models.

Despite these advancements, several challenges remain in the field of PMSLM fault diagnosis:

1. The unique topological structure of single-stator ironless PMSLM results in a symmetrical distribution of permanent magnets in the stator, with the winding coils positioned at the center of the air gap magnetic field. This structure means that electrical signal changes caused by demagnetization faults can only indicate anomalies at specific positions in the rotor winding, making it difficult to confirm which section of the permanent magnet has malfunctioned or to perform accurate quantitative calculations. Additionally, electrical signals in the rotor winding are highly susceptible to interference from inverter faults, which can lead to misjudgment of demagnetization faults and reduce the accuracy of fault detection.
2. Vibration signals generated by PMSLM, such as sound and torque, are highly sensitive to mechanical unbalance faults (e.g., bearings, balls, and guides) but are relatively weak in detecting demagnetization faults. When the degree of demagnetization is mild, the vibration signals are often too weak to be effectively detected, limiting the accuracy of fault diagnosis.
3. Obtaining the magnetic field strength of the air gap in PMSLM typically requires the use of a Gaussian meter (Hall sensor), which often involves invasive disassembly of the motor, potentially causing secondary damage to the equipment. Moreover, the signals obtained from such measurements are often difficult to transmit in real-time to the controller, making real-time monitoring of demagnetization faults challenging.

In summary, there is an urgent need in the industry to develop a new demagnetization fault signal acquisition method that overcomes the limitations imposed by the unique spatial topology of dual-stator coreless motors. Ideally, this method should enable the effective acquisition of demagnetization fault signals without invasive measurements, while also improving the accuracy of fault source detection by combining these signals with existing rotor winding signals. To address this need, we have designed a simple and efficient linear motor demagnetization fault diagnosis device, which utilizes advanced fault feature extraction techniques to achieve rapid and accurate identification of motor demagnetization faults.

Additionally, based on the actual operating scenarios of high-precision machine tools, we have developed a state-adaptive demagnetization fault signal processing algorithm. This algorithm adjusts key parameters in the feature extraction process in real-time according to the demagnetization fault signals under different working conditions, ensuring optimal performance and accurate extraction of multi-dimensional fault features. This innovation not only enhances the adaptability of demagnetization fault diagnosis for PMSLM but also strengthens the overall compatibility of the system. Furthermore, a comprehensive method of dimensionality reduction and enhancement based on multi-dimensional fault feature indicators is proposed, aiming to achieve efficient fusion of information between feature layers and decision layers. This approach leverages complementary information from multiple evidence sources for joint decision-making, further improving the reliability of demagnetization fault diagnosis in PMSLM. These efforts lay a solid theoretical foundation and provide feasible solutions for future advancements in fault diagnosis technology, helping the industrial sector achieve greater breakthroughs and success.

2 Methodology

We designed a method to analyze and collect the electromotive force signals of permanent magnet linear motors, extract features using a recurrence plot algorithm, and develop a deep learning model based on SqueezeNet [9] to achieve efficient real-time monitoring and accurate fault diagnosis of demagnetization in permanent magnet synchronous linear motors.

2.1 Data Collection

We divide the motor into 13 period arrays and number each period array. As shown in Figure 1, each period corresponds to 4 permanent magnets, including 2 N-pole permanent magnets and 2 S-pole permanent magnets. The 4 permanent magnets are numbered 1, 2, 3, and 4, so there are 15 types of permanent magnet demagnetization combinations as shown in TABLE Ⅰ.

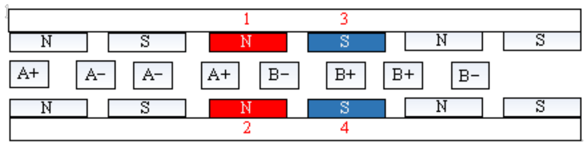

Fig. 1. permanent magnet synchronous linear motor cycle topology.

Table 1. Demagnetization Type Examples

Demagnetization type	Demagnetization quantity	Demagnetization permanent magnet combination
1	1	1
2	1	2
3	1	3
4	1	4
5	2	1-2
6	2	1-3
7	2	1-4
8	2	2-3
9	2	2-4
10	2	3-4
11	3	1-2-3
12	3	1-2-4
13	3	1-3-4
14	3	2-3-4
15	4	1-2-3-4

After determining the demagnetization type of the permanent magnet synchronous linear motor, we use the detection coil to collect the existing demagnetization signal data of the permanent magnet synchronous linear motor. The data is one-dimensional electromotive force signal data. After a series of preprocessing, we label and classify the data according to the demagnetization type.

2.2 Feature Extraction

After we collect and classify the data set, we derive the characteristics of the electromotive force signal data set through Recurrence Plot algorithm [10]and convert the one-dimensional data into a two-dimensional image.

Recurrence Plot are a method for analyzing and visualizing time series data. They show the dynamic behavior of data by studying the recurrence of states in a time series. Specifically, a recursion plot is a two-dimensional plane in which the points represent the encounter or recurrence of states of a time series at different time points. This type of plot can reveal periodicity, mutation points, and nonlinear dynamic characteristics in the data. Recurrence Plot are widely used in chaotic system analysis [11], classification detection and monitoring, and financial market analysis. In this study, recursion plots can well extract the timing feature information in the electromotive force demagnetization signal, thereby facilitating subsequent analysis and processing.

2.3 Model Selection

Convolutional Neural Network [12] can be simply understood as a network with a deep structure that contains convolution operations. It is a process of extracting features from data and making predictions through weight sharing and local connections. In practical applications, a multi-layer network structure is often used, so it is also called a deep convolutional neural network.

The fundamental structure of a convolutional neural network includes the following components: Input Layer, Convolution Layer, Pooling Layer, and Fully Connected Layer, as illustrated in Figure 2.

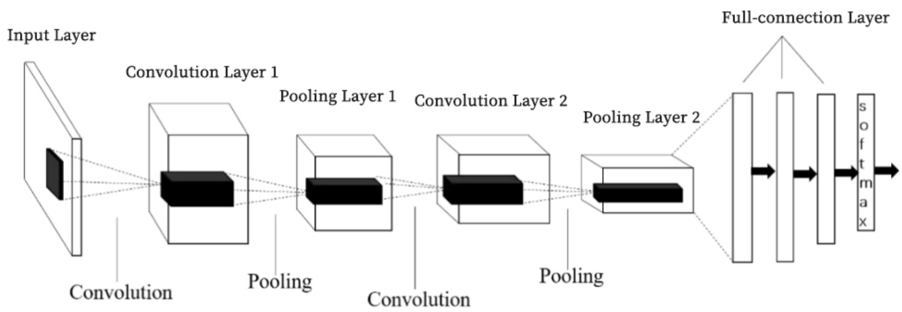

Fig. 2. Convolutional Neural Network Structure

1) Convolution Layer: The primary role of the Convolution Layer is to extract features from the input data using a convolutional kernel. This involves applying the convolutional kernel to the input image, adding a bias term, and passing the result through an activation function to generate the output of each neuron following the convolution process.

2) Pooling Layer: The Pooling Layer is designed to downsample the image, reducing its size and the computational complexity, thereby speeding up the training process of the convolutional neural network while maintaining key image features. It is primarily categorized into two types: Max Pooling and Average Pooling.

3) Full-connection Layer: The Fully Connected Layer combines the local features extracted by the convolutional and pooling layers using a weight matrix, ultimately producing a one-dimensional vector that is used for classification.

The SqueezeNet network employed in this experiment is a type of convolutional neural network. Introduced by UC Berkeley in 2016, it is a streamlined, lightweight version of traditional convolutional networks. The model is derived from the AlexNet [13] architecture but includes several modifications. Structurally, the SqueezeNet network begins with a convolutional layer, followed by 8 Fire modules, and concludes with another convolutional layer, using the Softmax activation function for classification output. In the Fire module, the number of convolution kernels in each layer gradually increases. The Fire modules consist of two components: the Squeeze layer and the Expand layer. The ReLU function is used as the activation function at the output of both the Squeeze and Expand layers. A Dropout layer with a rate of 50% is applied after the Fire9 module. This structure is illustrated in Figure 3.

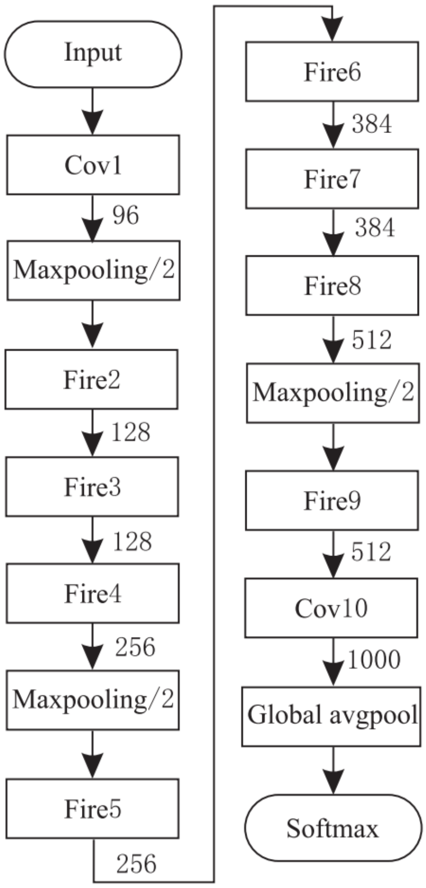

Fig. 3. SqueezeNet Neural Network Structure

Compared with the traditional convolutional neural network, our design strategy of SqueezeNet network is mainly about:

1) The convolution kernel of the neural network is reduced, which can reduce the number of network parameters.
2) The pooling operation is delayed to retain a larger feature map, making the transmitted information more accurate, while ensuring the accuracy of the network model while being lightweight.

2.4 Model Training

This experiment first imports the processed Permanent Magnet Synchronous Linear Motor demagnetization Recurrence Plot dataset, then builds the network, uses the convolution layer to extract image features, then performs downsampling through the Maxpooling layer[14], uses the Fire module for further dimensionality reduction, and then uses the contact method for feature fusion. Finally, an average pooling layer is added to integrate global spatial information, and the Softmax classifier[15] is used to output the classification. AS Shown in figure 4.

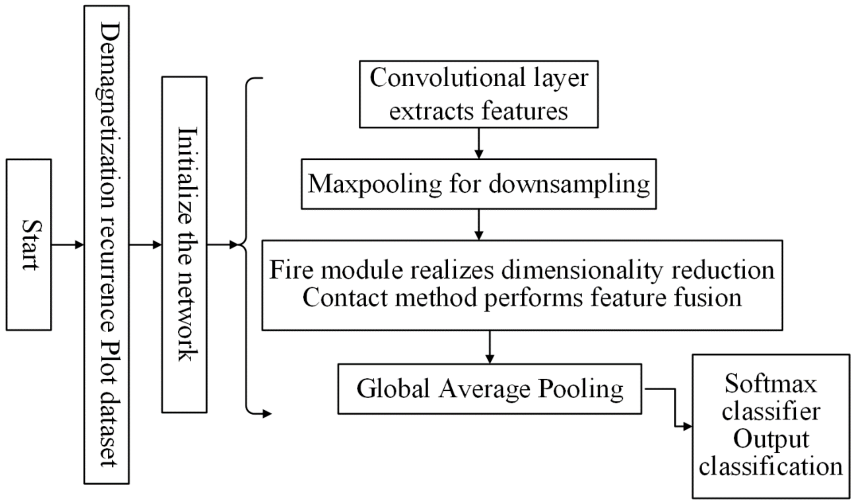

Fig. 4. Implementation Flowchart

3 Results

In a recent study, we successfully developed a deep learning-based fault diagnosis method for monitoring and assessing the performance of Permanent Magnet Synchronous Linear Motors (PMSLM). The core of this method lies in utilizing advanced data processing techniques to analyze the motor's loss function and classification accuracy in real-time. The experimental results show that the method achieved a classification accuracy of up to 97.9% on the training set, while the classification accuracy on the validation set reached up to 96.2%, demonstrating the model's strong generalization ability.

The figure below illustrates the loss function curve and the accuracy curve from the experiment. It is evident that the curves stabilize around the 200th iteration. This indicates that the model has learned the characteristics of the training data well and has shown high accuracy on the validation set after a sufficient number of iterations. This stability is crucial for ensuring the reliability of motor fault diagnosis.

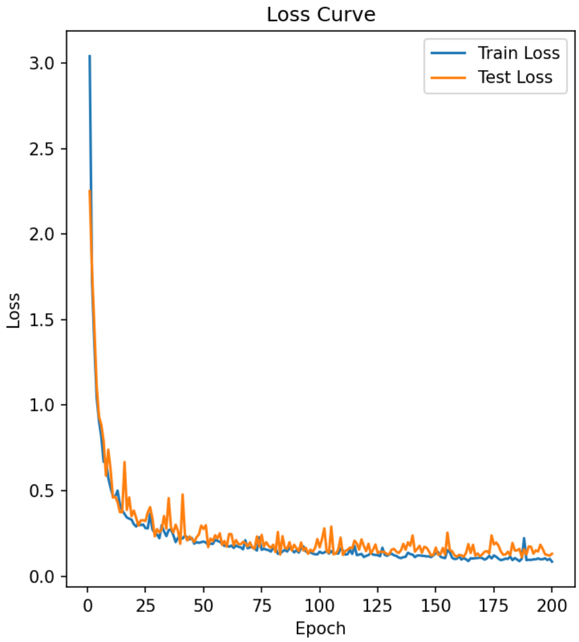

Fig. 5. Loss Function Curve

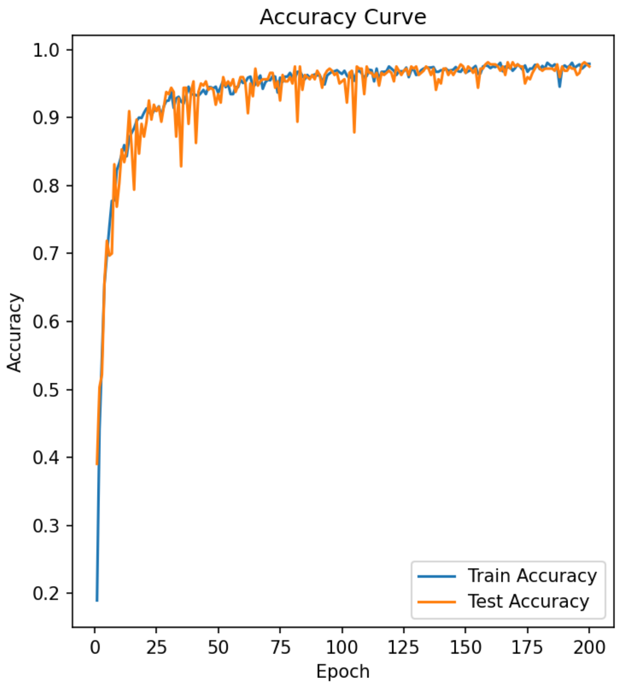

Fig. 6. Accuracy Curve

At the same time, we also compared the accuracy of the SqueezeNet model with other convolutional neural networks on the validation set as shown in the following table.

Table 2. Comparison table of accuracy of each neural network validation set

Model	Accuracy
SqueezeNet	96.2%
AlexNet	91.4%
ResNet50	92.6%
GoogLeNet	93.3%

From this table, it can be concluded that while SqueezeNet reduces the number of model parameters, the accuracy of the network is much higher than other models, and it can efficiently complete the classification task.

4 Conclusion

Following a comprehensive series of studies in this experiment, several important conclusions can be drawn regarding the advancements made in the field of demagnetization fault diagnosis for Permanent Magnet Linear Synchronous Motors (PMLSMs). The experimental research detailed in this document has yielded significant results, particularly in the optimization of the SqueezeNet neural network model. This innovative approach has achieved an impressive classification accuracy of up to 97.9% on the training set and 96.2% on the validation set. These results indicate that the SqueezeNet model, despite its lower parameter count compared to traditional convolutional neural networks, is highly effective in accurately classifying demagnetization faults in PMLSMs.

The success of this research can be attributed to the novel integration of a refined demagnetization fault signal acquisition method with the advanced capabilities of the SqueezeNet neural network. This new acquisition technique has been specifically designed to operate within the spatial constraints posed by dual-stator coreless motors. By enabling the collection of effective demagnetization fault signals without the need for invasive measurements, this method not only enhances the accuracy of fault signal sourcing but also paves the way for more efficient and non-destructive diagnostic approaches.

Moreover, the application of the Recurrence Plot algorithm to transform one-dimensional electromotive force signals into two-dimensional images for feature extraction has proven to be a highly valuable technique. This transformation facilitates a more comprehensive analysis of the data, allowing for the identification of patterns and characteristics that might remain hidden in the raw, one-dimensional signal format. The integration of these enriched features into the SqueezeNet model has significantly bolstered the overall diagnostic accuracy of the system.

Nevertheless, the research acknowledges certain limitations within the current dataset. The inherent complexities associated with collecting demagnetization data from PMLSMs have resulted in a relatively limited dataset, which constrains the potential for further enhancement of the diagnostic system's capabilities. To address this challenge, future research will prioritize the expansion of the dataset and the refinement of data collection methodologies. One promising approach under consideration is the introduction of detection coils specifically designed to gather demagnetization signals, which could lead to the creation of a more robust dataset. This enhancement would enable the model to learn from a broader spectrum of fault scenarios, thereby potentially increasing its diagnostic accuracy.

Additionally, the research seeks to broaden the applicability of this diagnostic framework to encompass other types of linear motors. This endeavor would involve adapting the model to recognize and classify demagnetization faults across various motor configurations and operational environments. Such an expansion would significantly enhance the utility of the diagnostic system, transforming it into a versatile tool for the maintenance and monitoring of diverse linear motor systems.

In summary, this research has made a substantial contribution to the field of motor fault diagnostics by developing a highly accurate and efficient method for identifying demagnetization faults in PMLSMs. The innovative use of the SqueezeNet model, combined with advanced data processing techniques, has demonstrated great promise. With further development and refinement, this approach has the potential to establish itself as a standard in the industry for motor health monitoring and maintenance, ultimately contributing to enhanced operational reliability and efficiency.

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