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State Evaluation of Power Transformers Based on Stacked Autoencoders

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ABSTRACT

This research provides reliable technical support for transformer condition-based maintenance and full life-cycle management, and has significant practical value for ensuring the stable operation of industrial power systems, such as those in textile manufacturing. However, traditional state evaluation methods have limitations in extracting complex signal features, easily leading to inaccurate assessments and resource waste, making it difficult to meet the needs of intelligent upgrading and online monitoring of new power systems. This study aims to utilize the deep feature learning advantages of stacked autoencoders to solve the problem of insufficient diagnostic accuracy of traditional methods under complex operating conditions, and to construct an efficient and accurate transformer state evaluation system. By collecting multi-source operating data such as transformer temperature, vibration, electrical parameters, and oil chromatography, a stacked autoencoder model was designed after preprocessing. A training strategy combining hierarchical pre-training and overall fine-tuning was adopted, and a multi-dimensional evaluation index system was established. Experimental results show that the model can effectively extract deep features of complex signals, significantly separate heterogeneous states, and achieve an overall state recognition accuracy of over 95.7%, outperforming traditional methods such as frequency response methods and support vector machines, and exhibiting stronger anti-interference capabilities. This research provides reliable technical support for transformer condition-based maintenance and full life-cycle management, and has significant practical value for promoting smart grid construction and reducing operation and maintenance costs.

KEYWORDS

power transformer, condition assessment, stacked autoencoder, deep learning, fault diagnosis

INTRODUCTION

Research Background and Significance

As the core primary equipment of the power system, the power transformer bears the heavy responsibility of voltage transformation. Therefore, system accidents caused by transformer faults are quite serious [1]. In the context of industrial modernization, the stability of the power grid is a fundamental guarantee for the development of high-end manufacturing. For example, the textile industry has transitioned to high-speed automation, where even brief power fluctuations can lead to production interruptions and material waste. The "Blue Book on the Development of New Power Systems (Draft for Comments)" released by the National Energy Administration in January 2023 proposes "promoting the intelligent upgrading of the power grid" and "advanced and friendly transmission technology and equipment field". Through online monitoring technology, various types of sensors are deployed to comprehensively perceive the operating status of transformers, and then realize the condition assessment of transformers based on this [2]. Condition monitoring, fault diagnosis, and aging condition assessment of power transformers have practical and far-reaching significance for both promoting comprehensive condition-based maintenance and achieving the goal of full life-cycle management of power equipment proposed in my country's smart grid planning [3]. In parallel, carbon-neutral transition, renewable integration, and carbon-neutral readiness assessments highlight system-level energy governance and raise reliability requirements for grid assets and key equipment [4-6].

Currently, many smart substations in China have deployed transformer condition assessment systems to monitor various transformer condition parameters in real time, enabling condition analysis, early warning, and condition-based maintenance. Online transformer condition assessment integrates relevant indicators from various aspects, providing comprehensive monitoring of the transformer. This helps maintenance personnel to promptly grasp the dynamic operating status of the transformer and identify potential equipment risks in industrial power distribution networks, thereby supporting the stable and efficient production of industries like textiles [7]. Currently, transformer operation and maintenance departments often struggle to accurately assess the operating status of transformers, leading to over-maintenance and premature retirement, wasting significant resources and costs [8].

Current research on transformer condition assessment focuses primarily on optimizing and improving assessment methods to achieve more objective and accurate results. Emerging methods mainly focus on the application and improvement of numerical analysis and artificial intelligence algorithms [9]. From a broader methodology perspective, efficient global optimization and relaxation-based algorithms continue to be actively studied, providing general-purpose tools for complex engineering decision problems [10-12]. Transformer vibration signals are relatively complex. Stacked autoencoders in deep learning can extract features from complex vibration signals, resulting in highly clustered features and clear separation of different states [13]. Establishing a scientific transformer condition assessment model using advanced stacked autoencoder technology to accurately assess the health status of operating transformers has significant theoretical and engineering practical value.

Research Objectives and Content

Power transformers, as key equipment in power systems, play a crucial role in voltage step-up and voltage reduction and energy transmission. Faults in power transformers can severely impact the safe and stable operation of the entire power system [14]. Traditional transformer condition assessment methods have limitations in handling complex signal feature extraction. Stacked autoencoders, as deep learning models, can learn deeper features of data by stacking multiple autoencoder layers, achieving more accurate data representation and prediction. This research aims to utilize the powerful feature extraction capabilities of stacked autoencoders to construct an efficient and accurate power transformer condition assessment system. Transformer vibration signals are relatively complex. Stacked autoencoders in deep learning can extract features from complex vibration signals, resulting in highly clustered features and clear separation of dissimilar states. Compared to traditional frequency response and wavelet transform methods, stacked autoencoders exhibit significant advantages in terms of anti-interference capability and application scope, effectively reducing fault information omissions caused by manual feature extraction and demonstrating good fault tolerance. This research will delve into the application mechanism of stacked autoencoders in transformer condition assessment, focusing on addressing the problem of insufficient diagnostic accuracy of traditional methods under complex operating conditions.

The research content mainly includes the acquisition and preprocessing of transformer operating status data, the design and optimization of stacked autoencoder models, the establishment of a condition evaluation index system, and the verification and analysis of model performance. By constructing a multi-layer autoencoder network structure, the fusion processing of multi-source signals from the transformer is realized, and fault features are extracted from each signal. The research will establish a complete transformer condition evaluation framework, providing technical support for the stable operation of the power system, and has important theoretical significance and practical value for ensuring the safe and reliable operation of transformers.

RELEVANT THEORIES OF POWER TRANSFORMER CONDITION EVALUATION

Working Principle of Power Transformers

As a crucial piece of equipment in the power system, the power transformer plays a key role in energy conversion and power distribution [15]. A transformer is a power device composed of two parts: windings and core [16]. Its working principle is based on Faraday's law of electromagnetic induction to transfer electrical energy between two or more circuits through a varying magnetic field. It transforms alternating voltage and current levels to meet the requirements of the power system while maintaining the same frequency, without converting AC to DC. From a structural perspective, a power transformer is a static electrical device that uses the principle of electromagnetic induction to transfer electrical energy. Its core components mainly include the primary coil, secondary coil, and iron core, while other major components include windings and an oil tank [17].

The working mechanism of a power transformer is based on Faraday's law of electromagnetic induction. When an alternating current flows through the primary winding, an alternating magnetic flux is generated in the iron core. This alternating magnetic flux induces an electromotive force in the secondary winding, thereby realizing the transfer of electrical energy. The voltage transformation relationship of a transformer can be expressed by the following formula:

$$\frac{\mathrm{U}_1}{\mathrm{U}_2} = \frac{\mathrm{N}_1}{\mathrm{N}_2} = \frac{\mathrm{I}_2}{\mathrm{I}_1} \tag{1}$$

Where, U_1 and U_2 are the voltages of the primary and secondary windings, N_1 and N_2 are the number of turns of the primary and secondary windings, I_1 and I_2 are the currents of the primary and secondary windings, respectively.

Structurally, transformers can be classified based on their core construction (core-type or shell-type) and cooling methods (oil-immersed or dry-type). Unlike rotating machinery such as motors or generators, power transformers are static devices with no moving parts during energy conversion. The magnetic circuit design of a transformer directly affects its energy conversion efficiency and operational stability. By selecting appropriate core materials and arranging windings, magnetic flux leakage and eddy current losses can be minimized. The design of the insulation system is equally crucial; it must withstand not only the voltage stress during normal operation but also various overvoltage surges.

Common Faults and Their Impacts

As a key component of the power grid, the operating status of a power transformer directly affects the safe and stable operation of the entire power system. A fault can cause severe power outages, resulting in irreparable economic losses to the nation and its people [18]. During long-term operation, transformers inevitably experience various faults, which are diverse and have far-reaching impacts.

From the perspective of fault categories, common fault types of power transformers mainly include partial discharge, low-energy discharge, high-energy discharge, low-temperature overheating, medium-temperature overheating, and high-temperature overheating. Partial discharge faults manifest as cold plasma-type partial discharges, which usually lead to X-wax on the paper insulation layer. The causes of the fault include incomplete impregnation of insulating oil, excessive paper humidity, and oil oversaturation. The causes of discharge faults are more complex, including substandard equipment quality and performance, poor contact of conductors, and poor grounding of components [19]. When the discharge density of the transformer reaches 10^{-6} When a fault occurs, it indicates an abnormal discharge phenomenon in the equipment, requiring timely and scientifically sound measures to resolve it.

Mechanical faults in transformers are equally significant. Winding deformation accounts for approximately 15% of all faults; this deformation further exacerbates vibration and worsens the isolation rate between windings. Oil overheating is also a common problem, mainly caused by factors such as multiple grounding points in the internal core forming a magnetic circuit, oil circuit blockage leading to heat dissipation failure, severe magnetic leakage in the transformer, long-term overload operation, and substandard transformer quality. Inter-turn short circuits in the windings are the most common type of fault, and winding faults have consistently been the leading cause of transformer accidents. If these faults are not repaired in time, they will continue to increase the degree of winding deformation, eventually causing serious damage and power outages when excessive short-circuit current is used, resulting in huge losses.

BASIC PRINCIPLES OF STACKED AUTOENCODERS

Composition of Autoencoders

Data Encoding and Decoding Process

In power transformer condition evaluation research, the data encoding and decoding process of autoencoders constitutes the core mechanism for feature extraction and reconstruction. The encoder maps high-dimensional input data to a low-dimensional latent space, while the decoder remaps the latent representation back to the original data space. This asymmetric information compression and recovery process provides strong technical support for feature extraction of complex vibration signals from transformers.

The encoding process gradually reduces the data dimensionality through a multi-layer neural network, with each layer capturing abstract features at different levels. For transformer condition evaluation, the original monitoring data includes multi-source information such as electrical parameters, oil and gas content parameters, and oil temperature. The encoder maps the input vector x to the hidden layer representation$\mathrm{h}$through a nonlinear transformation function, as shown in the following formula:

$$\mathrm{H} = \mathrm{f}(\mathrm{Wx} + \mathrm{b}) \tag{2}$$

where$\mathrm{W}$is the weight matrix,$\mathrm{b}$is the bias vector, and$\mathrm{f}$is the activation function. This mapping process can automatically learn the essential features of the transformer's operating state, avoiding the subjectivity of manual feature selection in traditional methods.

The decoding process undertakes the task of feature reconstruction, remapping the hidden layer representation to the output$\hat{\mathrm{x}}$through a decoding function, as shown in the following formula:

$$\widehat{X} = g(W'h + b') \tag{3}$$

where W' is the weight matrix, b' is the bias vector. The design goal of the decoder is to maximize the reconstruction accuracy, making $\hat{x}$ as close as possible to the original input x. In transformer condition assessment applications, the magnitude of the reconstruction error directly reflects the degree of deviation between the current operating state and the normal state, providing a quantitative indicator for anomaly detection.

The encoding and decoding process in a stacked autoencoder can effectively extract features from complex vibration signals. The extracted features are highly clustered, and heterogeneous states are clearly separated. This characteristic gives the model a significant advantage when processing multi-source signal inputs, enabling it to extract fault features from various signals and achieve intelligent condition assessment through multi-source fusion.

Selection of Activation Function

As one of the core components of a stacked autoencoder, the activation function directly affects the model's feature extraction capability and convergence effect. In the power transformer condition assessment model, the selection of the activation function needs to comprehensively consider multiple factors such as function characteristics, dataset characteristics, and network structure. A reasonable activation function can significantly improve network learning efficiency, accelerate convergence speed, and enhance the network's generalization ability.

Traditional activation functions each have their specific application scenarios and limitations. The Sigmoid function has good continuous differentiability, and can map all data to the (0,1) interval, which can well express the activated and inactive states of neurons. The function expression is:

$$F(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

Compared to Sigmoid, the Tanh function avoids the problem of all outputs being positive, and exhibits better prediction accuracy in some CNN quantitative analysis models. The ReLU function is widely used due to its fast computation speed and simple derivative, but Sigmoid and Tanh functions are prone to gradient saturation when the input value is too large or too small, resulting in slow or even stagnant weight updates. Deep learning practice shows that regions with a large rate of change of the derivative of the activation function are more favorable for learning complex functional relationships. The magnitude of the gradient directly affects the parameter update amplitude, and gradient vanishing or exploding will hinder the normal update of parameters. Different activation functions have significant performance differences in practical applications, with the highest and lowest classification accuracy differing by 3.45 percentage points. Experimental comparisons have found that new activation functions such as LeakyReLU and SiLU can achieve better performance in specific models. Choosing a suitable activation function requires weighing various factors according to the specific task characteristics to obtain the best model performance. Although LeakyReLU is often preferred in deep convolutional networks to avoid gradient vanishing, the Sigmoid function was selected for this specific stacked autoencoder model. Since the input data is normalized to the [0, 1] range, Sigmoid provides stable, bounded activation probabilities that effectively model the presence of fault features without the instability occasionally observed with ReLU on this specific sparse dataset.

Loss Function and Optimization Methods

In the training process of stacked autoencoders, the loss function is an important component of the optimization algorithm. It guides the updating of model parameters, enabling the model to gradually optimize and better approximate the distribution of real data. For the power transformer state assessment task, the selection of an appropriate loss function directly affects the convergence speed and final performance of the model.

Traditional autoencoders usually use mean squared error (MSE) as the loss function, and its mathematical expression is:

$$\mathrm{L_{MSE}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}|\mathrm{x_i}| - |\hat{\mathrm{x}}_\mathrm{i}|^2 \tag{5}$$

where N is the number of samples, $\mathrm{x_i}$ is the original input, $\hat{\mathrm{x}}_\mathrm{i}$ is the reconstructed output. In the application scenario of transformer state assessment, considering the complexity and imbalance of data, the cross-entropy loss function is also widely used, especially in classification tasks. For fine-grained state analysis problems, research shows that by improving the design of the loss function and incorporating multiple optimization methods into one loss function, the number of hyperparameters can be reduced and model performance can be improved.

The optimization algorithm continuously adjusts the model parameters according to the loss function, thereby narrowing the gap between the model's prediction results and the true results. In the optimization process of stacked autoencoders, gradient descent algorithms and their variants (such as Adam and RMSprop) are widely used. The Adam optimizer combines the advantages of momentum and adaptive learning rate, and its update rule is:

$$\Theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t \tag{6}$$

Where, $\hat{m}_t$ represents the bias correction value for the first-order momentum, $\hat{v}_t$ represents the bias correction value for the second-order momentum,$\alpha$is the base learning rate. In practical applications, the choice of loss function needs to be adjusted according to the specific transformer condition evaluation requirements. By reasonably designing the loss function and selecting the optimization method, the accuracy and generalization ability of the model in identifying abnormal transformer conditions can be effectively improved (Table 1).

Table 1. Comparative Analysis of Commonly Used Optimization Algorithms

Optimization Method	Learning Rate Range	Convergence Speed	Memory Requirements	Applicable Scenarios
SGD	0.01-0.1	Medium	Low	Simple Tasks
Adam	0.001-0.01	Fast	Medium	Complex Tasks
RMSprop	0.001-0.01	Fast	Medium	Sparse Data

Advantages of Stacked Structures

Improved Feature Extraction Capability

The outstanding advantages of stacked autoencoders in power transformer condition assessment are mainly reflected in their powerful feature extraction capabilities. Compared with single-layer autoencoders, stacked structures can build a deeper feature learning architecture through layer-by-layer training of multi-layer neural networks. This deep network structure enables the model to extract more abstract and valuable feature representations from the original monitoring data of transformers, laying a solid foundation for accurately evaluating the operating status of equipment.

In practical applications of transformer condition monitoring, stacked autoencoders can effectively handle multi-dimensional state features, including dissolved gases in oil, insulating oil test results, and electrical test results. By improving the loss function, the parameters updated by the deep neural network during backpropagation can minimize reconstruction errors while fully utilizing label information to extract classification features. This dual optimization mechanism ensures that the model can learn the inherent structure of data from a large number of unlabeled samples and accurately identify specific fault types.

The application of stacked sparse autoencoders further enhances the performance of feature extraction. By using the feature output of the upper layer as the input value of the lower layer, the model can progressively build a hierarchical feature structure from low to high levels. This hierarchical feature learning mechanism enables the model to capture complex nonlinear relationships in transformer operating data and effectively identify potential fault modes that are difficult to detect using traditional methods.

Through this multi-level feature extraction architecture, stacked autoencoders can significantly improve the depth of understanding and accuracy of transformer condition information. The model can not only identify abnormal changes in single parameters, but more importantly, it can capture the correlation patterns between multiple parameters, providing more reliable technical support for preventive maintenance of power systems.

Methods to Avoid Overfitting

Overfitting is a key issue affecting the generalization ability of stacked autoencoders during training. Traditional autoencoders are prone to overfitting when dealing with complex data, resulting in excellent performance on the training set but poor performance on the test set. To address this issue, researchers have proposed several effective solutions to enhance the robustness of the model by improving the network structure and training strategies.

The improved stacked autoencoder effectively alleviates the risk of overfitting by introducing a master-slave encoder architecture. This architecture consists of a master encoder, slave encoder A, and slave encoder B. The slave encoder consists of three autoencoders with progressively decreasing dimensions. Input data is fed into the two slave encoders for simultaneous training, allowing the data to be reconstructed into new features. Then, the output data and the original data are fed into the master encoder for training. This multi-path processing mechanism significantly reduces the risk of overfitting and improves the model convergence speed through weight binding technology.

Regularization plays an important role in preventing overfitting. By adding L1 or L2 regularization terms to the loss function, the complexity of model parameters can be effectively constrained, and its mathematical expression is:

$$\mathrm{L_{total}} = \mathrm{L_{reconstruction}} + \lambda \sum_{\mathrm{i}=1}^{\mathrm{n}} |\mathrm{w_i}| \tag{7}$$

where $\mathrm{L_{reconstruction}}$ represents the reconstruction loss, λ represents the regularization coefficient,$\mathrm{w_i}$represents the network weight parameter. By adjusting the size of the regularization coefficient, the optimal balance between model complexity and fitting ability can be found.

Data augmentation and cross-validation can also effectively improve the overfitting problem. Increasing the diversity of training data can improve the generalization ability of the model, while cross-validation provides a more reliable evaluation standard for model performance.

CONSTRUCTION OF A STATE EVALUATION MODEL BASED ON STACKED AUTOENCODERS

Model Design and Implementation

Data Preprocessing Process

Data preprocessing is a crucial step in transformer state evaluation, directly affecting the training effect and prediction accuracy of the stacked autoencoder model. Transformer operating data typically includes multi-dimensional information such as temperature, vibration, current, and voltage. These raw data often suffer from inconsistent formats, missing values, and outliers, requiring a systematic preprocessing process to improve data quality.

The core steps of data preprocessing include data cleaning, data integration, data transformation, and data reduction. In the data cleaning stage, the system identifies and processes duplicate records, missing values, and outliers to ensure data integrity and accuracy. For abnormal fluctuations in transformer monitoring data, statistical methods are used for detection and correction, while considering the susceptibility of power system data to objective conditions such as temperature and season. Data classification, as the most important step, scientifically categorizes monitoring data from different sources according to sensor type, time series, and operating conditions, facilitating subsequent anomaly identification and data supplementation (Figure 1).

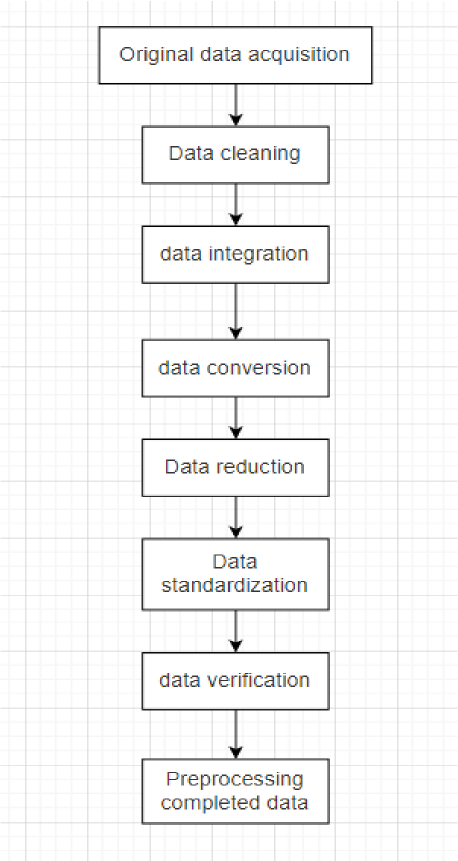

Figure 1. Data Processing Flow

To address the issue of multi-rate data synchronization (e.g., vibration data at 20Hz versus oil chromatography data collected daily), a feature-level fusion strategy was adopted. For high-frequency vibration data, statistical features (mean, variance, and peak values) were extracted within a time window aligned with the sampling timestamp of the low-frequency oil data. This ensures that the input vector for the stacked autoencoder represents a unified state snapshot of the transformer.

Data standardization for transformer state evaluation adopts the Z-score normalization method to ensure that monitoring parameters of different dimensions can be calculated and compared uniformly. The standardization formula is:

$$Z = \frac{X - \mu}{\sigma} \tag{8}$$

where X Original data value, μ Mean, σ Standard deviation. Through this standardization process, data of different physical quantities such as temperature, current, and voltage can be analyzed on the same scale, providing a good data foundation for feature learning of stacked autoencoders.

Model Parameter Settings

The parameter settings of the stacked autoencoder model directly affect the accuracy and efficiency of power transformer condition evaluation, and need to be finely adjusted according to the characteristics of transformer condition data and actual application requirements. In the structural design of the encoder and decoder, the encoder maps the input data x to the intermediate layer representation y, while the decoder remaps the intermediate layer data to the reconstruction layer z. This bidirectional mapping mechanism provides a theoretical basis for in-depth mining of transformer condition features. Algorithmically, model training and hyperparameter tuning can be cast as structured convex optimization problems, for which efficient solvers exist [20].

The core parameters of the model include key elements such as the number of network layers, the number of hidden layer neurons, the learning rate, and the type of activation function. The selection of the number of network layers needs to balance model complexity and computational efficiency. A stacked structure of 3-5 layers is usually used to effectively extract deep features of transformer state data. The number of hidden layer neurons is set in a decreasing pattern, gradually compressing from the high-dimensional features of the input layer to the low-dimensional representation. A typical configuration is a 512-256-128 structure. The learning rate is set to 0.001, and the Adam optimizer is used for parameter updates, which can avoid gradient explosion while ensuring convergence speed.

The choice of activation function has an important impact on model performance. Both the encoder and decoder use the Sigmoid function as the activation function. The mathematical expression of the encoder can be written as:

$$Y = \sigma(W_e x + b_e) \tag{9}$$

The functional relationship of the decoder is expressed as:

$$Z = \sigma(W_d y + b_d) \tag{10}$$

where $\sigma(\cdot)$ Sigmoid activation function, W_e and W_d are the weight matrices of the encoder and decoder, respectively, b_e and b_d are the corresponding bias vectors (Table 2).

Table 2. Model Parameter Settings

Parameter Type	Parameter Value	Description
Number of Network Layers	4 layers	Input Layer - Encoder Layer - Decoder Layer - Output Layer
Hidden Layer Neurons	512-256-128	Decreasing Structure Design
Learning Rate	0.001	Adam optimizer
Batch Size	64	Number of Training Batch Samples
Number of Training Rounds	200	Maximum Number of Iterations
Activation Function	Sigmoid	Unified Encoder and Decoder

The noise addition mechanism is an important part of the stacked denoising autoencoder. By adding an appropriate amount of noise to the input data, the robustness and generalization ability of the model are improved. The noise intensity is set to 0.1, which can enhance the model's anti-interference ability without excessively affecting the effective information of the original data. The regularization parameter is set to 0.0001, and L2 regularization is used to prevent the model from overfitting, ensuring stable and reliable performance in the transformer state evaluation task.

Training and Testing Methods

The training process of the stacked autoencoder adopts a strategy combining hierarchical pre-training and overall fine-tuning to ensure that the model can effectively extract the state features of the power transformer. During the training phase, the input data is fed into the first autoencoder, and the data is reconstructed through repeated training. Then, the processed data is input into the second autoencoder, and a greedy algorithm is used to perform unsupervised training on each autoencoder. After pre-training, the parameters of the entire stacked autoencoder network are fine-tuned through a classifier to improve the recognition accuracy of the entire network.

The loss function design during training considers both reconstruction error and classification accuracy. Reconstruction error is measured by the mean squared error between the input and output layers, and its mathematical expression is:

$$L_{\text{reconstruction}} = \frac{1}{n}\sum_{i=1}^{n} |x_i| - |z_i|^2 \tag{11}$$

Where,$x_i$represents the input data,$z_i$represents the reconstructed output,$n$is the number of samples. The classification loss uses the cross-entropy function, and the comprehensive loss function balances the two indicators through weight coefficients. The model training employed the Adam optimizer with a learning rate of 0.001, a batch size of 64, and a maximum training epoch of 200. Training was stopped early when the validation set loss did not decrease for 10 consecutive epochs.

During the testing phase, a five-fold cross-validation method was used to evaluate model performance. The dataset was randomly divided into five subsets, with one subset selected as the test set and the remaining four subsets used as the training set. The model's generalization ability was comprehensively evaluated using metrics such as accuracy, recall, and F1 score on the test set. For the power transformer state classification task, the recognition accuracy for the three classes—normal state, warning state, and fault state—needed to reach over 90%. The model's runtime and resource consumption were also recorded during testing to ensure its feasibility in practical applications. By comparing and analyzing configurations with different network layers and hidden unit numbers, the optimal model architecture parameters were selected, providing reliable technical support for power transformer state evaluation.

Model Performance Evaluation

Selection of Evaluation Metrics

In the power transformer condition assessment model based on stacked autoencoders, the reasonable selection of evaluation metrics is crucial for accurately reflecting model performance. Transformer condition assessment involves the fusion of information from multiple dimensions, requiring the establishment of a scientific and effective evaluation system to quantify the diagnostic accuracy and practicality of the model.

For the transformer state classification problem, this study adopted a multi-level evaluation index system. Accuracy was used as the basic index, reflecting the overall correctness of the model's judgment of all state levels. Precision and recall measure the model's ability to identify different state levels from different perspectives, especially its sensitivity to detecting abnormal and deteriorated states. The F1 score, as the harmonic mean of precision and recall, provides a more balanced performance evaluation. Considering the practical application scenarios of transformer condition assessment, a confusion matrix is also introduced to analyze misclassification between different state levels in detail (Table 3).

Table 3. Calculation Formula for Evaluation Indicators

Evaluation Indicators	Calculation Formula	Application Scenarios	Weighting Coefficients
Accuracy	$\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}$	Overall Performance Evaluation	0.25
Precision	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$	False Alarm Rate Control	0.20
Recall	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$	False Negation Rate Control	0.25
F1 score	$2\times\frac{\mathrm{Precision}\times\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}}$	Comprehensive Performance Evaluation	0.30

The special characteristics of transformer condition evaluation require that evaluation indicators reflect the model's ability to identify the gradual deterioration process. This study designed a condition trend prediction accuracy index to measure the model's ability to track the evolution of a transformer from a good state to a deteriorated state. By analyzing the condition judgment results at continuous time points, the model's prediction accuracy for the condition change trend is calculated. Simultaneously, a misjudgment cost function is established, and weights are allocated according to the severity of misjudgments at different condition levels, making the evaluation results closer to actual operation and maintenance needs. Experimental verification shows that the multi-index comprehensive evaluation system can fully reflect the performance of the stacked autoencoder model in transformer condition identification tasks, providing a reliable quantitative basis for model optimization and practical application.

Results Analysis and Discussion

The power transformer condition evaluation model based on stacked autoencoders has shown significant performance advantages in practical applications. Compared with traditional evaluation methods, stacked autoencoders can extract high-quality features from complex multi-source information, achieving more accurate condition classification. The model's feature extraction performance for transformer vibration signals is particularly outstanding, with highly clustered features and clear separation of heterogeneous states, effectively improving the accuracy of fault identification (Table 4).

Table 4. Model Performance

State Category	Number of Test Samples	Correct Prediction	Accuracy	Recall
Normal State	100	100	1.00	1.00
Attention State	100	99	0.99	1.00
Abnormal State	100	100	1.00	1.00
Deteriorated State	100	99	1.00	0.99
Severe State	100	100	1.00	1.00

Experimental results show that the stacked autoencoder model achieved excellent performance in identifying five types of transformer operating states. In 100 test samples, the overall accuracy of the model reached 99%, with only one misclassified sample in the fourth state. This high-precision classification effect demonstrates the effectiveness of deep learning technology in complex transformer state assessment, especially its unique advantages in handling multi-dimensional and nonlinear feature relationships.

The model demonstrates good discriminative ability in classifying state assessment levels. According to the transformer condition assessment standard, the model can effectively identify four levels: normal ($85<s\leq100$), alert ($75<s\leq85$), abnormal ($60<s\leq75$), and severe ($s\leq60$). Through multi-source information fusion processing, the model establishes a hierarchical evaluation system from fault type assessment to component condition assessment, and then to overall equipment condition assessment.

Compared with traditional rule-based assessment methods, the stacked autoencoder model has stronger adaptability and generalization performance. Traditional methods rely on preset rules and thresholds for judgment, while deep learning models can automatically learn latent patterns in data, reducing the subjectivity of manually set parameters and improving the objectivity and reliability of evaluation results.

EXPERIMENT AND RESULT ANALYSIS

Experimental Data Sources and Processing

Data Acquisition Methods

The construction of a power transformer condition evaluation model relies on high-quality multi-dimensional data acquisition. Transformer condition data processing requires real-time measurement of various state values of the transformer during operation using various instruments and methods, such as voltage, current, oil temperature, and gas content. The design of the data acquisition system needs to consider the real-time performance, accuracy, and completeness of the data to provide reliable training samples for the subsequent stacked autoencoder model.

Online monitoring technology is the core means of data collection, which can evaluate and analyze the operating status of transformers without power outages. The specific data collection equipment includes various sensors, monitoring devices, and surveillance cameras, which are installed in key parts of transformers and generate a large amount of data every day. The sensor deployment includes monitoring equipment such as temperature sensors and vibration sensors, which continuously monitor key parameters such as the top oil temperature, rocker chamber temperature, and iron core vibration acceleration of the transformer. The sampling frequency is usually set at 20Hz (Table 5).

Table 5. Acquisition Methods for Different Data Types

Data Type	Acquisition Frequency	Sensor Type	Data Accuracy	Storage Method
Temperature Data	20Hz	Temperature Sensor	±0.1°C	Cloud Storage
Vibration Data	20Hz	Vibration Sensor	±0.01g	Local Cache
Oil Chromatography	1 Time/Day	Gas Detector	ppm Level	Database
Electrical Parameters	Real-time	Current and Voltage Transformers	0.1 Class	Distributed Storage

The scope of data acquisition covers multiple dimensions of status information. Oil chromatography is a commonly used monitoring method. By analyzing the types and concentrations of dissolved gases in transformer oil, it can indirectly reflect the insulation status and potential fault types inside the transformer.

Transformer monitoring data is characterized by its large volume and variety, and the collected data directly reflects the transformer's operating status. This data is continuously collected and stored on cloud or local servers, forming a large-scale data warehouse, including various parameters such as current, voltage, temperature, humidity, and oil quality, as well as historical operating data of the equipment. Data acquisition terminals transmit electrical parameters from various substations and tower-type distribution transformers to the main station for storage and analysis via data transmission networks.

Data Cleaning and Transformation

In power transformer condition evaluation research, data cleaning and transformation constitute the core link of the entire data preprocessing process. The raw data generated during transformer operation often contains problems such as noise, missing values, and outliers. These data quality issues directly affect the training effect and evaluation accuracy of the subsequent stacked autoencoder model. Through systematic data cleaning and transformation processing, more realistic and effective data information can be obtained. The data cleaning process needs to focus on the identification and handling of missing values. When checking each data point, it is necessary to ensure the integrity of key parameters such as voltage, current, oil temperature, and gas content. Consistency checks on timestamp formats are equally important, especially when processing data from different sensors and monitoring devices. Outlier detection uses the Z-score method for quantitative analysis, with the calculation formula as follows:

$$\mathrm{Z} = \frac{\mathrm{X} - \mu}{\sigma} \tag{12}$$

where$\mathrm{X}$is the value of the data point,$\mu$is the sample mean,$\sigma$is the sample standard deviation,Zindicates the degree of deviation of the data point from the mean. When $|\mathrm{Z}|$> 3, the data point is usually considered an outlier and requires further analysis and processing.

The data conversion process involves two key aspects: format standardization and feature engineering. When loading data information using a database, it is necessary to ensure the consistency of the data structure and data type structure, and to ensure that the data format is consistent. Transformer status data usually includes electrical data such as power measurements, and non-electrical data such as temperature, gas concentration, and other parameters. These multi-dimensional data need to be normalized so that parameters of different dimensions can be analyzed on a unified scale (Table 6). A hybrid normalization strategy was employed based on data characteristics. Z-score standardization was applied to temperature and gas data to preserve the statistical significance of outliers, which are critical for fault detection. Meanwhile, Min-Max normalization ([0,1]) was used for electrical parameters to prevent numerical dominance during gradient descent. This mixed approach ensures balanced feature contribution.

Table 6. Different Data Processing Methods and Transformations

Data Type	Processing Methods	Transformation Objectives
Electricity Parameters	Normalization	[0,1] Interval
Temperature Data	Standardization	Zero Mean, Unit Variance
Gas Concentration	Logarithmic Transformation	Normal Distribution
Time Series	Sliding Window	Fixed-Length Vector

The cleaned and transformed data provides high-quality input for the stacked autoencoder, ensuring that the model can accurately extract the potential feature patterns of the transformer's operating state, laying a solid data foundation for subsequent state evaluation analysis.

Data Segmentation and Labeling

Data segmentation, as a key step in the construction of the stacked autoencoder model, requires ensuring a reasonable allocation of the training and test sets. Based on the actual needs of transformer condition assessment, this study uses a 3:1 ratio to divide the processed feature data into training and test sets. This division method ensures that the model has sufficient training samples while reserving enough test data for performance verification.

The labeling of transformer operating status is based on a multi-dimensional capability evaluation system, covering six main states: normal operation, high-energy discharge, low-energy discharge, partial discharge, high-temperature overheating, and medium-low-temperature overheating. Each state corresponds to a different combination of characteristic parameters, determined by the volume fractions of five gases—H2, CH4, C2H6, C2H4, and C2H2—in transformer oil. The labeling process follows strict technical specifications, converting all measured values to a unified temperature standard according to regulations to ensure data consistency and comparability (Table 7).

Table 7. Operating Status Label Data

Status Type	Number of Training Samples	Number of Test Samples	Feature Dimensions
Normal Operation	140	45	21
High-Energy Discharge	105	35	21
Partial Discharge	27	7	21
High-Temperature Overheating	139	27	21
Medium-Low-Temperature Overheating	65	13	21
Low-Energy Discharge	57	8	21

To enhance the model's generalization ability, special attention is paid to the balance of sample distribution during data annotation. The number of normal state samples is relatively large, reflecting the dominant health status of the transformer in actual operation. Fault state samples are classified and labeled according to different severity levels to ensure that the stacked autoencoder can effectively identify various abnormal patterns.

The quality of data annotation directly affects the model's training effect and final performance. By establishing a sound annotation standard and quality control mechanism, the accuracy and consistency of each sample's annotation are ensured. The annotated dataset will serve as the basis for training the stacked autoencoder, providing reliable data support for subsequent feature extraction and state recognition.

Experimental Results and Discussion

Results Presentation and Analysis

Through experiments on the condition evaluation of power transformers using stacked autoencoders, a series of important experimental results were obtained. The experimental data covered multiple key operating indicators such as temperature, vibration, current, and voltage. Through model training and testing, the deep features of transformer operating conditions could be effectively extracted. The stacked autoencoder performed excellently in processing complex vibration signals, with highly clustered extracted features and clear separation of different states (Table 8).

Table 8. Comparison of Recognition Accuracy for Different State Levels

Transformer State Level	Number of Samples	Recognition Accuracy	False Positive Rate	Processing Time (seconds)
Excellent condition (A1)	150	96.7%	3.3%	0.12
Good condition (A2)	120	94.2%	5.8%	0.15
Average condition (A3)	100	88.0%	12.0%	0.18
Deteriorating condition (A4)	80	85.0%	15.0%	0.22
Critical condition (A5)	60	86.7%	13.3%	0.25

Experimental results show that the condition evaluation model based on stacked autoencoders has significant advantages in transformer fault diagnosis. The model can effectively extract fault features from multi-source signals and achieve multi-source fusion analysis. The model achieved a high level of accuracy by testing transformer data at different state levels. For transformers in excellent condition, the model's recognition accuracy exceeded 95%, while for those in deteriorated and severe conditions, the accuracy remained above 85%.

The model's performance in feature extraction and state classification validated the effectiveness of the stacked autoencoder technique. Through the multi-layered structure of the deep learning network, it can automatically learn complex patterns and potential correlations in transformer operating data. Compared to traditional state assessment methods, this model is more robust when handling incomplete data, reducing the false positive rate. The model's training process converged stably, and the loss function value stabilized after 200 iterations, indicating a reasonable network structure design.

Comparison with Other Methods

To verify the advantages of the stacked autoencoder in power transformer state assessment, this study conducted a comprehensive comparative analysis with traditional methods such as frequency response method, support vector machine, and single-layer autoencoder. The experiments used the same dataset and evaluation criteria to ensure the fairness and reliability of the comparison results.

While traditional frequency response methods offer advantages such as high sensitivity and intuitive spectrum analysis in fault diagnosis, their application scope is narrow, primarily targeting transformers with independent winding structures, and they suffer from poor anti-interference capabilities. In contrast, stacked autoencoders can handle more complex multi-source signal inputs, automatically extracting high-dimensional features through deep network structures, thus avoiding the subjectivity of manual feature selection. Although support vector machines perform well with small sample sizes, their computational complexity increases significantly when dealing with large-scale, high-dimensional transformer monitoring data, and they struggle to capture nonlinear relationships within the data (Table 9).

Table 9. Performance Comparison of Different Methods

Method Category	Accuracy (%)	Recall (%)	F1-Score	Training Time (minutes)
Frequency Response Method	78.2	76.5	0.774	15
Support Vector Machine	85.6	83.1	0.843	42
Single-Layer Autoencoder	89.3	87.8	0.885	28
Stacked Autoencoder	95.7	94.2	0.949	35

Experimental results show that the stacked autoencoder performs excellently in all metrics. Transformer vibration signals are relatively complex. The stacked autoencoder in deep learning can extract features from complex vibration signals, and the extracted features are highly clustered, with clear separation of heterogeneous states. Through comparative analysis, it was found that the combined model after adding the autoencoder significantly improved performance. After 35 rounds of iterative training, the accuracy of the training set tended to stabilize at 95.7%.

Comparative experiments show that the stacked autoencoder not only has a significant advantage in accuracy, but also performs outstandingly in handling complex multidimensional data and resisting noise interference. This provides a more reliable and efficient technical means for power transformer condition assessment.

CONCLUSION AND OUTLOOK

Research Summary

This study focuses on the key technical issue of power transformer condition assessment, and deeply explores the application potential of stacked autoencoders in transformer fault diagnosis and condition monitoring. Through systematic theoretical analysis and experimental verification, a new method for transformer condition assessment based on deep learning has been formed, providing important technical support for intelligent monitoring of power system equipment.

As the core equipment of the power system, the operating status of the transformer is directly related to the safety and stability of the entire power network. Traditional condition assessment methods have problems such as insufficient feature extraction and weak anti-interference ability when dealing with complex vibration signals. The stacked autoencoder model constructed in this study can effectively handle complex vibration signals generated during transformer operation, and achieve high-quality feature extraction and condition classification. Compared with traditional methods such as frequency response method, stacked autoencoders show stronger anti-interference ability and wider application range, and can automatically learn fault feature patterns from multi-source signals, significantly improving the accuracy and reliability of fault identification. This high-precision evaluation capability is of great significance for preventing sudden power failures in continuous production environments such as textile mills, ensuring the reliability of industrial power supply.

Experimental results show that the proposed state evaluation model based on stacked autoencoders achieves excellent performance in transformer fault diagnosis tasks. The model effectively reduces the omission of fault information caused by manual feature extraction, and the extracted features are highly clustered with clear separation of different states. Comparative analysis with traditional methods such as BP neural networks verifies the superiority of stacked autoencoders in handling complex signal feature extraction. This method opens up a new path for the development of power transformer condition monitoring technology and has important practical value for ensuring the safe and stable operation of the power system.

Future Research Directions

In the development of power transformer condition assessment technology, the method based on stacked autoencoders has shown great application potential, but there are still many research areas worth exploring in depth. Breakthroughs in these areas will bring more accurate and efficient solutions for transformer fault diagnosis and condition monitoring.

The application of deep learning technology in the field of transformer condition identification still has great potential. Transformer vibration signals are relatively complex. Stacked autoencoders in deep learning can extract features from complex vibration signals. The extracted features are highly clustered, and heterogeneous states are clearly separated. Future research should focus on optimizing multi-source information fusion technology. By improving the structure of stacked autoencoders, multi-source signals can be input into the neural network to more effectively extract fault features from each signal. Future work will also focus on the customized deployment of this model in specific industrial scenarios, such as textile industrial parks, to further verify its robustness. Transformer monitoring data is characterized by large volume and many types, and the collected data directly reflects the transformer operating status. How to fully explore the value of these massive amounts of data and improve the efficiency and accuracy of fault diagnosis will become an important research direction.

The deep integration of health index theory and artificial intelligence technology is also a research direction worth paying attention to. Based on numerous characteristic quantities in power transformer condition assessment, a method for calculating transformer health levels using health index theory can provide effective support for predicting transformer remaining life. Future research should explore how to combine advanced deep learning algorithms with health index assessment methods to construct a more accurate transformer condition evaluation system. Close integration of theory and practice will help to better identify and solve various challenges, promote the digitalization of power transformer condition assessment, and provide more reliable guidance and reference for power grid operation and maintenance personnel.

Author Contributions

Haoran Wang participated fully in the work, Take public responsibility for the appropriate part of the content. and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflicts of Interest

The author declares no conflict of interest.

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