2024 9th International Conference on Automation, Control and Robotics Engineering (CACRE) | 979-8-3503-5030-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/CACRE62362.2024.10635036

Research on Defect Category Identification Method for Rough Surface Thick Wall Steel Plate Based on Autoencoder-BP Neural Network

Biao Xue
Gongzui Hydropower Plant of Guoneng Dadu River Basin Hydropower Development Co., Ltd
Leshan, China
biao.xue.c@chnenergy.com.cn

YuHang Wang
Gongzui Hydropower Plant of Guoneng Dadu River Basin Hydropower Development Co., Ltd
Leshan, China
yuhang wang.c@chnenergy.com.cn

Yang Yang
College of Electrical Engineering ,Sichuan University
Chengdu, China
18190200895@163.com

LiJun Dang
College of Electrical Engineering ,Sichuan University
Chengdu, China
3285769594@qq.com

SongYi Dian
College of Electrical Engineering ,Sichuan University
Chengdu, China
scudiansy@scu.edu.cn

***Abstract*—For the processing of echo signals in defect detection, wavelet transform and principal component analysis are mostly used to extract features. However, the feature values obtained by these methods often lead to redundancy, resulting in the waste of a lot of resources for defect identification. This paper, in the context of defects in thick-walled steel plates with rough surfaces, proposes a defect category recognition classification method based on an autoencoder-BP neural network. It uses signals from electromagnetic ultrasonic and pulsed eddy current composite detection as the neural network learning signals. Impedance analysis is used to more comprehensively reflect the characteristics of defects, thereby improving the accuracy of defect identification. Autoencoder is selected to extract the geometric features of the composite detection signals, which can effectively extract useful features from the dataset. The feature dataset is then divided into training and testing sets. Simulation experiments show that the trained neural network model has achieved a classification accuracy of 90.8% in the testing.**

Keywords— Impedance Analysis Method; Defect Identification; Backpropagation Neural Network; Autoencoder

I. INTRODUCTION

The quality inspection requirements for large-scale equipment have become increasingly stringent, especially for thick-walled components widely used in water conveyance pipelines, aerospace, and other large-scale equipment [1]. Due to issues such as production processes, wear and tear, and material quality, thick steel plates often exhibit defects like welds, cracks, and holes [2]. Therefore, defect detection is of significant importance and value in ensuring product quality and timely identifying unknown potential hazards. It plays a crucial role in quality monitoring during product use.

A classification method combining the fractal dimension of dynamic indicators and directional propagation neural network based on the Duffing system has been proposed for the recognition of minor defects [3]; A hierarchical clustering binary tree SVM multi-classification method based on inter-class separability has been proposed for the recognition of pipeline defects [4]; An efficient method has been established to assist inspectors in quickly and accurately identifying the types of pipeline defects by combining deep learning and image processing techniques [5]; A method for recognizing pipeline corrosion defects has been proposed, which is based on the reflection signal of ultrasonic guided waves, using genetic algorithms and providing feedback to the classifier [6]. However, most of the aforementioned studies are based on thin-walled pipelines or flat panels, and the non-destructive testing data sources are based on one method of ultrasonic guided waves or eddy current detection. In such cases, there may be insufficient defect information in the detection data, leading to inaccurate defect identification, as well as long training times and oversized training sets for the neural network model.

This paper focuses on thick steel plates with rough surfaces. To improve the accuracy of defect identification, we use the results of composite detection based on electromagnetic ultrasound and pulsed eddy current, which can more comprehensively reflect the geometric features and positional information of defects. We propose a classification method based on an autoencoder BP neural network, using impedance analysis to obtain the detection results, then using the autoencoder to extract useful features from the dataset, and finally importing them into the BP neural network for learning and classification.

II. METHODOLOGY DISCUSSION

Electromagnetic acoustic testing has a certain blind area near the surface of the steel plate being tested because the wave source is generated on the surface, making it suitable only for detecting defects on the lower surface and inside the steel plate. Pulsed eddy current testing is sensitive to surface and near-surface defects of the steel plate due to the skin effect, but it cannot accurately detect when the thickness of the steel plate exceeds a certain range. Therefore, the composite detection of the two methods can complement each other's shortcomings, thereby expanding the detection range and improving the accuracy of detection.

In ultrasonic testing and eddy current testing, the most commonly used analysis method is impedance analysis. Changes in the impedance of the detection coil can reflect whether there are defects. This paper will collect the impedance signals and extract geometric features through an autoencoder, and then import the feature values into a Backpropagation Neural Network for learning and classification.

A. Electromagnetic Ultrasonic and Pulsed Eddy Current Composite Inspection

Principle of Electromagnetic Acoustic Transduction Inspection[7] : it is a non-contact inspection method that generates ultrasonic waves in conductive materials using an electromagnetic field. EMAT utilizes a coil to create an alternating magnetic field. When the coil is brought close to the conductive material, the alternating magnetic field induces currents in the material. These currents interact with the magnetic field to produce a Lorentz force, which results in the generation of ultrasonic waves at the surface of the material. EMAT can detect the internal structure and defects of materials, but it is difficult to detect near-surface defects.

Principle of Pulsed Eddy Current Testing[8] : it is an inspection method based on the principle of electromagnetic induction, suitable for detecting surface and near-surface defects in conductive materials. In PECT, a transient excitation current is passed through a coil, generating a transient magnetic field. When this magnetic field acts on conductive materials, eddy currents are induced within the material. The secondary magnetic field generated by these eddy currents is detected by the detection coil. By analyzing the signals received by the detection coil, it is possible to determine the presence or absence of defects.

This article adopts a mechanism-level composite inspection, which has a higher detection efficiency than the system-level composite. Mechanism-level composite refers to the common points between electromagnetic ultrasonic and pulsed eddy current in the detection principle, achieving simultaneous pulsed eddy current and electromagnetic ultrasonic detection under the same excitation source and detection hardware conditions[9]. Since both detection processes have the same physical process, both are achieved by detecting the changes in the eddy current on the conductor surface that cause changes in the electromotive force of the detection coil to obtain detection information. Therefore, it is possible to use a common detection coil, use the same excitation source, and obtain a composite detection signal containing pulsed eddy current and electromagnetic ultrasonic from the composite sensor. By separating the electromagnetic ultrasonic and pulsed eddy current signals, and then performing independent signal processing for each, the data fusion is carried out to obtain the detection information.

B. Impedance Analysis Method

For the composite inspection circuit, it can be equivalent to a circuit loop, and then according to Faraday's law of electromagnetic induction, the output impedance of the sensor coil can be expressed as：

$$R_{\mathrm{s}} = R_{\mathrm{c}} + \frac{\omega^2 M^2}{R_{\mathrm{t}}^2+(\omega L_{\mathrm{t}})^2} R_{\mathrm{t}} = R_{\mathrm{c}} + \Delta R \quad (1)$$

$$L_{\mathrm{s}} = L_{\mathrm{c}} - \frac{\omega^2 M^2}{R_{\mathrm{t}}^2+(\omega L_{\mathrm{t}})^2} L_{\mathrm{t}} = L_{\mathrm{c}} - \Delta \mathrm{L} \quad (2)$$

Rc and Lc are the resistance and inductance of the probe coil, respectively; $R\,t$ and $L\,t$ are the resistance and inductance of the target specimen, M is the mutual inductance coefficient between the probe coil and the target specimen. The complex impedance of the coil can be expressed as：

$$Z = \frac{U}{I} \quad (3)$$

When inspecting the steel plate, if there are defects, then the voltage signal on the receiving coil will be abnormal, and moreover, changes in parameters such as the location and size of the defects can also cause varying degrees of changes in the voltage signal. Therefore, we can determine the changes in impedance based on the detected voltage signal, and based on the characteristics of the impedance, we can infer the relevant information about the defects, meeting the requirements for defect detection.

C. Autoencoder

The autoencoder is shown in Fig.1, with the encoding and decoding networks respectively performing the functions of importing the original data and exporting the feature quantities. The amount of input data is equal to the number of output features.

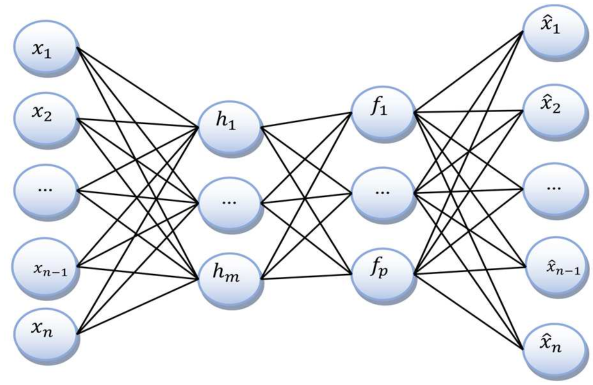

Fig. 1. Autoencoder

The goal of the autoencoder is to reconstruct the input by taking the output of one layer as the input of the next, thereby reducing the difference between the input and output to achieve the purpose of feature extraction. There are many factors that affect the quality of the feature quantity, such as the number of hidden layers, the number of nodes per layer, the type of activation function in the hidden layers, the learning rate, the vector dimension, but the most significant influence comes from the number of hidden layers. When the encoder has too few layers, the features extracted by the autoencoder do not closely fit the original data; when the encoder has too many hidden layers, overfitting occurs, which prevents the extracted features from well reflecting the most essential characteristics of the original data. Considering all these factors, we specify that this autoencoder uses 2 hidden layers, which can achieve better feature extraction in the context of this paper.

In this context, the role of the encoding network is to encode the input data X to obtain feature variables with dimensions lower than X. The encoding process is as follows:

$$h_i = f(\sum_{i=1}^{n} wx_i + b) \tag{4}$$

$$f_i = f(\sum_{i=1}^{m} w_1 h_i + b_1) \tag{5}$$

The role of the decoding network is to restore the obtained low-dimensional feature variables to their original dimensions. The decoding process involves:

$$\hat{x}_i = f(\sum_{i=1}^{p} w_2 f_i + b_2) \tag{6}$$

x_i represents the original input data of the autoencoder; h_i and f_i are the outputs of the first and second layers, respectively; $\hat{x}_i$ is the output of the encoder.

To ensure that the extracted feature quantities are what we need and to avoid redundancy or repetition in the features, we need to add a sparsity penalty term $\Omega_{sparity}$ to the network for selection, making the network more selective.

The loss function G after incorporating the sparsity constraint is:

$$G = G_{MSE} + \alpha\Omega_{weights} + \beta\Omega_{sparity} \tag{7}$$

G_{MSE} refers to the mean squared error loss function, $\Omega_{weights}$ and $\Omega_{sparity}$ are the L2 regularization term and sparsity penalty term, α and β are the regularization coefficients. After incorporating the sparsity penalty term into the system, it becomes possible to control the inactivation degree of the neurons in the hidden layer, thereby achieving the intended goals of improving network performance and accelerating the convergence rate.

D. Backpropagation Neural Network

The BP neural network consists of three parts: the input layer, the hidden layer, and the output layer. It adjusts the parameters during the forward propagation phase based on the error feedback from the output until the output results meet the expected requirements or a set number of computations is reached. Within its structure, nodes between each layer are connected by weights, and after each new computation, the weights are adjusted based on the results. The structural network is depicted in Fig.2.

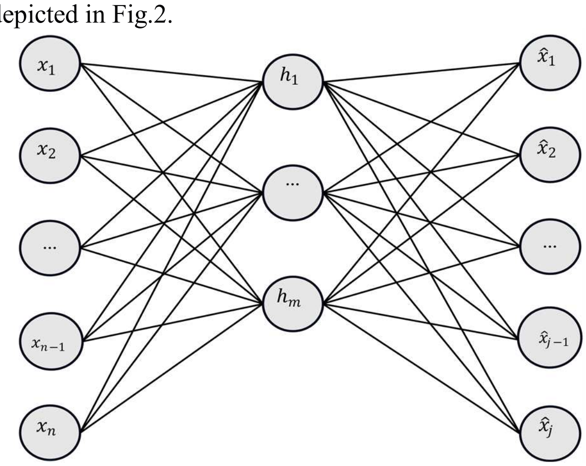

Fig. 2. BP neural network structure diagram

The transfer function from the input layer to the hidden layer is

$$h_i = f(\sum_{i=1}^{n} wx_i + b) \tag{8}$$

The transfer function from the hidden layer to the output layer is

$$\hat{x}_i = f(\sum_{i=1}^{m} w_1 h_i + b_1) \tag{9}$$

x_i represents the original input data of the autoencoder network, h_i is the output of the first layer, $\hat{x}_i$ is the output of the encoder, which is the extracted feature quantity, w and b are the weights and biases, respectively.

E. Finite Element Simulation Model Construction

Finite Element Analysis is a numerical simulation technique that employs the Finite Element Method to generate a virtual environment within a computer to simulate a variety of physical phenomena.

COMSOL Multiphysics is a finite element analysis software capable of solving and simulating multi-physics problems. COMSOL offers a physics-based traditional user interface and a system for coupling partial differential equations. It provides an integrated development environment and a cohesive workflow for applications in the fields of electrical, mechanical, fluid, acoustic, and chemical engineering. Therefore, we have chosen COMSOL as the platform for conducting finite element analysis of the electromagnetic acoustic and pulsed eddy current composite inspection model.

Geometric modeling and material parameter configuration: the composite detection model is a three-dimensional model. The simulation model for the electromagnetic acoustic and pulsed eddy current composite detection is shown in Fig.3. The composite detection model is composed of a transmission coil, a reception coil, test specimen, a permanent magnet, and air region. The coil material is copper, which is used to excite the initial magnetic field and to receive the electromotive force feedback from the pulsed eddy current and electromagnetic ultrasound. The specific geometric and physical parameter settings are detailed in Table I.

The electromagnetic ultrasonic and pulsed eddy current composite detection model involves the coupling of electric fields with magnetic fields, as well as the coupling of electromagnetic fields with solid mechanics. The static magnetic field of the permanent magnet utilizes the no-current magnetic field feature in the AC/DC module, while other model regions, including the air domain, coils, and the test specimen, employ the magnetic field of the AC/DC module.

TABLE I. IMULATION PARAMETER SETTINGS

	Transmission/Reception Coil	Permanent Magnet	Steel Plate
Width/Radius[mm]	4	5	30
Height[mm]	5	3	33
Electrical Conductivity [S/m]	6e7	7.14e5	8.7e6
Number of Turns	100/150	-	-
Lift-off [mm]	2/1.5	8	-
Young's Modulus[Pa]	-	-	3e11
Density [Kg/m^3]	-	-	3900
Poisson's Ratio	-	-	0.222

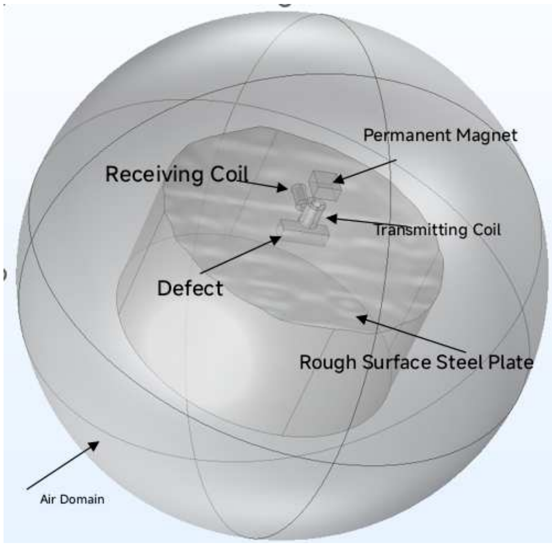

Fig. 3. Simulation model

The solid mechanics module is utilized within the test specimen to simulate the generation and propagation of electromagnetic acoustics. In the physical field coupling settings for the electric and magnetic fields, the electromagnetic field coupling interface pre-defined by COMSOL is applied, encompassing Ampere's law, magnetic insulation, and initial value settings, among others. The excitation source is excited through the means of external current density.

Mesh division: the mesh division significantly influences the outcomes of simulations, with several critical factors at play, such as the method of dividing the geometric model and the shape and size of each mesh element. These factors directly impact the computational time, memory requirements, and accuracy of the model's solution. A mesh that is too coarse can result in low precision and inaccurate outcomes; conversely, a mesh that is too fine can exponentially increase the computational time.

In order to ensure computational precision while keeping the simulation duration brief, the mesh is refined in regions where the electromagnetic field is concentrated. The air and within the permanent magnet, utilize a free mesh division to minimize computation, as depicted in Fig.4. For the interior of the test specimen, which needs to simulate the propagation of ultrasonic waves, the mesh division should typically not be finer than one-twelfth of the wavelength.

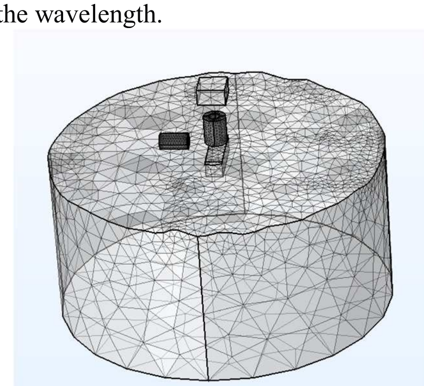

Fig. 4. Mesh division (with air domain hidden)

Simulating by continuously changing the geometric features of the defects, such as width, thickness, and position, width thickness, depth, changing the position relative to the coil, a total of 128 sets of data were ultimately obtained.

III. SIMULATION ANALYSIS

For this part of the experimental simulation, 128 sets of defect data were chosen, sourced from simulation experiments performed on COMSOL—electromagnetic acoustic and pulsed eddy current composite detection for thick steel plates featuring rough surfaces. The data encompasses surface defects, internal defects, and variations in defect shapes and locations. Initially, the acquired 128 sets of data are fed into a sparse autoencoder to extract valuable features; subsequently, these feature datasets are introduced to a Backpropagation Neural Network for the purpose of learning and classification. The parameter design of the sparse autoencoder is as shown in Table II.

TABLE II. SPARSE AUTOENCODER PARAMETERS

Parameter Name	Value
Maximum Number of Training Epochs	400
L2 Regularization Coefficient	0.004
Control Coefficient for Sparsity Regularization	4
Expected Proportion of Training Samples	0.15

Following a comparison of the feature quantities extracted by the autoencoder, features with similar curves were manually filtered out as they are considered redundant information and have a less significant effect on defect identification and classification. The selected feature quantities for the subsequent experimental simulation are presented in Table III.

The feature data derived from the sparse autoencoder's output is split into training and testing sets in a ratio of approximately 4:1, which is then fed into the Backpropagation Neural Network (BPNN) for learning and classification. The parameter design is detailed in Table IV.

TABLE III. SELECTED FEATURE QUANTITIES

Average	$\bar{s} = \frac{1}{N}\sum_{i=1}^{N} s_i$
Waveform Factor	$RMS/\left(\frac{1}{N}\sum_{i=1}^{N} \lvert s_i \rvert\right)$
Standard Deviation	$\rho_t = \frac{1}{N}\sum_{i=1}^{N} \left(s_i - \bar{s}\right)^2$
Kurtosis	$\frac{1}{N}\sum_{i=1}^{N} \frac{(s_i - \bar{s})^4}{\rho_t^4}$
Impulse Factor	$s_{max}/\left(\frac{1}{N}\sum_{i=1}^{N} \lvert s_i \rvert\right)$
Minimum Value	S_{min}

Margin Factor	$s_{max}/\left(\frac{1}{N}\sum_{i=1}^{N}\|s_i\|\right)^2$

TABLE IV. BP NEURAL NETWORK PARAMETERS

Parameters	value
Maximum Number of Iterations	1000
Target Training Error	0.000001
Learning Rate	0.01

Data labeled as category 1 signifies defective data, whereas data labeled as category 2 signifies non-defective data. Fig.5 and Fig.6 demonstrate that utilizing the features extracted by the autoencoder with a Backpropagation Neural Network for defect identification achieves a commendable level of accuracy. For category 1, the accuracy rates for the training and testing sets are 97.4% and 90.9%, respectively; for category 2, the accuracy rates for the training and testing sets are 63.6% and 83.3%, respectively.

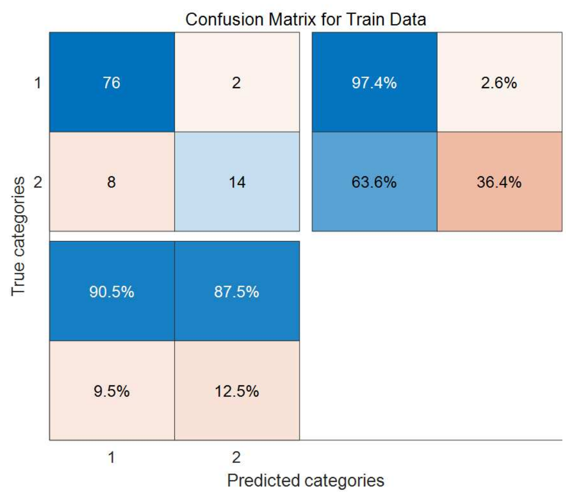

Fig. 5. Training Set Recognition Results

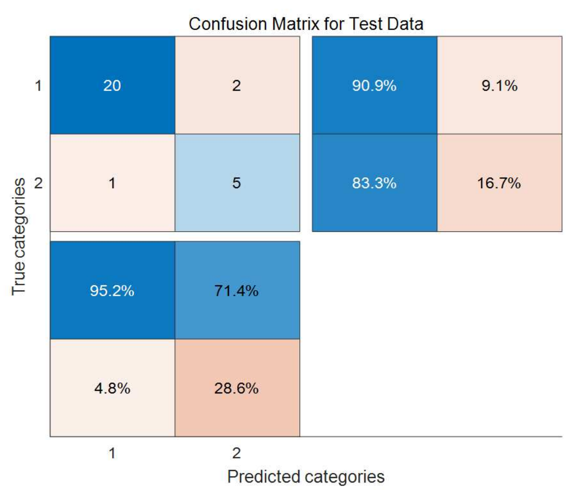

Fig. 6. Test Set Recognition Results

IV. CONCLUSION

Employing electromagnetic ultrasonic and pulsed eddy current composite detection can more thoroughly reveal the geometric information of defects in thick steel plates with rough surfaces. Utilizing impedance analysis to examine the echo signals from defects, followed by the application of an autoencoder to extract geometric features from the dataset, the autoencoder inherently provides effective feature extraction, preventing information redundancy. The Backpropagation Neural Network possesses strong learning capabilities and can achieve a high level of classification accuracy, making it suitable for the identification and categorization of defects in thick steel plates with rough surfaces.

REFERENCES

[1] Jia D ,Hua G Y .Structural Fatigue Analysis on Expansion Joints of Diversion Penstock of Hydropower Station[J].Applied Mechanics and Materials,2011,117-119(117-119):262-268.

[2] HaiBo L ,Yi W ,Hai Y .Study on Ultrasonic Detection Pattern Recognition of Natural Gas Steel Pipeline Defects[J].Russian Journal of Nondestructive Testing,2023,58(10):903-916.

[3] YoungIn H ,MuKyung S ,Geun H O , et al.Detection and Classification of Artificial Defects on Stainless Steel Plate for a Liquefied Hydrogen Storage Vessel Using Short-Time Fourier Transform of Ultrasonic Guided Waves and Linear Discriminant Analysis[J].Applied Sciences,2022,12(13):6502-6502.

[4] Shijiu J X Z J L .An automatic flaw classification method for ultrasonic phased array inspection of pipeline girth welds[J].INSIGHT,2013,55(6):308-315.

[5] Niannian W ,Duo M ,Xueming D , et al.An automatic defect classification and segmentation method on three-dimensional point clouds for sewer pipes[J].Tunnelling and Underground Space Technology incorporating Trenchless Technology Research,2024,143

[6] ACCIANI G, CHIAANTONI E, et al. Automatic evaluation of flaws in pipes by means of ultrasonic waveforms and neural netwoks[C].IEEE, 2006;892-898.

[7] Yu Z ,Ma Q ,Yuan H , et al.Defect identification method for ultrasonic inspection of pipeline welds based on cross-modal zero-shot learning[J].Measurement Science and Technology,2024,35(2)

[8] Qingyi L ,Ailong J ,Duo F , et al.Intelligent recognition of defects in vermicular graphite cast iron engine cylinder head by ultrasonic testing[J].Journal of Physics: Conference Series,2021,1894(1):

[9] Liu J ,Xu G ,Ren L , et al.Defect intelligent identification in resistance spot welding ultrasonic detection based on wavelet packet and neural network[J].The International Journal of Advanced Manufacturing Technology,2017,90(9-12):2581-258.