Parameter estimation method of yield strength for ferromagnetic materials based on Pulsed Eddy Current

Kaiyu Li, Wenjuan Gao*, Ping Wang[a], Yanyan Zhang and Cheng Hang

College of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, China

*Corresponding author e-mail: gwj8586@163.com, [a]1149122396@qq.com

Abstract. In the current iron and steel industry production, the detection of the yield strength of ferromagnetic materials relies on loss detection. By determining the yield strength of the material through tensile tests, the material needs to be stretched to the yield limit, which greatly increases the cost of testing. This paper presents a method for estimating the yield strength parameters of ferromagnetic materials based on pulsed eddy currents. Firstly, the characteristics of time-domain and frequency-domain of pulsed eddy current response signals are extracted. Then, the back propagation neural network model of each signal characteristic and material yield strength is established, and finally the neural network is used to predict the yield strength of the material. Using the BP neural network model trained by features of pulsed eddy current, the yield strength of the specimens can be estimated. As a non-destructive testing method, the method has a prediction error of 5% or less, and has a certain practical value for reducing the detection cost of industrial production and improving the detection efficiency.

1. Introduction

Ferromagnetic materials, such as steel, are widely used in railways, military affairs, aerospace, energy and construction, whose quality control directly affects the safety of many major equipment. In the current iron and steel production industry, online inspection for the yield strength of ferromagnetic materials plays an important role in the detection of early damage and early warning of failures.

At present, the method of measuring the yield strength is mainly the traditional offline tensile test method, which is based on the irreversible stretching of the material and is a destructive detection method. The traditional offline tensile test method can only be used to guide the process adjustment and stabilize the product quality, so that non-destructive online testing has become the current development trend [1-2].

Pulse eddy current signal contains a wide spectrum and is very sensitive to changes in material conductivity and permeability, pulsed eddy current technology is widely used in the quantitative detection of electromagnetic properties of ferromagnetic materials [3-5]. However, how to promote pulsed eddy current technology to the mechanical properties of ferromagnetic materials remains a difficulty to be solved in the current research of pulse eddy current testing technology.

In order to promote pulsed eddy current technology to the mechanical properties of ferromagnetic materials, this paper carries out a study on the parameter estimation of yield strength of ferromagnetic materials based on pulsed eddy currents. By establishing the mapping relationship between the characteristics of pulsed eddy current signals and the yield strength of materials, the yield strength of materials is estimated. For the purpose of ensuring small samples and non-linear mapping conditions, a reasonable and efficient mathematical model needs to be adopted.

Back propagation neural network (BP neural network), which is a multi-layer feed-forward neural network trained according to the error reverse propagation algorithm, has strong learning ability and excellent nonlinear mapping ability [6-7]. It can maintain good prediction accuracy even in the case of small samples. This paper introduces BP neural network model into the pulsed eddy current non-destructive testing. Firstly, the signal characteristics of pulse eddy current signal are extracted in time domain and frequency domain, then the BP neural network model is established for each signal characteristic and material yield strength. Finally, the yield strength of the material is estimated by the trained neural network model.

2. Principle and experiment system

2.1. Detection principle of pulsed eddy current testing

The pulsed eddy current testing technology uses a square wave with a certain duty cycle as the excitation signal, then the pulsed eddy in the excitation coil generates a rapidly decaying pulsed magnetic field, which induces a pulsed eddy current in the ferromagnetic sample, whose amplitude, phase, and flow patterns are affected by the conductivity and magnetic permeability of the sample.

The yield strength (R_p) can be expressed as a function of the material micro structure parameters, such as Austenite content, Martensite content, etc., as shown in equation (1). The features extracted from the pulsed eddy current response signal are represented as P_k , so P_k can also be expressed as a function of a series of micro structure parameters of the material, as shown in equation (2). Combining equations (1) and (2), we can express the material yield strength as a function of the characteristics of various pulse eddy current response signals, as shown in equation (3). By selecting a suitable algorithm model, collecting a large amount of experimental sample data and training the model, the mapping relationship between material yield strength and the features of pulse eddy current response signals can be established to realize the estimation of the yield strength of the material.

$$R_p = f(C_1, C_2 ... C_n) \tag{1}$$

$$P_k = f^{'}(C_1, C_2 ... C_n) \tag{2}$$

$$R_p = F(P_k) \tag{3}$$

2.2. Experimental system

Pulse eddy current testing system is shown in Figure1. The system consists of five parts: pulse signal generation module, probe, test sample, signal conditioning module and data acquisition module. The pulse signal source module is used to generate an excitation pulse signal and apply the signal to both ends of the excitation coil. The excitation coil generates a pulse excitation magnetic field on the tested part, the probe is composed of a magnetic sensor and a magnetic core for detecting the magnetic induction intensity. The data acquisition and processing module is applied to collect and process the detection signals, and control the DAQ Card to collect the data and save it for subsequent signal analysis and processing.

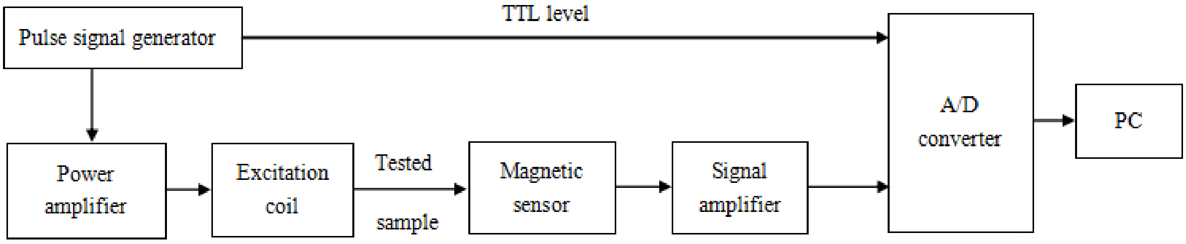

Figure 1. Pulse eddy current testing system

The experiment settings are as follows, the probe excitation coil of this system uses an enameled wire with a diameter of 0.2 mm, and the number of excitation coils is 400 turns. The coil resistance is 18.16Ω and the inductance is 40mH. Hall sensor UGN3503, which has high sensitivity to changes in magnetic flux density, is selected as magnetic sensor. It has the advantages of low output noise and wide linear range. The detection range is -650G~650G and the output bandwidth is 23 kHz, which can meet the requirements of this experiment. Data acquisition card PCI-9111HR is selected to realize the signal A/D conversion. The excitation signal of the experiment is a square wave signal with a duty cycle of 50%, which has amplitude of 8V, a frequency of 20Hz and an output power of approximately 2.2 W. The sampling frequency is 20 kHz and each sampling time is 1s. The test sample is 11 pieces of steel materials with different yield strengths in the specimen library, numbered from 1 to 11, whose characteristics are shown in Table 1. Twenty repeated samples were taken for each specimen and a total of 220 samples were obtained.

Table 1. Yield strength values of 11 specimens

Specimen number	1	2	3	4	5	6	7	8	9	10	11
Yield strength(MPa)	301	321	335	338	404	412	440	524	1061	1093	1149

3. Feature extraction and analysis

Materials with different yield strengths often have different electromagnetic properties due to the difference in microstructure while pulse eddy current signals are very sensitive to changes in the electromagnetic properties of materials. Therefore, time and frequency domain features are extracted from the pulsed eddy current signals collected from specimens with different yield strengths. Time domain features include single period integration value (F_g), peak value of differential signal (PV_t), peak value of the difference between the signal and the reference signal (PV_d), frequency domain features include DC component (ω_d), first harmonic amplitude (ω_1) and third harmonic amplitude (ω_3). The definition and calculation of each feature are as follows:

(a) F_g means the integral value of a pulsed eddy current response signal over a complete period. The formula is shown in equation (4). In the formula, B (t) is the pulsed eddy current response signal and T is the signal period.

$$F_g = \int_0^T B(t)dt \tag{4}$$

(b) PV_t is the peak value of the differentiated pulsed eddy current in one cycle. It reflects the rate of change of the magnitude of the magnetic induction intensity. The formula to calculate PV_t is shown in equation (5).

$$PV_t = \max_{0\le t\le T}\{\frac{\partial B}{\partial t}\} \tag{5}$$

In the formula, B is the pulsed eddy current response signal and T is the signal period.

(c) PV_d means peak value of the difference between the signal and the reference signal. First of all, select one cycle of the time domain response signal of one specimen as the reference signal, then subtract the reference signal from the one cycle response signal of the other specimen to obtain the differential signal, and then extract the peak value of the differential signal as the feature named PV_d . PV_d represents the degree of difference between other signals and the reference signal. The formula to calculate PV_d is shown in formula (6).

$$PV_g = \max\{B - B_{ref}\} \tag{6}$$

(d) Frequency domain features (ω_d , ω_1 and ω_3). The extraction method of frequency domain feature is as follows: a fast Fourier transform is performed on the response signal to obtain the frequency spectrum of the signal, the ordinate value corresponding to ω=0 in the frequency spectrum is the direct current component of Signal (ω_d), the ordinate value corresponding to ω=1 in the frequency spectrum is the first harmonic amplitude of Signal (ω_1), and the ordinate value corresponding to ω=3 is the third harmonic amplitude of Signal (ω_3).

4. Yield strength estimation results and analysis

4.1. BP Neural Network Model Construction

There is a complicated nonlinear relationship between the signal characteristics and the yield strength of the specimen, so it is difficult to establish a mathematical model by using traditional mathematical formulas. However, a well-designed BP neural network can be trained to learn the input and output of the system, and to approach arbitrarily complex nonlinear functions theoretically. Therefore, BP neural network is used to establish the prediction model.

First, it's necessary to establish a sample database to determine the input and output of the model. The N types of specimens in the specimen library are divided into a training set and a test set. The signal characteristics of the N types of specimens can be obtained through experiments and feature extractions. A training sample database D1 and test sample database D2 would be established after repeated sampling of each specimen. Each sampling is taken as a sample, which includes six input data and one target data. The six input data are the six characteristic values of the pulsed eddy current response signal, and the target data is the true value for yield strength of a specimen. A sample's attribute feature sequence and label information are shown in Equations (7) and (8) respectively.

$$X_i = [F_g, PV_t, PV_d, \omega_d, \omega_1, \omega_3] \tag{7}$$

$$X_o = R_e \tag{8}$$

Second, a BP neural network prediction model is established based on the input and output of the model. In order to improve the accuracy of prediction and the convergence speed of the function, the double hidden layer BP neural network is selected, whose structure includes the input layer, double hidden layer and output layer. The model input is the attribute feature sequence of the training sample set, which consists of the extracted six pulse eddy current response characteristics, and the output data is the estimated data of the yield strength of the specimen in one estimation. That is, the input layer dimension is 6, and the output layer dimension is 1.

According to the specimen size and the parameter estimation accuracy to be achieved, the parameters of the neural network model for this experiment are set as follows: the number of nodes in the two hidden layers is 10, the learning rate is 0.01, the momentum factor is 0.9, the maximum number of trainings is 100, and the end condition of training is that the mean square error is less than 4e-5.

Finally, train the BP neural network. The parameters are optimized according to the training results. After the training, the BP neural network model is obtained, then the model is used to estimate the yield strength parameters of the test specimen, the error and the pass rate are calculated. Parameter estimation includes two steps: model prediction and averaging. The attribute feature sequence of the sample in the test set database is used as the input of the neural network model to obtain the yield strength estimate of the corresponding sample. The attribute feature sequences of n test samples obtained by n acquisitions on a certain test piece are respectively input as models, and n output values are obtained. Then, the formula for estimating the yield strength of the test sample is shown in Equation (9). Denotes the estimated data of yield strength of the specimen.

$$r_e = \frac{1}{n}\sum_{k=1}^{n} r_k \tag{9}$$

The pass rate (relative error<10%) is calculated as shown in Equation (10). The pass rate (relative error<10%) reflects the percentage of test samples with less than 10% error in the total test sample.

$$Q_{10} = \frac{n_{10}}{n} \times 100\% \tag{10}$$

In the above equation, n denotes the total number of test samples, and denotes the total number of test samples with a relative error of less than 10%.

4.2. *Estimation results*

The original signal obtained from the experiment is preprocessed and six signal features are extracted to obtain 220 sets of data (20 sets of data for each test piece). Randomly take 90% of the 220 sets of data obtained from the experiment to train, and 10% is used for test. The specific division of training set and test set, that is, the numbers of test sets and training sets in 20 sets of data for each specimen is shown in Table 2.

Table 2. Numbers of test sets and training sets for each specimen

Specimen number	1	2	3	4	5	6	7	8	9	10	11	Total
Test sets	1	3	0	3	1	3	0	5	2	0	4	22
Training sets	19	17	20	17	19	17	20	15	18	20	16	198

The prediction results of the test set samples are shown in Table 3. The comparison between the estimated yield values of the test set samples and the actual values is shown in Figure2. The relative error of yield strength estimation of the test set is shown in Figure3. The abscissa “test sample” in Figure2 and Figure3 is the number of the test set sample.

Table 3. Estimation results of test set yield strength

Pass rate (relative error<5%)	Pass rate (relative error <10%)	Relative error average	Maximum relative error
90.91%	100%	1.63%	7.76%

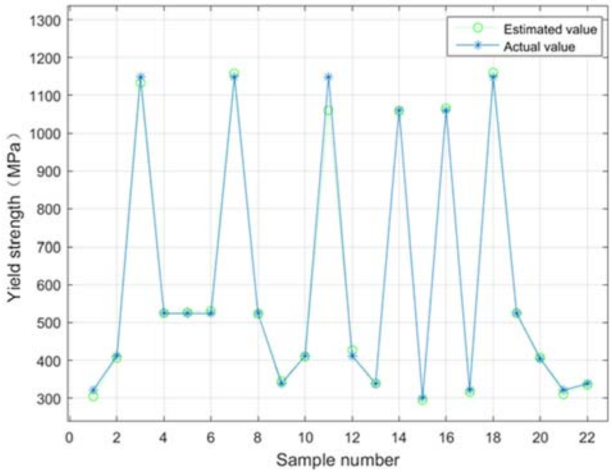

Figure 2. The comparison between the estimated values and the actual values

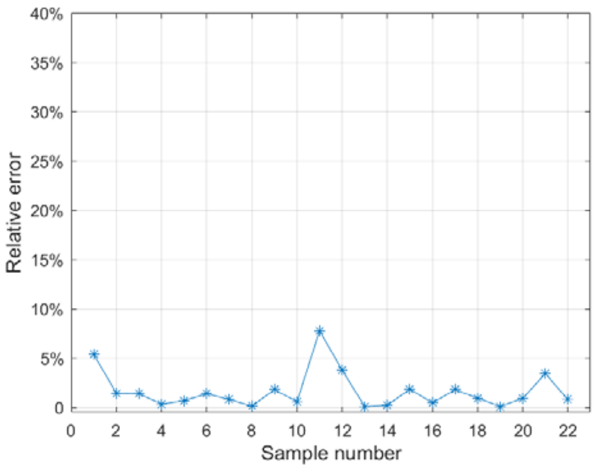

Figure 3. The relative error of yield strength estimates of the test set

From Table 3, Figure2 and Figure3, it can be seen that the relative error of the test set sample parameter estimation is less than 10%, and 90.91% of the test sample parameter estimation error is less than 5%.The overall accuracy rate is pretty high, which indicates that it is feasible to estimate yield strength parameters based on PEC method is feasible, and it is also effective to estimate the yield strength parameter by the six selected features. In the experiment, each sampling of each specimen is performed independently, although each experimental test condition (such as temperature, humidity, lift-off height, etc.) of the same specimen may have slight changes, so the data of each test is independent. In addition, the division of the test set and the training set is random. More than 80% of the 20 sets of data for each specimen are divided into the training set, and less than 20% are classified into the test set, showing that when part of the data of a specimen is involved in the training of the model, the remaining data can be used to estimate the yield strength of the specimen and achieve a higher accuracy. If a specimen library contains a total of X specimens with N different yield strengths, a standard specimen for each yield strength can be taken. The pulsed eddy current response signals of these samples are collected to extract the signal characteristics. Then a sample database is established and a BP neural network model is trained, which reflects the mapping relationship between the pulse eddy current signal characteristics and yield strength of N specimens. Therefore, the model can be used to estimate the yield strength of the remaining specimen in the specimen library. The speed of estimation through the trained BP neural network model is as fast as only about 1s, it can save time to a great extent and avoid stretching each specimen. Experiments save a certain amount of material resources and reduce material losses. This experiment demonstrates it is effective to apply pulsed eddy current technology to estimate the yield strength of materials.

As a whole, the parameter estimation method proposed in this paper can provide a more accurate and efficient estimation of the yield strength parameters of ferromagnetic specimens. This provides a certain reference for the ferromagnetic material yield strength nondestructive testing, and provides the probability of the application of pulse eddy current technique in mechanical property testing of materials

5. Conclusion

By extracting the time-domain and frequency-domain characteristics of the pulse eddy current and training the neural network model, it is possible to estimate the yield strength parameters of the ferromagnetic material. The estimated error of the yield strength parameter can reach less than 10%, which is in accordance with the requirements of industrial production on the detection accuracy. This method facilitates on-line inspection of in-service products, and provides an effective way for nondestructive testing of yield strength parameters of ferromagnetic material.

Feature extraction is a key step in the estimation method of yield strength based on pulsed eddy currents. Feature extraction in the time-frequency domain will follow and further analysis will be conducted. In order to further improve the accuracy of the estimation, the research on the optimization method of the neural network model will be carried out later.

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