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An advanced magnetic nondestructive system coupled with artificial intelligence analyzer for detection of decarburized layer of steels

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Abstract

An artificial intelligence method is presented for on-line microstructural characterization of decarburized steels. Detection of microstructural changes is a great importance matter in production lines of steel parts. A new method for microstructural characterization based on the theory of magnetic Barkhausen noise nondestructive testing method is introduced using artificial neural network (ANN). In order to obtain the accurate depth of decarburized layer of carbon steels and to eliminate the frequency effect on the magnetic Barkhausen noise outputs, the magnetic responses were fed into the ANN structure in terms of position, height and width of the Barkhausen profiles. The obtained results showed that the ANN is able to detect and characterize microstructural changes, accurately, despite serious effect of the frequency on the outputs. In other words, implementing multiple outputs simultaneously enables the ANN modeling to approach to the accurate results using only height, position and width of the magnetic Barkhausen noise peaks without knowing the amount of the used frequency.

Keywords: *Artificial Neural Network, Magnetic Barkhausen Noise, Nondestructive Testing, Decarburized Steels*

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Introduction

Detection of microstructural changes is a great importance matter in production lines of steel parts. To implement such a task, many destructive tests including metallography, hardness measurement, mechanical tests, etc. are involved in industries; however, these conventional tests are expensive and also time consuming. Therefore, there has been resurgence of interest for application of modern types of nondestructive testing.

Nowadays, there is a broad range of nondestructive testing techniques based on different physical principles. Among them, magnetic Barkhausen noise (hereafter denoted as MBN) has been widely used for nondestructive characterization of a wide range of ferromagnetic materials under various conditions [1]. The MBN technique can be performed with magnetic sensors positioned locally on top of the surface of a part, which enable the MBN for in-process measurement with extremely short measuring time [2].

As a time varying magnetic field increases, when a ferromagnetic material is subjected to an external varying magnetic field, the nucleation, the motion and the annihilation of magnetic domain walls occurs which result in the nucleation and growth of magnetic domains. The MBN originates from discrete motion of magnetic domain walls overcoming various pinning such as precipitates, grain boundaries, inclusions, dislocation pile-ups, etc. This irreversible movement of magnetic domain walls is responsible for the production of a pulsating magnetization (a noise like signal) corresponding to the changes of magnetic flux [3-6].

Typical utilization of the MBN testing includes extracting of certain features of the signal and comparison of this information to the studied material properties. However, quantitative prediction of material properties using the MBN measurement is a very challenging task due to complex interactions between material properties and each MBN outputs [7]. On the other hand, another important issue to be considered is to find the best magnetizing frequency. This frequency can be anywhere between 0.5 to 10 Hz or even higher [8]. Since the frequency of the output is rich in information, it can seriously affect the MBN outputs and corresponding results which complicate the situation of nondestructive testing. Nevertheless, in order to increase the applicability of the MBN as a reliable nondestructive testing tool, it is necessary to establish an accurate relationship between the features of the MBN signals measured by the sensor and the material's microstructure. This goal can be achieved by means of artificial intelligence methods.

In the current study, a novel approach of using artificial intelligence was considered to overcome to the probable inaccurate results of the MBN. Fulfilling this task, having in mind very complex and non-linear relationships of affecting parameters, a variety of useful soft computing techniques can be utilized. Among them, artificial neural networks (ANNs) are powerful computational approaches that were first inspired from the human nervous systems by organizing a model consisting of several computing units, called neurons, connected in a comprehending network [18]. ANN involves solving variety of complex and non-linear engineering problems such as classification, function estimation and also pattern recognition by especial kind of computing implementing on simultaneous interconnections of neurons [19]. ANN has inherent ability to being learnt from available examples and to recognize patterns in a series of inputs and outputs, which often solves problems much faster than other approaches; therefore, it has become widely popular in the last few years [18].

In this study, applicability of a new nondestructive system coupled with ANN is investigated. This more robust artificial intelligence system is implemented to assessment of decarburized depth of the heat treated carbon steels. Fulfilling this task, features of the MBN peaks is simultaneously fed to the ANN structure in order to achieve more accurate and reliable results.

Method

MBN measurements were carried out using a tailor-made experimental system developed at the authors' laboratory. A schematic diagram of the designed setup is shown in Fig. 1. The unit implemented for magnetizing the samples and sensing the MBN signals is consisted of a U-core of Fe-Si with a driving coil of 1000 turns wound around it and a pick up coil with 500 turns wound on the test sample. A triangular voltage waveform with the frequencies between 5 to 12 Hz was used in which generates the magnetizing force applied to the sample through the U shape coil. Consequently, the pick-up coil sense the MBN signal as the desired output during the magnetization process. The induced output signal was pre-amplified with a gain of 40 dB, band pass filtered (3-200 kHz), re-amplified with a gain of 40 dB, and then digitized by an A/D card, which is linked to a personal computer for further signal processing. The data was processed using a MATLAB script for obtaining MBN envelope characteristics. It has to be noted that, the MBN signal was packaged into an envelope profile which was provided via the RMS of the signal as a function of magnetizing field. For each sample, 5 signals were used and averaged.

The magnetic responses were fed into the ANN structure in terms of position, height and width of the MBN envelopes, taking into account the depth of decarburized steels as system outputs. Fig. 2. shows a typical MBN signal with an RMS profile. The used architecture of the ANN shown in Fig. 3, consists of three different layers in which utilizing parallel interconnections of neurons results in solving this complex modeling challenge. Typically the input layer is not counted as a layer, because its only task is to distribute inputs over the neurons of the first hidden layer. Numbers of the hidden layer and the node in each hidden layer play a noteworthy role in the neural network performance. Selection of suitable numbers of them does not follow any specific rule or trend, but significantly depends upon the analyzer's experience and problem's nature [9].

In feed-forward back propagation algorithm, the most popular training algorithm of neural computation in supervised networks, the initial weights are chosen randomly. Then, inputs pass through the network and finally, outputs are compared with desired values and error is calculated [10].

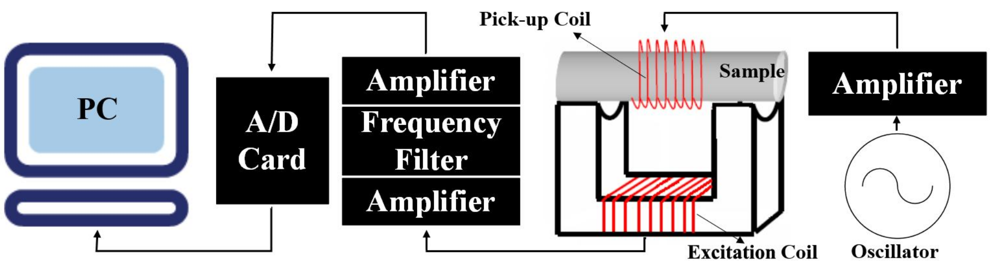

Fig. 1. A schematic diagram of the designed MBN setup.

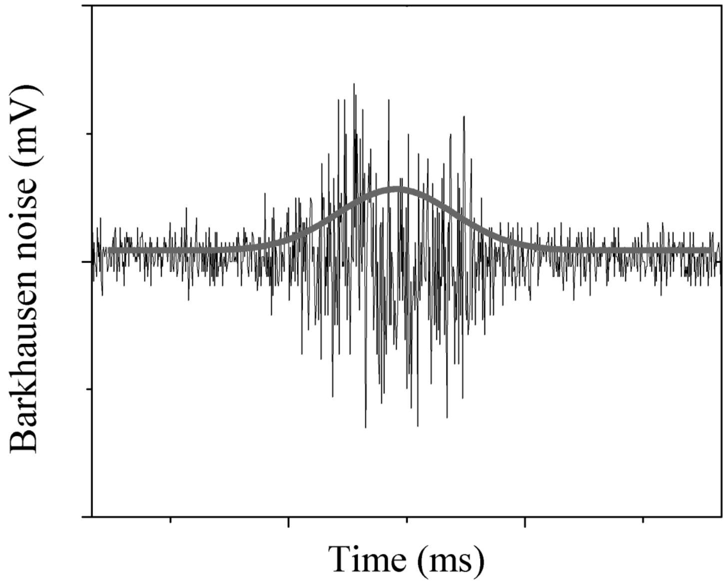

Fig. 2. Typical Barkhausen noise signal with the RMS envelope

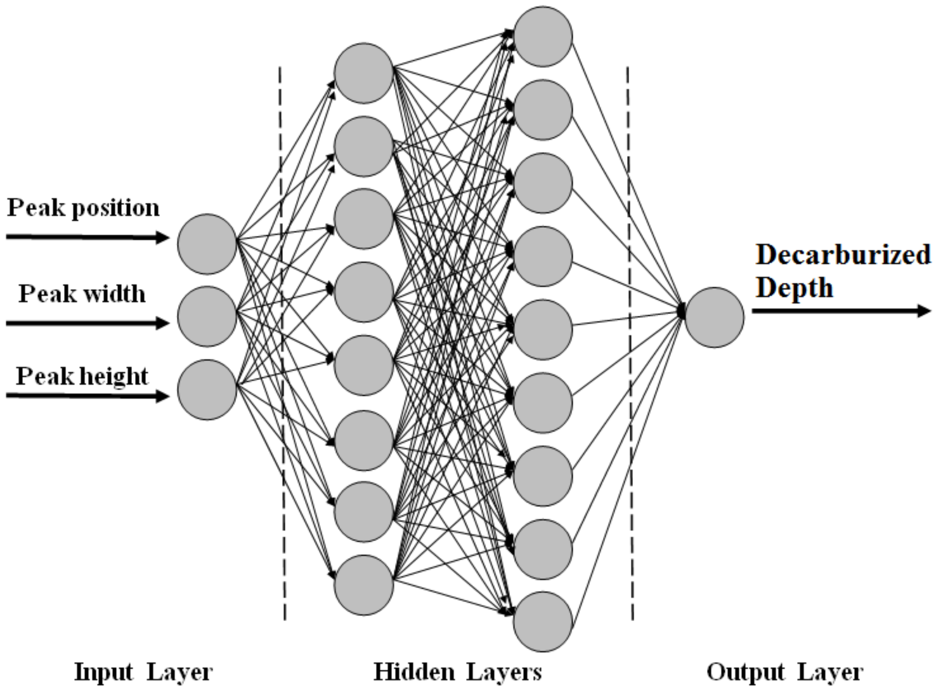

Fig. 3. The used ANN structure

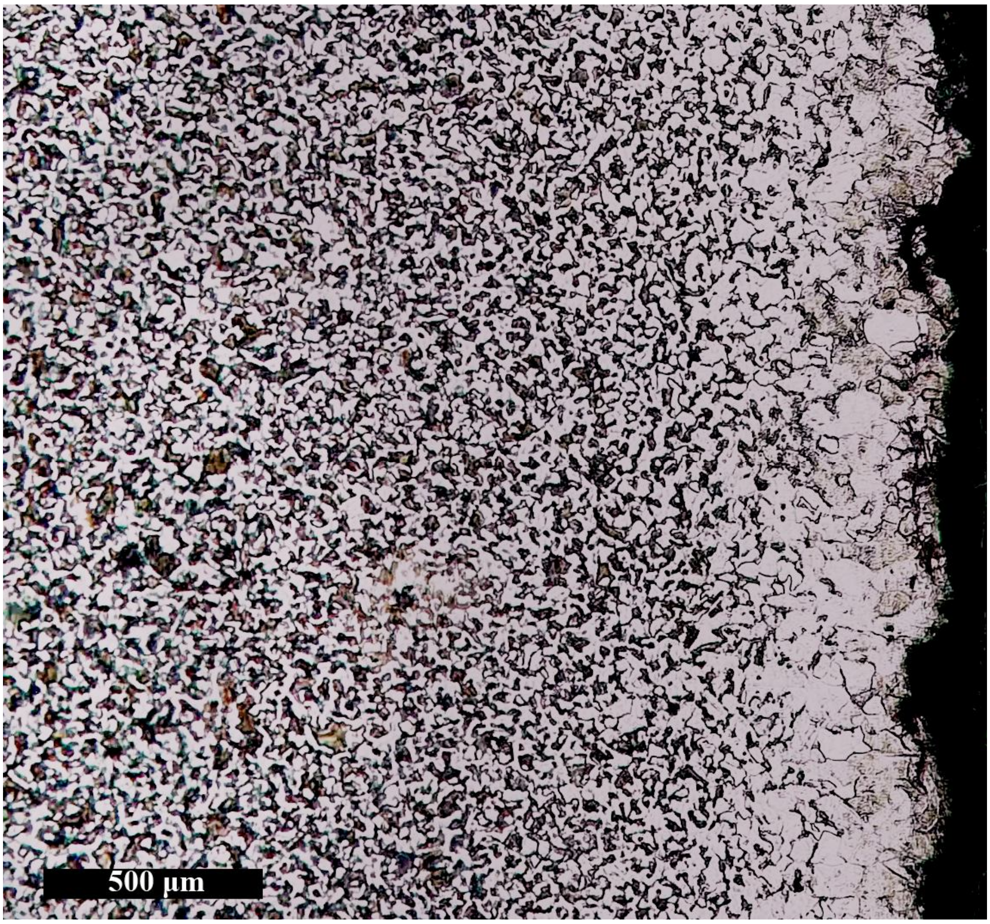

Fig. 4. Optical micrograph of the decarburized sample with a 0.45 mm decarburized layer

Results and Discussion

Fig. 4 shows the microstructure of the decarburized steel which has a decarburized layer at its surface with 0.45 mm of depth. After processing data and obtaining MBN envelope characteristics, i.e. height, width and position, these data were fed into the ANN structure. Normalization of the input data to values in a specific range is the first step of the calculation before using ANN approach and consequently, the last step is the denormalization of outputs. It has to be added that, normalization is done due to assurance of having sensitivity and accuracy for network, and the purposes of denormalization are calculating the actual desired values and achieving real errors. Using the following equation which puts data in a range with mean and standard deviation of 0 and 1 respectively, the normalization of the input data of the current study was carried out.

$$X(normal) = \frac{X(actual) - X(mean)}{X(STD-DEV)} \quad (1)$$

Where X (actual), X (mean) and X (STD-DEV), are respectively, the actual value, the mean value of all data and standard deviation of actual values, which produce X (normal) as a final normalized value for introducing as an input to ANN structure.

Table 1. The MBN peak characteristics at different frequencies for various decarburized depth of steels used for constructing ANN model.

Test Run	Frequency (Hz)	Height (mV)	Width (ms)	Position (A/m)	Depth (mm)
1	5	4762	1406	334	0.32
2	5	4561	1371	306	0.45
3	5	3207	1251	289	0.52
4	5	2393	1114	278	0.64
5	5	2342	1094	270	0.69
6	6	2323	764	208	0.32
7	6	2279	783	216	0.45
8	6	2262	780	213	0.52
9	6	2147	755	211	0.64
10	6	2257	767	206	0.69
11	7	1919	583	156	0.32
12	7	1928	580	153	0.45
13	7	1894	571	151	0.52
14	7	1876	577	148	0.64
15	7	1650	519	141	0.69
16	8	2752	645	117	0.32
17	8	2172	615	106	0.45
18	8	3723	687	99	0.69
19	9	1928	758	93	0.45
20	9	1800	733	89	0.52
21	10	1766	420	80	0.32
22	10	1721	419	75	0.45
23	10	1623	389	72	0.52
24	10	1755	313	73	0.64
25	10	1613	389	65	0.69
26	12	1857	336	59	0.32
27	12	1823	332	56	0.45
28	12	1860	332	55	0.52
29	12	1855	328	53	0.64
30	12	1843	323	47	0.69
31	11	2192	397	74	0.32
32	11	2174	396	69	0.45
33	11	2172	393	68	0.52
34	11	2167	388	64	0.64
35	11	2163	386	60	0.69

Table 2. Training parameters used in this study.

Neural network settings	Value/Type
Network type	Feed-forward back-propagation
Training function	Levenberg–Marquardt
No. of layers	3
Hidden layer 1	8 neurons (Tansig transfer functions)
Hidden layer 2	9 neurons(Tansig transfer functions)
Output layer	1 neuron (Purelin transfer function)
Performance function	Mean square error (MSE)
Epochs	150
Max fail	45
Min_grad	1 x 10^{-10}
mu	0.005
mu_inc	10
mu_dec	0.1
mu_max	1 x 10^{10}

Then, database of Table 1 was divided into two sets. The first 30 data were chosen for both training and validating, and the remaining 5 data were held out for verification purpose. Last category was about the new data evaluating the performance and efficiency of the proposed network.

To train the neural network of this study, several ANN structures with varying number of neurons in hidden layers were tested. According to the least mean square error (MSE) criterion, a structure of neural networks with two hidden layers, eight nodes for first layer and nine nodes for layer two, was implemented. Table 2 represents neural network settings used ultimately for this study. Supervised feed-forward architecture with a Levenberg–Marquardt back propagation training algorithm was utilized in an attempt to approach the true minimum of the error surface. Across plot of the testing predictions, which naturally present the lowest possible prediction accuracy of the network, was used to assess network performance. Potent pattern-recognition capability, a difficulty related with the calibration of neural networks, can sometimes leads to the unwanted problems like overfitting, overtraining and memorization. These problems take place due to the large network architecture, which can memorize data rather than recognizing trends among them. In the present study, this drawback overcame by cross validation and selection of reasonably small numbers of layers and neurons. Tan-sigmoid transfer functions were used in both hidden layers to allow the network to establish nonlinear and also linear relations and patterns between inputs and outputs. Finally for having output of network, a linear purlin transfer was used in structure of output layer.

After achieving the most proper and efficient calibrated structure, the validation data sets (Test runs of 31-35) were introduced into ANN models to assess their recognition skill of microstructural characteristic predicting when facing unseen situation as well. Fulfilling this duty, both coefficient of determination (R^2) and normalized root mean squared error (NRMSE) as the representatives of model's performance were calculated and put into comparison for neural network results. Fig. 4 indicates regression graphs for prediction of decarburized depth using ANN model while facing unseen data. As can be clearly seen from the graphical results, the act of intelligence model is acceptable for test data on the whole.

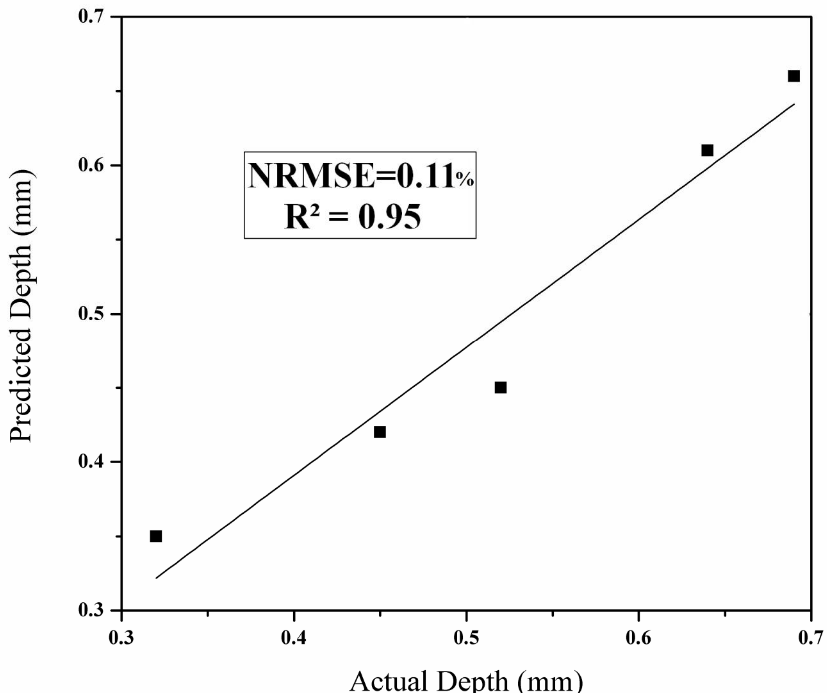

Fig. 5. Regression graph for modeled and actual decarburized depths while facing unseen data of 11 Hz.

Conclusions

This study has intended to analyze a new system for layer's depth characterization of decarburized steels which is introduced using an expert nondestructive testing system based on MBN method, taking into account artificial intelligent modeling. In comparison to original experimental results, the new presented magnetic nondestructive system is more adjustable. Feeding multiple MBN outputs simultaneously, was enabled the ANN modeling to approach to the most accurate results using only height, position and width of the MBN peaks. While considering unseen data, high calculated correlation of coefficient (R^2=0.95) confirmed that using ANN model to predict the decarburized depth was successful. Also, the modeled output was obtained without knowing the amount of frequency. Therefore it can obtain the accurate results with eliminating the frequency effect on the MBN outputs. In order to be used as a robust tool for industrial nondestructive inspection, the presented magnetic nondestructive system needs only to be calibrated on reference samples of known decarburized depth and then, it can separate the convenient and inconvenient samples, carefully.

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