



Application of Artificial Neural Network and Multi-magnetic NDE Methods to Determine Mechanical Properties of Plain Carbon Steels Subjected to Tempering Treatment

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ABSTRACT

The present paper shows the results of applying an artificial neural network to three non-destructive magnetic methods including magnetic hysteresis loop (MHL), eddy current (EC), and magnetic flux leakage (MFL) techniques to determine mechanical features of plain carbon steels with unknown carbon contents subjected to tempering treatment. To simultaneously evaluate the effects of carbon content and microstructure on the magnetic and mechanical properties, four grades of hypoeutectoid steel samples containing 0.30, 0.46, 0.54, and 0.71 wt.% carbon were austenitized in the range of 830-925 °C and then subjected to quench-tempering treatments at 200, 300, 400, 500 and 600 °C. In the next step, mechanical properties including tensile strength, elongation, and hardness were measured using tensile and hardness tests, respectively. Finally, to study the electromagnetic parameters, MHL, MFL and EC non-destructive electromagnetic tests were applied to the heat-treated samples and their outputs were fed to a generalized neural network designed in this work. The results revealed that using a proper combination of electromagnetic parameters as the ANN input for each mechanical parameter enables us to determine the hardness, UTS and elongation of hypoeutectic carbon steel parts after tempering treatment with high accuracy.

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1. INTRODUCTION

In recent years, there is a high demand for reliable and quick methods to be used for nondestructive characterization of materials. Electromagnetic techniques such as eddy current (EC) and magnetic hysteresis loop (MHL) measurements with a high sensitivity to microstructural changes have the potential to be used as alternatives to the traditional methods for the examination of microstructure and mechanical properties of steel parts [1]. Recent investigations in this field have been focused on microstructural changes due to the various heat-treating processes. For instance, pearlite/ferrite fraction [2], prior austenite grain size [3], microstructural changes during recovery process [4], the thickness of induction [5-7], carburized [8], and

decarburized [9-11] layers in mild carbon steels, retained austenite fraction [12], precipitation of alloy carbides [13] and secondary hardening occurrence [14] in tool steels as well as variations in mechanical properties of API X65 [15], powder metallurgical [16] and Hadfield [17] steels have been characterized using EC and MHL methods.

Besides, the nondestructive magnetic flux leakage (MFL) method is a fast and easy technique to determine flaws in ferromagnetic materials and has widely used to characterize and determine hidden corrosion occurred in the gas ferromagnetic pipelines [18, 19], rail tracks [20] and wire ropes in suspension bridges [21]. In this method, Hall effect sensors sense the leakage flux in the area near the defect.

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The proposed method in this paper takes advantage of artificial neural networks (ANN) to combine the results of the MHL, EC, and MFL electromagnetic subsystems described before. ANNs are inspired by the neural structure of the human brain and could be considered as a Machine Learning (ML) method. Clustering, regression, and classification problems could be solved using a well-trained ANN. Training an ANN consists of some standard mathematical algorithms by which the parameters of the network are determined and the trained network could then give correct answers to new inputs [22, 23].

Since ANNs may be more reliable, more accurate, and have better performance in many regression and classification problems than classic algorithms, they are widely used in practical applications of non-destructive evaluation methods. For example, in [14], after measuring four different electromagnetic properties of a given heat-treated H13 tool steel sample, Kahrobaee et al. have utilized a standard ANN (Generalized Regression Neural Network, GRNN) to estimate the hardness of the steel sample. They have reported that their proposed method could be used to non-destructively estimate the sample hardness with less than 1% RMS error if a training dataset with only 30 samples is used to train the network.

In the present paper, an application of a GRNN has been introduced to increase the prediction accuracy of the three MHL, MFL, and EC NDE electromagnetic methods in determining the mechanical properties of plain carbon steels with various carbon contents subjected to different tempering temperatures. In this methodology, a set of experimental data have been collected to obtain the initial database used to train and test the proposed ANN. The main novelties of the present paper are as follow:

- MHL, MFL, and EC outputs are combined to enhance the accuracy and reliability of determining the mechanical properties.

- NDE outputs obtained from the samples with known carbon contents and tempering temperatures are fed to the proposed ANN as intermediate variables that create a link from NDE outputs to the values of mechanical properties.

- The artificial neural network used in this research is a Generalized Regression Neural Network (GRNN). GRNNs could reportedly be trained much faster than standard Multilayer perceptron (MLP) neural networks and due to their high accuracy, they are widely used in regression, prediction, and classification problems.

- Apart from its high accuracy, using the GRNN as the estimator makes the proposed method more reliable and robust.

2. EXPERIMENTAL PROCEDURE

2. 1. Sample Preparation and Mechanical Tests

Four groups of plain carbon steel specimens (100×20×4

mm) containing various weight percentages of carbon (0.30, 0.46, 0.54, and 0.71) were austenitized for 50 min at 925°C, 900°C, 860°C, and 830°C, respectively. After water quenching all the samples, except for one in each group, the others were submitted to the tempering process at various temperatures (200 to 600 °C). To determine the mechanical features of the heat-treated samples as the ANN outputs, tensile tests were carried out according to the ASTM E8M tensile standard using Zwick testing machine. For each sample, an average value corresponds to three tensile specimens has been reported. For each sample, ultimate tensile strength (UTS) and elongation (E) were determined from its plotted engineering stress-strain graph. Moreover, hardness (Rockwell C) tests were performed at several points on each sample and the mean value has been reported as the third mechanical property.

2. 2. Magnetic Non-destructive Methods After performing the mechanical tests to produce the outputs of the designed ANN, three nondestructive methods based on electromagnetic properties including MHL, MFL, and EC were carried out on the samples. The outputs of the NDT methods were utilized as the ANN inputs to evaluate their relationship to mechanical properties. Figure 1 demonstrates the schematic block diagram of MFL, MHL, and EC methods, whose outputs are used as the input of the proposed ANN.

In the MFL and MHL measurement systems, two 1500-turns in-series coils wound on two arms of a laminated Fe-Si U-shaped yoke are utilized as excitation coils to magnetize the sample. These coils are excited by a triangle waveform whose frequency and amplitude can be completely adjusted in a LabVIEW program. The waveform generated by the LabVIEW program, which is available from one of the analog ports of the Advantech PCI-1720U-AE DAC card, does not have enough power to magnetize the sample to saturation point. Therefore, a two-stage bi-polar and linear current amplifier, specifically designed and built for this and similar researches in our research laboratory, is used to amplify the excitation current.

In the MHL method, two other in-series 1000-turns coils wound on the former yoke are exploited to gauge the induced voltage (emf) in the samples. This voltage is sampled with the sampling rate of 500 Hz using an Advantech PCI-1714UL-BE ADC card and then is integrated over time and rescaled in a MATLAB program to give B-field (the magnetic flux density). To draw a hysteresis loop in the MHL method, the H-field (magnetic field strength) is also required. Since the field strength is completely proportional to the current given to excitation coils and the current amplifier used in this research is perfectly linear at the frequency of excitation (0.1 Hz), the excitation current and the waveform generated in the LabVIEW program have a linear relationship and therefore one could consider an

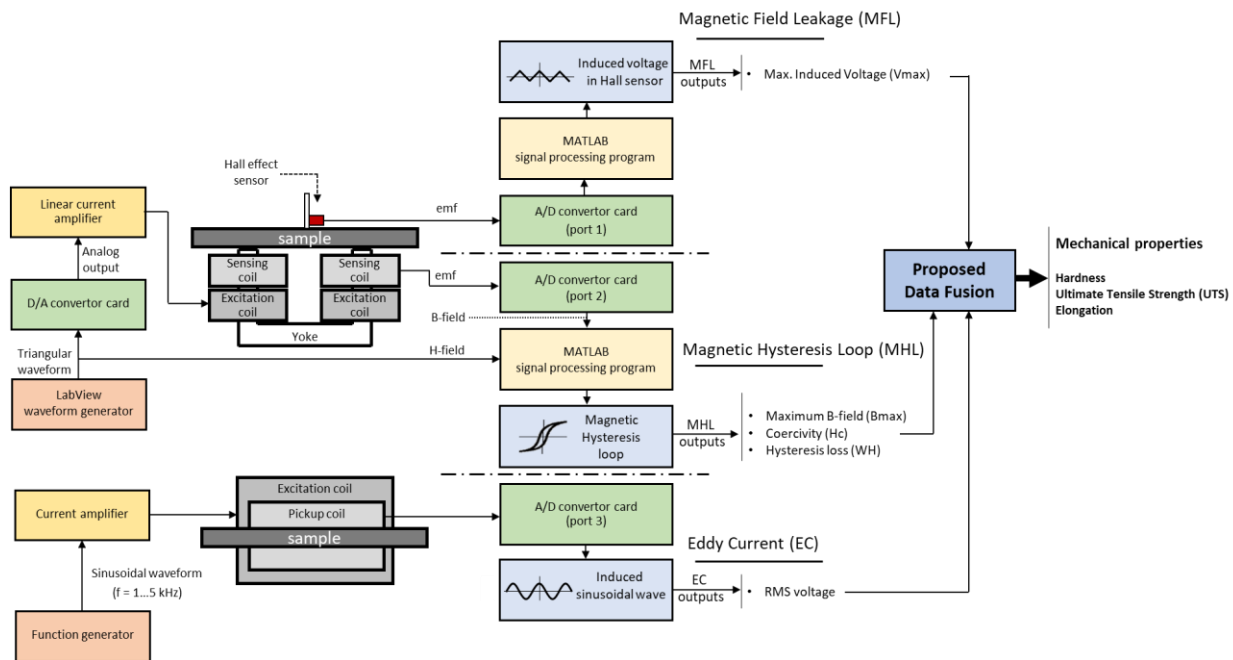


Figure 1. Schematic diagram of three nondestructive electromagnetic methods

appropriately scaled version of LabVIEW waveform as the magnetic field strength. Using both measured magnetic field strength and magnetic flux density, the BH curve (hysteresis loop) is drawn and three important magnetic parameters are extracted: B_{max} (maximum B-field), H_c (coercivity), and WH (hysteresis loss).

In the MFL subsystem, a Hall effect sensor (HW-108C) is placed 1 mm over the sample to measure the magnetic flux leakage. This voltage is then given to another port of the ADC card and sampled with the sampling rate of 500 Hz. The magnetic flux leakage is a function of the sample parameters and its maximum value in a company with the output of MHL and EC subsystems could be used to extract mechanical properties of the sample.

In the EC method, two coaxially wound coils (excitation and pickup coils with respectively 400 and 800 turns) with a length of 30 mm, were used. A laboratory function generator is used to generate a 1-5 kHz sinusoidal waveform. After it is appropriately amplified, this waveform is fed to the excitation coil. The pickup coil voltage (which is mainly due to the eddy current inside the sample) is then given to the third analog port of the A/D conversion card and its root mean square (RMS) extracted using a MATLAB signal processing program, besides the results of MFL and MHL methods, is used as the inputs of the proposed DF.

2. 3. Structure of the Designed Artificial Neural Network In this research, a GRNN (Generalized Regression Neural Network) has been utilized to

determine the mechanical properties of given plain carbon steel samples. GRNNs, which are based on RBF (Radial Basis Function) neural networks, were introduced in 1991 by D. F. Specht [24]. Figure 2 demonstrates the schematic block diagram of a typical GRNN [14]. In the input layer, one single neuron (neural cell) is dedicated to each input variable and in the radial basis layer, one radial-basis cell is dedicated to each training data point. Neurons of the third layer (output layer) are used to add the outputs of the former layer together and give out the network output. Since GRNNs can be easily trained much faster than other types of neural networks, they are increasingly used for solving different types of problems, like classification and regression problems.

3. RESULTS AND DISCUSSION

3. 1. Mechanical Properties Versus Tempering Temperature Figure 3 demonstrates the changes in mechanical properties for the samples containing various amounts of carbon subjected to different temperatures of the tempering process. Each point in the graphs is an average of three tests performed on three samples with constant conditions (carbon content and tempering temperature). As expected, tempering at higher temperatures reduces the values of hardness and UTS and enhances the elongation. A similar trend is observed for the steel samples containing various carbon contents: the higher amounts of hardness and UTS as well as the lower

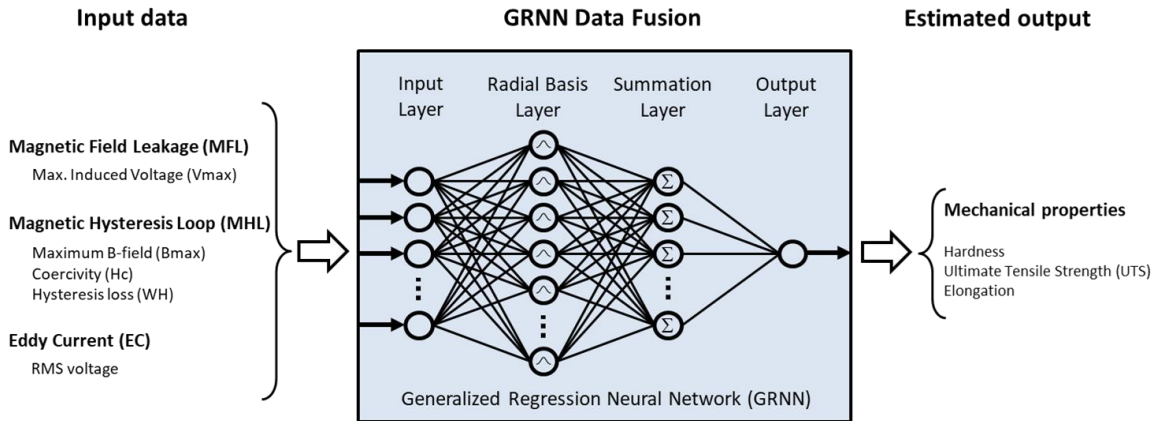


Figure 2. Schematic block diagram of a generalized neural network (GRNN).

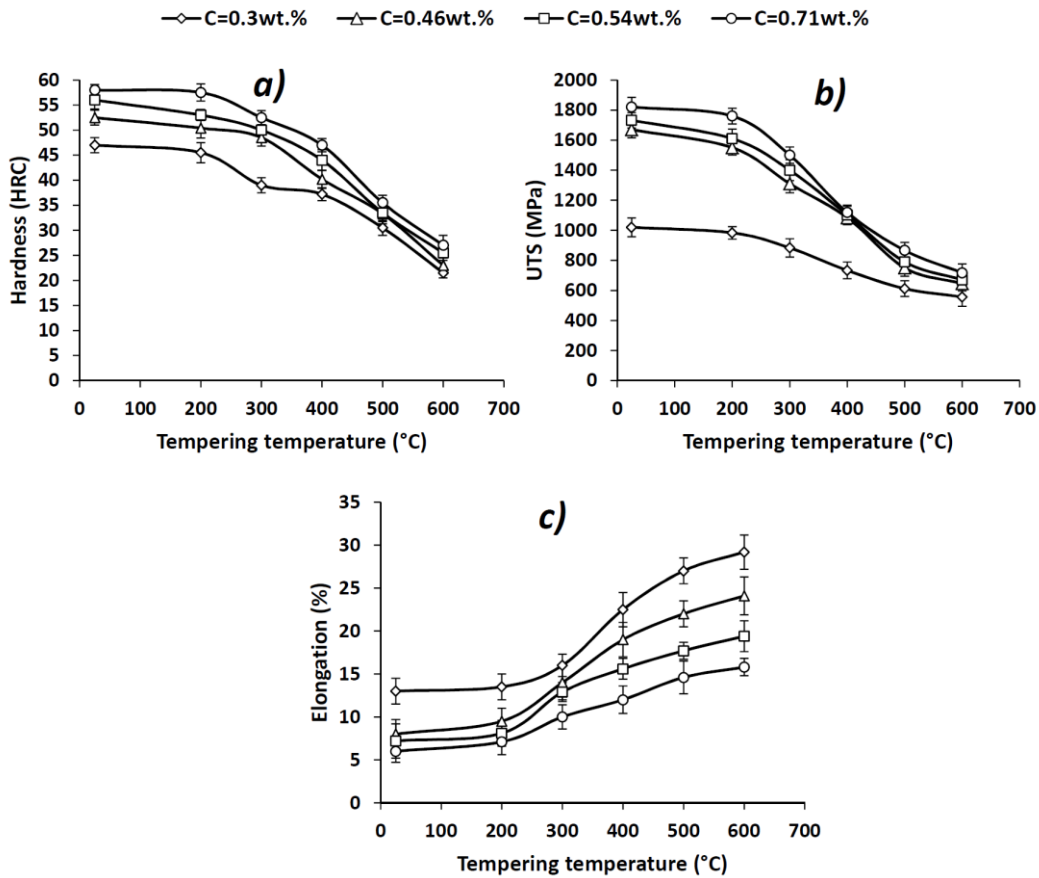


Figure 3. ANN outputs: mechanical properties including a) hardness, b) UTS, and c) elongation, as the function of tempering temperature for heat-treated samples containing different amounts of carbon

values of elongation have been obtained at the higher carbon contents.

3. 2. Magnetic NDE Parameters Versus Tempering Temperature Figure 4 shows the output changes of the three NDE methods (Bmax, Hc, and WH for MHL,

Vmax from MFL, and VRMS from EC) used in this work. The NDE tests were performed four times for all of the samples and the average values have been reported in this figure. The low and high values of respectively “Bmax and VRMS” and “Hc, WH and Vmax” for as-quenched samples in each group are mainly attributed to

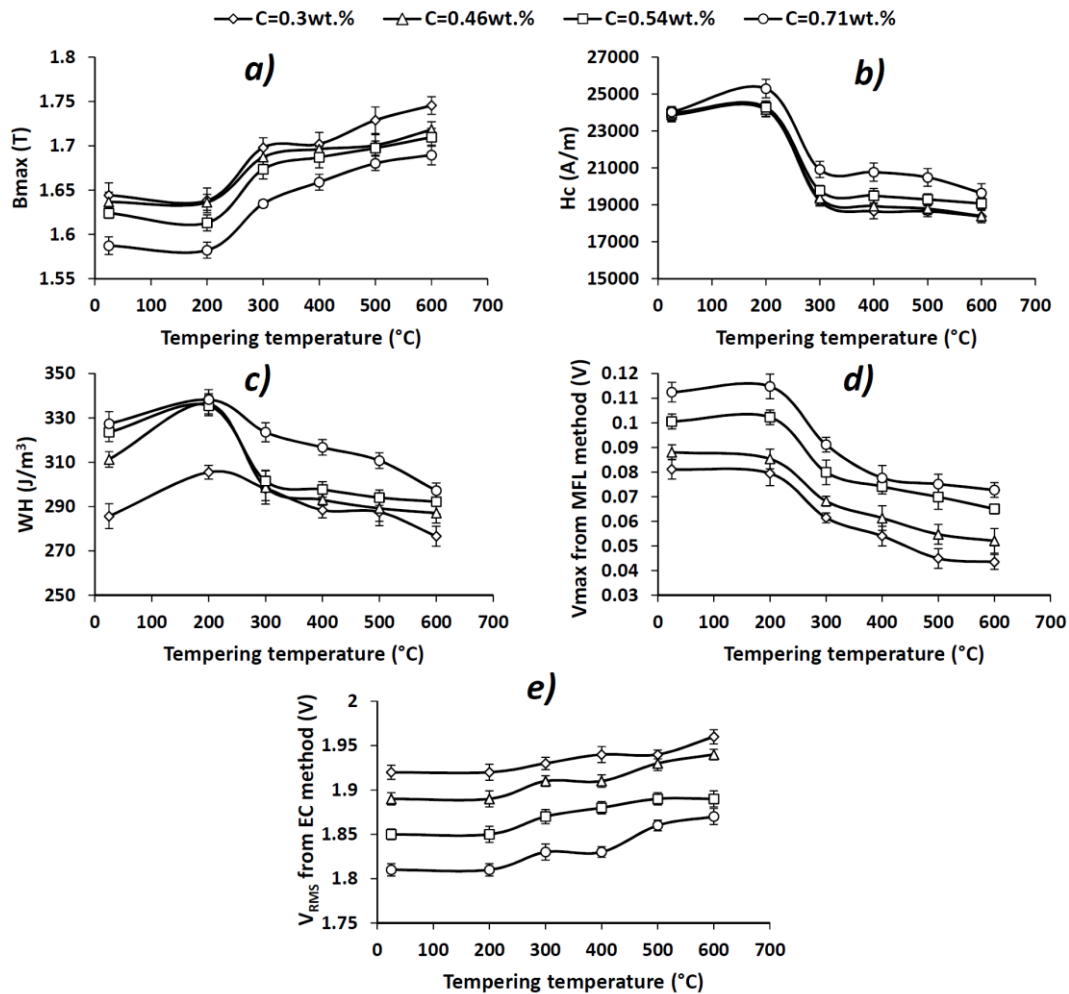


Figure 4. ANN inputs: outputs of NDE tests including a) B_{max} from MHL method, b) H_c from MHL method, c) WH from MHL method, d) V_{max} from MFL method, and e) voltage RMS from EC method, versus tempering temperature for heat-treated specimens containing different amounts of carbon.

the high dislocations density resulted from shear deformation of martensitic transformation. Therefore, higher magnetic fields are required for the motion of domain walls in the magnetization process. As a result, for the martensite microstructures, MHLs are created in short and wide shapes and as a result, show low values of B_{max} and high values of H_c and WH . Besides, due to the direct relationship between B_{max} and the amount of flux density near the surface (which is equal to EC output: VR_{MS}) and the inverse relationship between B_{max} and flux leaked from the surface (which is equal to MFL output: V_{max}), lower values of VR_{MS} and higher amount of V_{max} have been obtained for martensitic microstructure. As it can be seen in Figure 4, for all four grades of steels, a slight increase in H_c and WH values have been obtained for the specimens tempered at 200°C. Indeed, the formation of transition carbide (ϵ -carbides) occurred by tempering at 200°C [25], increases the

strength of the pinning sites versus the motion of domain walls in the magnetizing process. This in turn leads to a slight increase in H_c and WH values. At higher tempering temperatures, reduction in residual stresses (crystalline defects especially dislocations density) as well as, the transformation of retained austenite (paramagnetic phase) to the soft ferromagnetic ferrite and bainite (for medium and high carbon grades) facilitate the magnetizing process. Therefore, by tempering from 200 to 600°C, “ B_{max} and VR_{MS} ” values show a continuously increasing trend, while H_c , WH , and V_{max} ones exhibit an opposite moderate decrease.

Figure 4 also shows various values of NDE outputs for samples with different carbon content. Indeed, for all the heat-treated groups of samples, an increase in carbon content increases H_c , WH , and V_{max} , and reduces B_{max} and VR_{MS} . The reverse trend of B_{max} (and VR_{MS}) versus carbon content is expected since the increase in

carbon content causes an increase in the c/a (lattice tetragonality) ratio which in turn results in a higher cementite fraction after the tempering process. On the other hand, when correlating H_c (and WH) with carbon content in the steels, the tendency was opposite. Indeed, coercivity represents the intensity of the applied magnetic field required to reduce the magnetization of that material to zero. Steel groups containing higher carbon contents showed the higher H_c , because of their weak response to the applied magnetic field due to the high c/a (high distortion due to the confinement of carbon atoms). Therefore, higher carbon contents restrict the domain walls' motion in the magnetization process, and hence, higher applied magnetic fields or in other words, higher coercivities are required to eliminate the magnetization of the steel.

3.3. Results Obtained from Applying ANN Here in this research, three different magnetic parameters extracted from the MHL method (B_{max} , WH , H_c), one

parameter from the EC method ($VRMS$) and another parameter from the MFL method (V_{max}) is separately measured. These parameters could be given to a GRNN of Figure 2 to simultaneously determine three mechanical properties of the specimen (including elongation, UTS, and hardness). Each of the five available inputs (B_{max} , WH , H_c , $VRMS$, and V_{max}) and all of their combinations, (a total of 31 different cases) may be thought of as the network input. As it can be seen in Figure 5, the accuracy of estimation is not the same for all these combinations; therefore, one should choose an appropriate combination of available inputs for each desired mechanical property. Plots of Figure 5 demonstrates the %RMS error of mechanical properties estimated using the proposed method vs the number of data points used for training for all 31 possible cases. The values not used in the training process are utilized to study the performance of the proposed method. The %RMS error is defined as Equation (1):

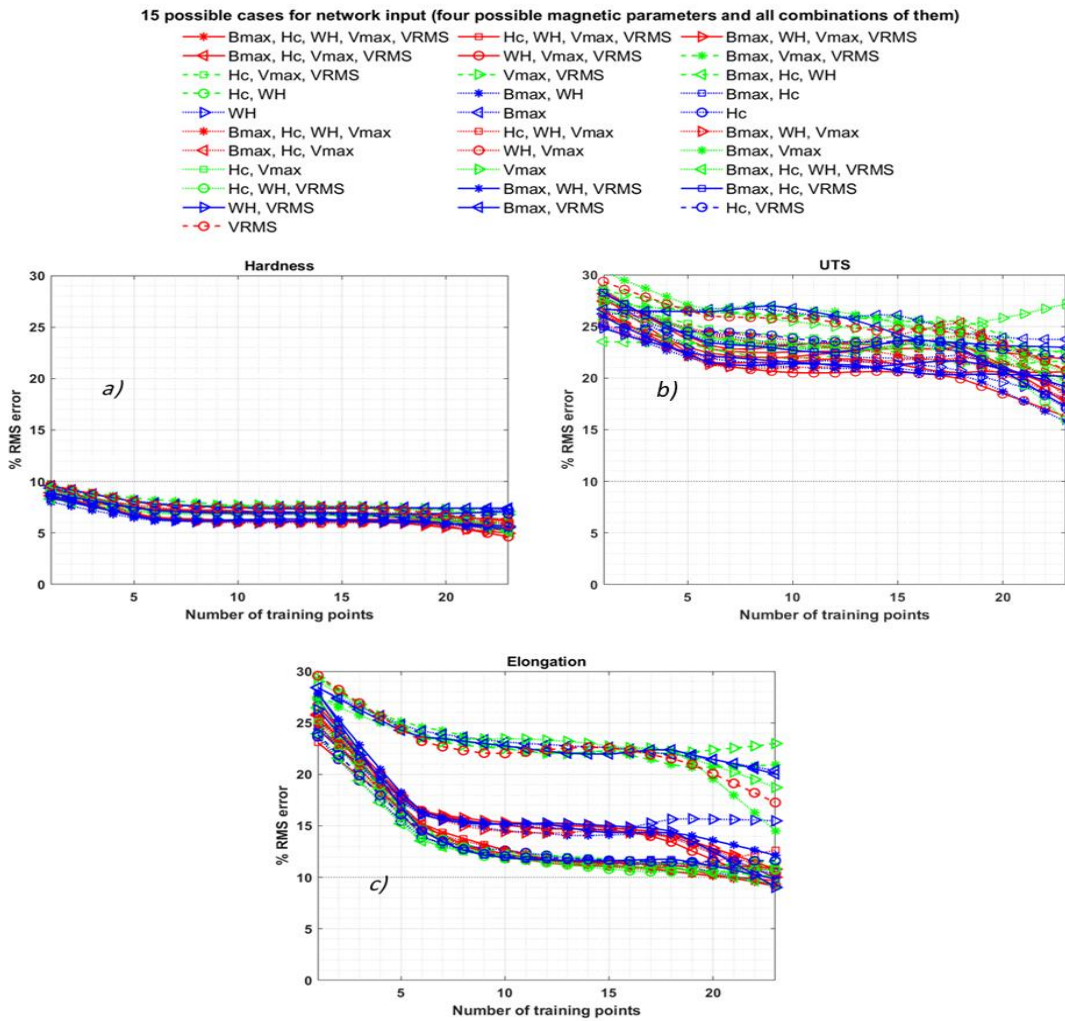


Figure 5. %RMS error of estimated mechanical properties including a) hardness, b) UTS, and c) elongation versus the number of data points used for training the network for all 31 input cases

$$\%RMS\ error\ (N) = \frac{100 \sqrt{\frac{\sum_{n=1}^{(24-N)} (\text{mech. par. } est. - \text{mech. par. } meas.)^2}{(24-N)}}}{\max(\text{mech. par. } meas.)} \quad (1)$$

where N is the size of the dataset used for training the network and (24-N) is the size of the test dataset.

Figure 6 summarizes the accuracy of the method proposed in this work for each of the mechanical parameters estimated and for each input case (from all possible 31 cases). Each category of bars demonstrates the %RMS error of the three estimated mechanical properties (hardness, UTS, elongation) for five available

inputs (Bmax, WH, Hc, VRMS, and Vmax) and any combination of them. As it is highlighted by red bars, to estimate elongation, UTS, and hardness, the best input sets are respectively: “Bmax, Hc, WH, and Vmax”, “Bmax and WH” and “Bmax, Hc, Vmax and VRMS”. Using these magnetic parameters as the network input, the accuracy of hardness, UTS and elongation estimation for 23 training points would be respectively: 4.9, 16.5 and 9.1%. This could also be seen from Figure 5, in which for the hardness, UTS, and elongation, the curves of “Bmax, Hc, Vmax, and VRMS”, “Bmax and WH” and “Bmax, Hc, WH, and Vmax” are respectively below the others.

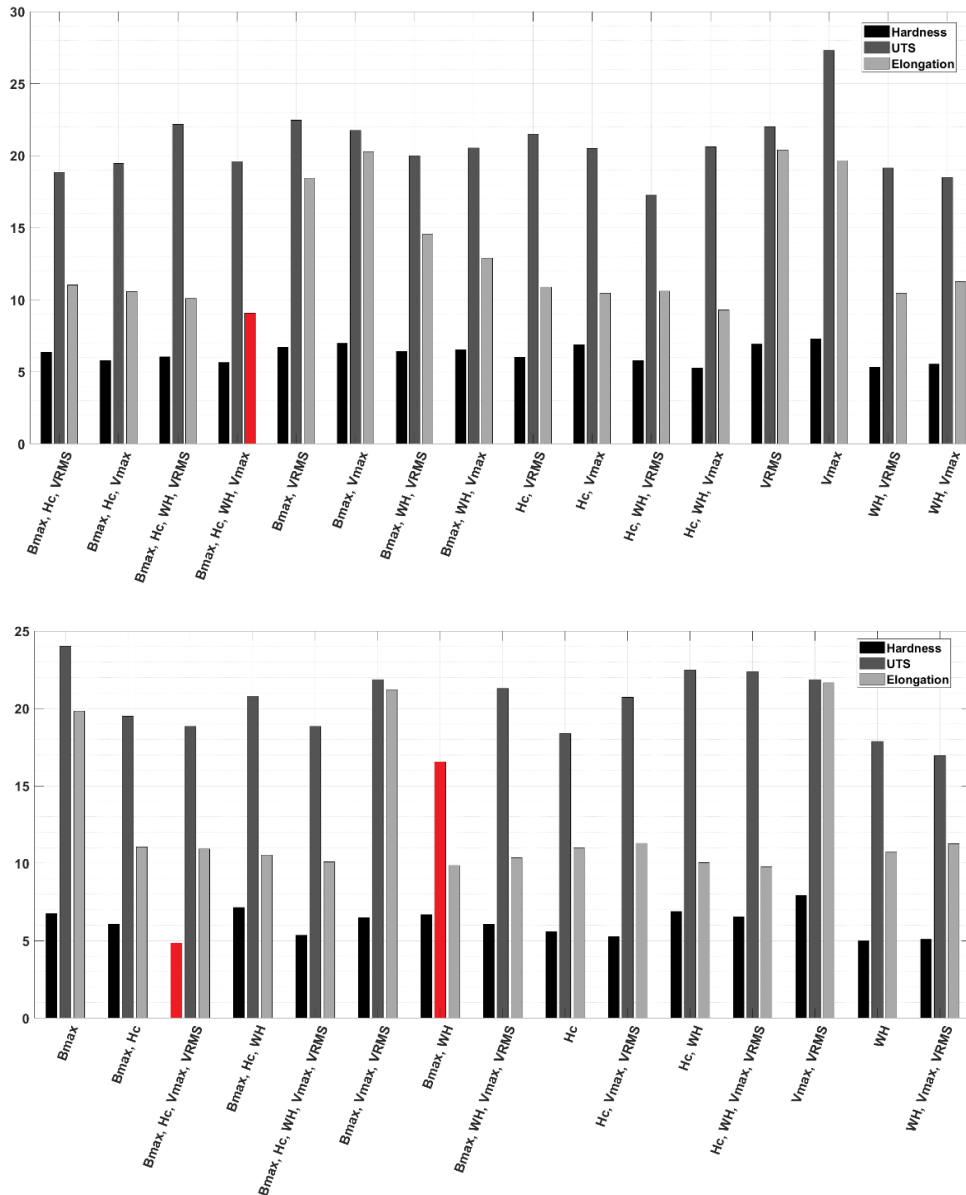


Figure 6. %RMS error (23) for each mechanical property estimated using the proposed method and for each input case

This is an important point and means among all possible cases, one should only use “Bmax, Hc, Vmax and VRMS”, “Bmax and WH” and “Bmax, Hc, WH and Vmax” as the network input.

Although the accuracy of hardness estimation is remarkable and for almost all applications it is completely acceptable for elongation, results do not show a high accuracy for UTS estimation. This could be due to the fact that UTS points (as shown in Figure 2-b) for tempering temperature of 400°C for different carbon contents fall on each other, which in turn reduces the accuracy of prediction. Calibrating the measurement/prediction system with more samples could prevent this problem and improve the results.

4. CONCLUSION

In this work, in the first step, relationships among electromagnetic parameters (Bmax, Hc, WH, VRMS, and Vmax) extracted from MHL, EC, and MFL methods and three important mechanical parameters (hardness, UTS, and elongation) of a set of four heat-treated hypoeutectoid plain carbon steel grades were studied. Based on the results, three proposed NDE techniques including MHL, MFL, and EC methods showed high sensitivity to mechanical properties and carbon content of the plain carbon steels during the tempering process. Reverse trends have been observed for increasing carbon content and tempering temperature versus NDE outputs. In the next step, the mechanical parameters were simultaneously estimated using a generalized neural network (GRNN) with the magnetic parameters as its inputs. The results show that using “Bmax, Hc, Vmax and VRMS”, “Bmax and WH” and “Bmax, Hc, WH, and Vmax” as the network inputs and 23 training data points, 4.9, 16.5, and 9.1% RMS error for estimation of hardness, UTS and elongation.

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Persian Abstract

چکیده

در این مقاله، نتایج حاصل از اعمال یک شبکه عصبی مصنوعی بر خروجی‌های حاصل از سه آزمون غیرمخرب مغناطیسی شامل حلقه هیستریزیس مغناطیسی، جریان گردابی و نشت شار مغناطیسی، به منظور تعیین خواص مکانیکی فولادهای ساده کربنی بازپخت شده با درصد کربن نامعلوم ارائه شده است. به منظور بررسی همزمان تاثیر درصد کربن و ریزساختار بر خواص مغناطیسی و مکانیکی قطعات فولادی، چهار گروه از فولادهای هیپوپوتکتوید حاوی 0/30، 0/45، 0/54 و 0/71 درصد وزنی کربن در دمای 950 °C آستنیته و سپس تحت عملیات کوئنچ و بازپخت در محدوده دمایی 200-600°C قرار گرفتند. پس از عملیات حرارتی، توسط آزمون کشش و سختی‌سنجی خواص مکانیکی قطعات شامل استحکام کششی، انعطاف‌پذیری و سختی اندازه‌گیری شد. در نهایت به منظور بررسی خواص الکترومغناطیسی قطعات، آزمون‌های غیرمخرب حلقه هیستریزیس مغناطیسی، جریان گردابی و نشت شار مغناطیسی انجام و از خروجی این آزمون‌ها به عنوان ورودی شبکه عصبی طراحی شده استفاده شده است. نتایج حاصل نشان می‌دهد که در صورت استفاده از ترکیب مناسبی از خواص الکترومغناطیسی به عنوان ورودی شبکه عصبی، امکان تعیین سختی، استحکام کششی و درصد ازدیاد طول فولادهای هیپوپوتکتوید پس از عملیات بازپخت با دقت بالا وجود دارد.
