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ARTIFICIAL NEURAL NETWORKS FOR MODELLING THE MICROHARDNESS OF PLASMA IMMERSION ION IMPLANTED AISI 304 SS

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Abstract

This paper reports on the effectiveness of a back-propagation artificial neural network model that predicts the microhardness of 304 austenitic stainless steel samples which have been implanted with nitrogen using plasma immersion ion implantation (PIII) at different temperatures between 350 and 500°C. Artificial Neural Networks (ANNs) have the capacity to eliminate the need for expensive and difficult experimental investigation in testing and manufacturing processes. This paper shows that ANNs can be employed for optimizing the process parameters of AISI 304 austenitic stainless steel. Predicted values from the model and experimental values are in close agreement and this indicates the usefulness of applying ANNs in predicting hardness results.

Key words: plasma immersion ion implantation, austenitic stainless steel, microhardness, ANN, back propagation algorithm

1. INTRODUCTION

Plasma immersion ion implantation (PIII) is a widely used technique for implanting nitrogen in material surfaces in a plasma environment. In PIII, the substrate is immersed in nitrogen plasma and bias-pulsed negative at high repetition rates. Ion bombardment raises the temperature of the substrate, and hence the implanted ions diffuse to depths much greater than the penetration depth based on the kinetic energy of the ions. It gives rise to increased surface hardness, and a nitrogen-strengthened diffusion zone is produced that extends well beyond the implantation range and improves the load-bearing capacity of the implanted layer (Mukherjee et al., 2002; Mukherjee et al. 2; 2002). The most important advantage for PIII in processing of austenitic stainless steels is the formation of expanded austenite as a solid solution phase in the modified surface layer without, or with little precipitation of, CrN, which has a destructive effect on the corrosion resistance (El-Rahman et al., 2004). Several authors have reported the PIII processing of austenitic stainless steels with the aim of enhancing both hardness and wear resistance [Saklakoglu et al., 2007; Saklakoglu et al., 2006; Lo´pez-Callejas et al., 2004; Ram Mohan Rao et al., 2005).

ANNs, also called ‘‘Neural Networks’’, ‘‘Parallel Distributed Processing’’ and ‘‘Connectionist’’ models, developed out of the areas of artificial intelligence and cognitive science in their attempts to model the brain and its learning process. ANNs are collections of small individual interconnected processing units with weights associated with each con-

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nection (Bahrami, 2005). Neural networks are simplied models of the biological structure found in human brain (Meulenkamp and Alvarez, 1999). Neural network modelling is suitable for simulations of correlations which are hard to describe by physical methods (Vasudevan et al., 2005).

An ANN can be considered as a black box that has the capacity to predict an output pattern when it recognizes a given input pattern. Neural networks are basically connective systems, in which various nodes called neurons are interconnected. A typical neuron receives one or more input signals and provides an output signal depending on the processing function of the neuron (Fig. 1) (Anijdan et al., 2007). The neural network must first be ‘‘trained’’ by processing a large number of input patterns and evaluating the output that results from each input pattern. Once trained, the neural network is able to recognize similarities when presented with new input patterns, and is able to predict an output pattern. The ANN models are composed of various nonlinear computational elements interrelated through a network of connections (Jia and Davalos, 2006). The most popular neural networks are feed-forward networks. During the training process, the network adjusts its weights to minimize the error between the predicted and actual outputs. The most common algorithm for adjusting the weights is Back-propagation Algorithm (Su et al., 2005). Back-propagation networks consist of an input layer, one or more hidden layers and an output layer (Fig. 1). This ANN incorporates a hidden layer that is used to establish the interrelationships between the input variables and their relationship with the output to minimize the error between the actual and predicted output (Sterjovski et al., 2005).

In the past few years there has been a steady increase in interest in neural network modeling in different fields of materials science. The basic unit in an ANN is the neuron. The neurons are connected to each other by a weight factor. A network is usually trained using a large number of inputs with corresponding output data (Durmuş et al., 2006).

A fundamentally different application of using artificial neural networks (ANN), which is to model the material behaviour directly from the experimental data. Because of this ability to learn and generalize interactions among many variables, ANN technology has potential in modelling the material behaviour (Singha et al., 2001). ANNs have been reported to be very effective in analysing the tensile properties of welds in power plant steels, the effect of carbon content on the hot strength of steels, and the impact toughness of welds based on common welding parameters (Sterjovski, 2005). S. Dhanasekaran and R. Gnanamoorthy investigated the abrasive wear characteristics of sintered steels containing molybdenum di sulphide powders and they developed the artificial neural network model predicts the wear volumes (Dhanasekaran and Gnanamoorthy, 2007). Mehmet Sirac Ozerdem and Sedat Kolukisa used the artificial neural network approach to predict mechanical properties of, hot rolled, nonresulfurized AISI 10xx series carbon steel bars (Ozerdem and Kolukısa, 2008).

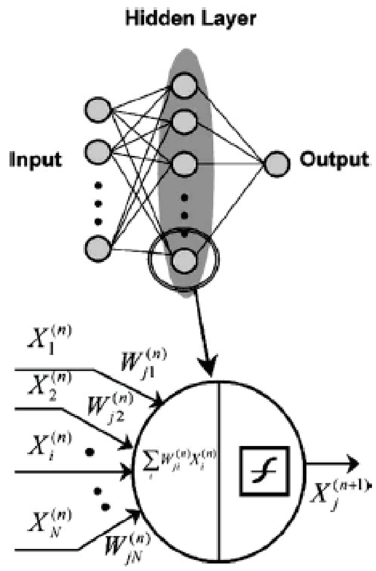

Fig. 1. Schematic description of artificial neural network configuration (upper part). The lower part gives the relationships between the input and output vectors of one neuron (Anijdan et al., 2007)

The present work aimed to develop an artificial neural network model that could predict the hardness of PIII treated 304 stainless steel depending on PIII process temperature. Furthermore, it was showed that the microhardness could be predicted using the trained network. Hence, the main objective of the current work is to employ neural networks to model the obtained results from the microhardness of PIII treated 304 stainless steel depending on PIII process temperature, an area not tackled to date by ANN modelling approaches.

2. EXPERIMENTAL PROCEDURE

All samples were polished to a mirror finish and given a 3 minute ultrasonic clean in ethanol to remove the residues from sample polishing. PIII treatment procedure is given at Table 1. The spectral analysis at Table 2 was obtained using a Spektrolab machine. Material hardness was measured using an FM700 Microhardness Future Tech indenter system. This was achieved by performing hardness tests directly on the surface at loads of 5, 10 and 50 g. Five indents were made at each load on each sample from which average values were calculated. After PIII treatment, the surfaces were examined using a JEOL-6060 SEM.

Table 1. *PIII treatment procedure*

Operating Voltage	30kV
Time	5 hr
Temperature	350, 390, 420, 500 C
İmplantation Dose	~9x1017 N.cm-2

Table 2. *Chemical composition of AISI 304 stainless steel (weight %)*

C	Si	Mn	P	S	Cr	Ni	Mo	V	Al	Fe
0.076	0.432	1.37	0.091	0.0033	17.60	9.15	0.112	0.064	0.020	71.08

3. ARTIFICIAL NEURAL NETWORK MODELLING

Neural networks are essentially connectionist system, in which different nodes called neurons are interconnected. A typical neuron accepts one or more input signals and procures an output signal trusting in the procedure function of the neuron. This output is conveyed to connected neurons in varying intensities, the signal intensity being decided by the weights. Feed forward networks are jointly used. A feed forward network has a consecutive of layers consisting of a number of neurons in each layer. The output of neurons of one layer come to exists input to neurons of the achieving layer. The first layer, called an input layer, accepts data from the outside world. The last layer is the output layer, which sends knowledge out to users. Layers that lie between the input and output layers are called hidden layers and have no direct touch with the environment. Their presence is needed in order to procure complexity to network architecture for modeling non-linear functional kinship. After choosing the network architecture, the network is tested by using back propagation algorithm, where back propagation algorithm is the productive optimization method used for underrating the error through weight arrangement. The trained neural network has to be experimented by supplying testing data (Taşkın and Çalıgülü, 2006).

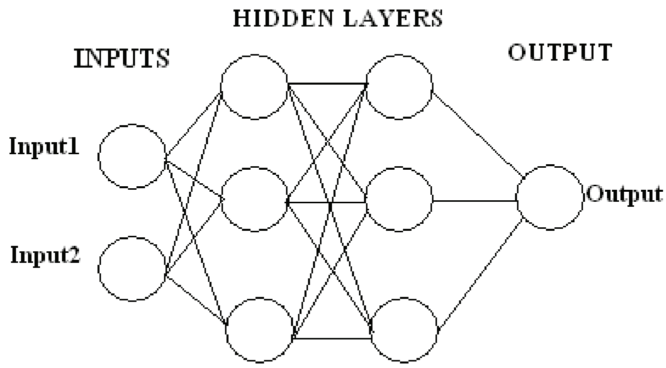

Fig. 2. *The structure of ANN used in this study*

A database of 13 hardness values was used to train the ANNs. In this study, the momentum and learning rate values are taken as 0.9 and 0.6, respectively. These values were found from the result of pre-trials. A back-propagation algorithm is used in the optimization in which the weights are modified. The ANNs architecture is illustrated in Figure 2, and comprises many simple processing neurons organized in a sequence of layers: input, intermediate (hidden) and output layers. In the trials, neural networks with different structures are employed (2 2 2 1; 2 3 3 1; 2 4 4 1; 2 5 5 1; 2 6 6 1; 2 3 1). The training finished in two minutes approximately. A very good agreement between the predicted values from the trained neural network and the validating data is achieved.

4. RESULTS AND DISCUSSION

Fig. 3 shows the cross-section of the PIII (500°C) treated sample. There is a modified layer approximately 5 μm thick on the treated surface. For lower PIII process temperatures, lower thickness formation is expected.

The measured vickers microhardness for the PIII treated and untreated samples were plotted as a function of the applied load. The results, presented in Fig.4 show a significant increment on the surface, which can be attributed to the formation of nitrides and the improvement of the surface properties of the workpiece. It is clear that for low load applied (5 g) the obtained microhardness values (1400 ± 50 HV) are independent of the process temperature and correspond to those of the treated surface. On the contrary, for the case of the highest load applied (50 g), the hardness profiles become broader as temperature increases: from ~300 HV (base metal hardness) at 350°C, to ~ 600 HV at 500°C. This last observation indicates the expected increase of the thickness of the modified (harder) layer with the temperature.

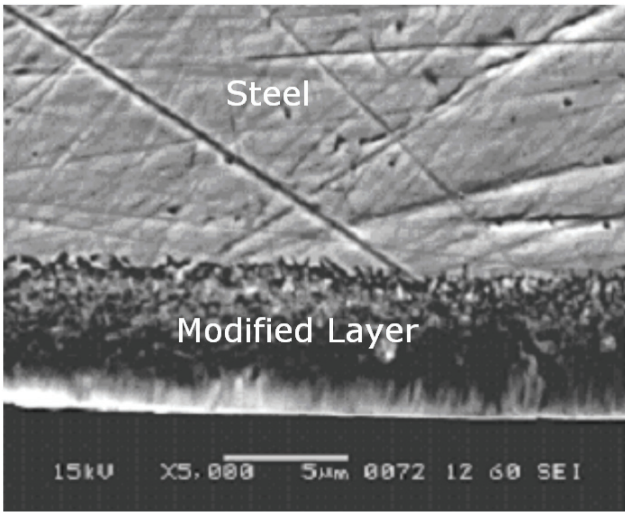

Fig. 3. Modified layer for PIII (500°C) sample

The hardness tests were performed directly onto the surface at loads of 5, 10 and 50 g. A.E. Muñoz-Castro et al. (2005) indicated that for PIII nitrided AISI 304 SS at between 250 and 400°C indent depths were about 3 μm by using a 50 g load (Muñoz-Castro et al, 2005). Therefore, it can be deduced the measured hardnesses observed at our present study correspond to somewhere between a "nitrided layer" and a "composite stratified structure" (hard surface layer/ soft base metal).

The prediction of microhardness production is performed using the ANN model. An ANN model with 2 hidden layers and 3 neurons in hidden layers is an appropriate method for prediction of micro-hardness in PIII treated 304 stainless steel, where temperature and hardness-measuring load are input parameters (Fig. 4). The microhardness value is found by trial and calculation (Fig. 5). The mean error was 4,66% for the learning phase.

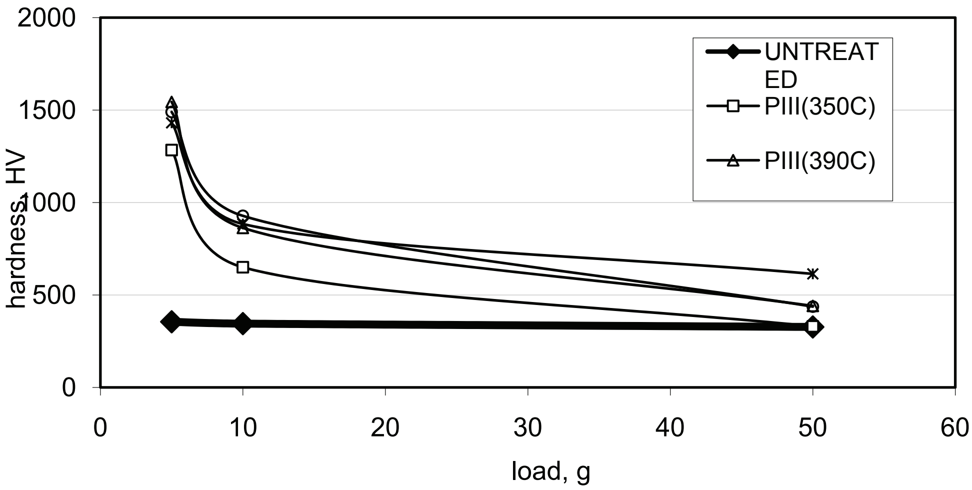

Fig. 4. Hardnesses plotted as a function of applied load in HV

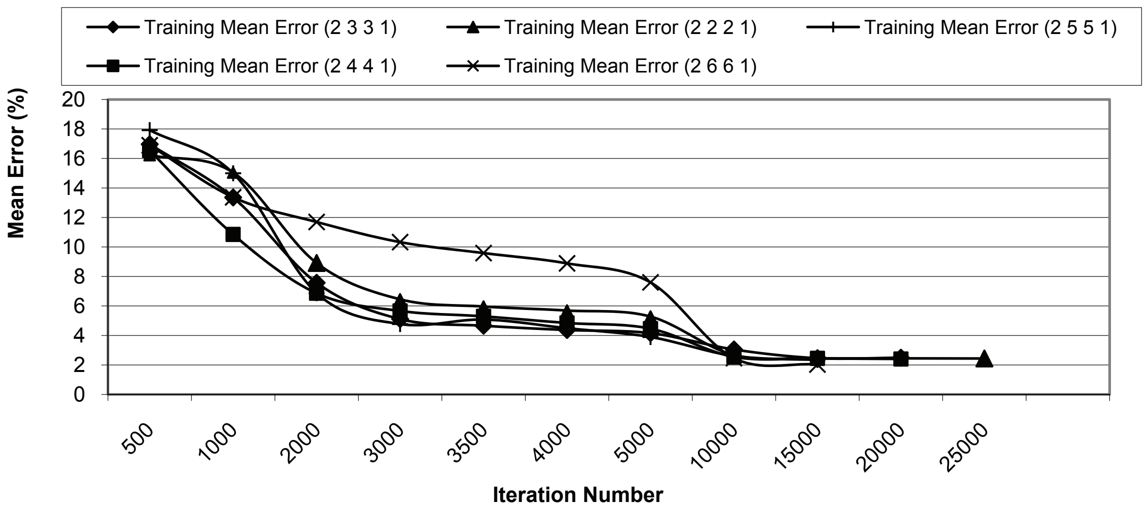

Fig. 5. The relations between iteration number and Mean Error (%) for different combinations of number of hidden neurons (Learning rate: 0.9, Momentum coefficient:0.6)

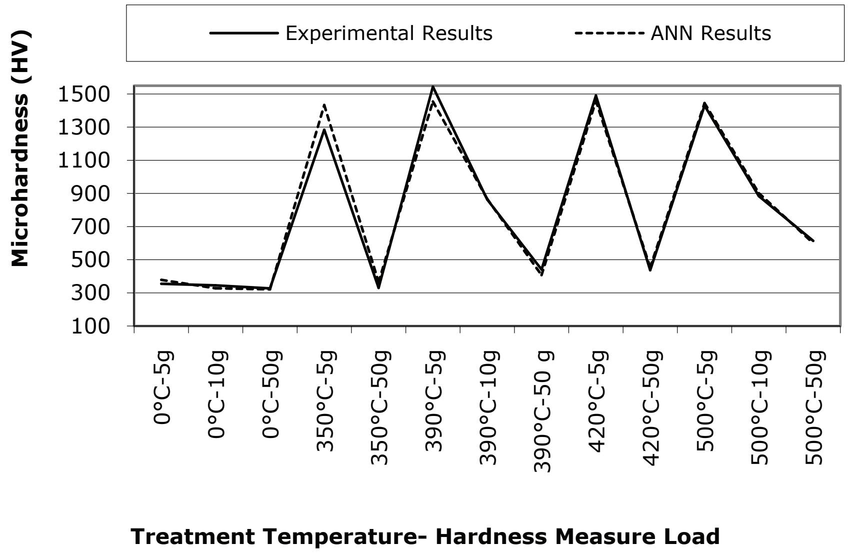

Fig. 6. The Comparison of Experimental and ANN Microhardness Values

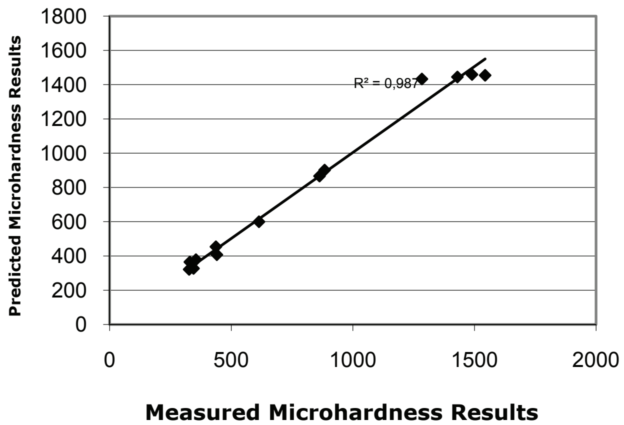

Fig. 7. Comparison of ANN and Experimental Mikrohardness values

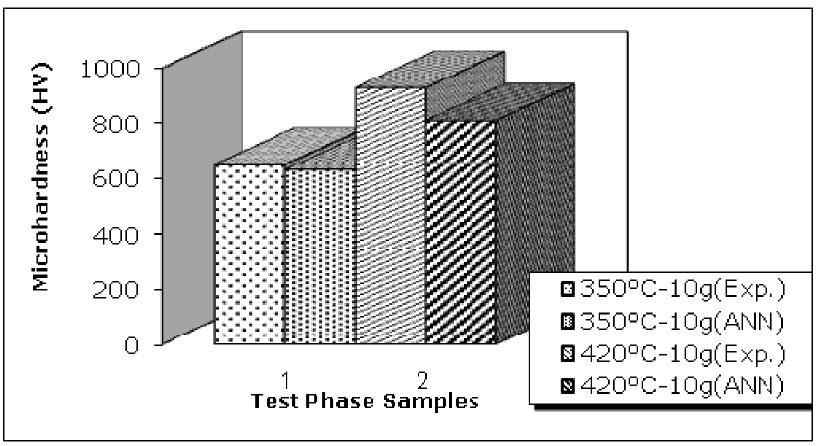

Fig. 8. The comparison of experimental microhardness values predicted by ANNs and the sample test results

Microhardness is considered as an output. A step-by-step method was carried out on the trained ANN by differing iteration numbers and different hidden neurons. For every input parameter, the percentage was changed in the output as a result of the change in the input parameter.

Results obtained from the neural models are given in Figure 6. As seen from the figures, neural network models are able to establish a high correlation between ANN and experimental values. Figure 7 shows the predicted microhardness against measured values. The overall correlation coefficient for all the datasets is 0.9875. This figure shows that the used network would be capable of accurate microhardness prediction.

For the testing phase, two samples were selected. In fig.8, ANN and experimental hardness values are shown. The mean error was 1, 44 % for the testing phase. This degree of agreement is very pleasing. For different hidden neurons, the test mean errors were calculated, and for 2:3:3:1 ANN architecture and 3500 iteration, the lowest test mean error was obtained (Fig. 9). For this ANN architecture, the optimum iteration number is 3500. 3500 iterations gave the lowest learning and testing mean errors.

Very good performance of the trained neural network was achieved. The predictions were in good agreement with the experimental values. ANN has the potential to minimize the need for expensive experimental investigation and/or inspection of stainless steels used in various applications, hence resulting in large economic benefits for organizations. The training phase finished in 2 min. whereas the experimental study lasted a number of days.

5. CONCLUSION

Plasma immersion ion implantation of AISI 304 stainless steel at temperatures ranging from 350°C to 500°C produced hard surface layers.

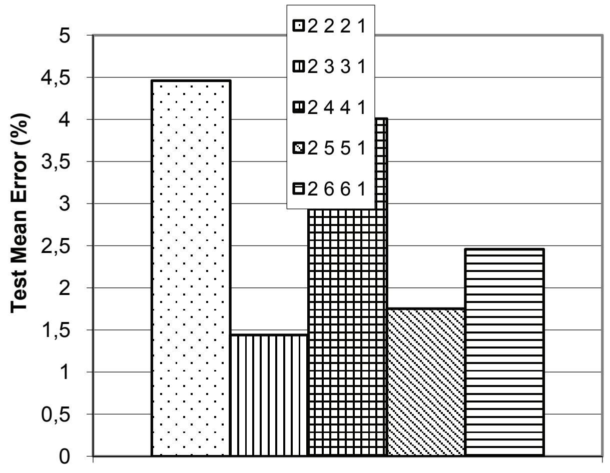

Fig. 9. *Test Mean Errors change at 3500 Iterations and different hidden layers*

While surface hardness was not tightly dependent on the process temperature, the increase of the thickness of the modified (harder) layer was a function of the temperature.

In this study, neural network was used for calculation of the microhardness in PIII treated 304 stainless steel. An ANN model with 2 hidden layers and 3 neurons in hidden layers was proven to be powerful tool for prediction of microhardness in PIII treated 304 stainless steel, where temperature and hardness-measuring load were input parameters.

The overall performance of the model was quite satisfactory. The results showed that the ANN approach could be considered an alternative and practical technique to evaluate the hardness in PIII treated 304 stainless steel. These features enable the use of ANNs in PIII treated stainless steel and will assist studies in this field. Hence, experimental studies can be reduced to a minimum in situations where the use of ANNs is appropriate. Given and predicted values of the ANN system can also be employed at no cost. This can be handled as a cost saving item at advanced production planning.

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SZTUCZNE SIECI NEURONOWE W MODELOWANIU MIKROTWARDOŚCI STALI NIERDZEWNEJ AISI 304 PO IMPLANTACJI JONOWEJ PLAZMOWYM ZANURZENIEM

Streszczenie

W artykule opisano efektywność modelu opartego o sieć neuronową wstecznej propagacji, który przewiduje mikrotwardość stali nierdzewnej AISI 304 poddanej implantacji jonowej plazmowym zanurzeniem w różnych temperaturach pomiędzy 350 i 500°C. Sztuczna sieć neuronowa (SNN) stwarza możliwość ograniczenia kosztownych i trudnych badań doświadczalnych i prób w warunkach przemysłowych. W artykule pokazano, że SNN możę zostać zastosowana do optymalizacji parametrów procesu dla austenitycznej stali nierdzewnej AISI 304. Zaobserwowano dobrą zgodność między przewidywaniami modelu i obserwacjami doświadczalnymi, co potwierdza przydatność SNN w modelowaniu twardości wyrobów po implantacji jonowej plazmowym zanurzeniem.

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