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Microhardness Simulation for 2024 and 7075 Aluminum alloys using Artificial Neural Network

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Abastract: In the present work, Vicker microhardness for 2024 and 7075 aluminum alloys was simulated as a function of cold rolling degree, ageing time, load and temperature using artificial neural network (ANN). ANN was trained on the available data of two cases. Many epochs were designed to obtain the best performance. Performance show good agreement with the experimental data. Mathematical formula was obtained to describe microhardness. Then, the capability of the ANN techniques to simulate the experimental data with almost accuracy recommends the ANN to dominate the modelling techniques in microhardness.

Index Terms- Microhardness ,Artificial neuralnetwork.

1 INTRODUCTION

Age-hardening 2024 and 7075 aluminum alloys with high strength and low density are widely used in the aerospace field. The mechanical properties of these alloys can be influenced by artificial ageing and plastic deformation, such as equal channel angular pressing, high pressure torsion and cold rolling. El-Baradie and El-Sayed (1996) enhanced the mechanical properties of 7075 alloy by adopting two-step thermomechanical treatment. Furthermore, using thermomechanical treatments on the same alloy, an increase of 25 % in the fatigue stress was achieved (Ostermann 1971)[1]. The present effort introduce the artificial neural network (ANN) for modeling microhardness measurements on the samples treated at several temperatures (170 and 190 ^{o} C for 2024 alloy , 130, 150, 170 ^{o} C for 7075 alloy) at different times under a 200 and 300 g loads for 2024 and 7075 alloy, respectively . The rest of paper is organized as follows; Sec. 2 Experiment procedure, Sec. 3 describes the artificial neural network, Sec.4 shows the proposed system and finally the results and discussion in Sec. 5.

2- Experimental procedure

The materials investigated [1]are 2024 and 7075 alloys supplied in the form of 2- and 2.5-mm thick plates, respectively. Their chemical compositions are given in Table 1. Specimens are prepared by cutting coupons of 10×10 mm^2 from the alloys plates. The as-received 2024-T3 and 7075-T6 alloys are solution heat-treated respectively at 485 and 465 °C for 24 h and then water-quenched. Immediately, some samples are one-directionally cold-rolled (CR) with a reduction thickness of 15, 30, 50 and 75 %. Multi-pass rolling is used to get a relatively uniform deformation along the plate thickness direction, with typically less than 6 % of reduction per pass. Microhardness measurements on the samples treated at several temperatures (170 and 190 °C for 2024 alloy; 130, 150 and 170 °C for 7075 alloy) for different times are performed using Shimadzu HMV-M3 Vickers microhardness tester under a 200 and 300 g loads for 2024 and 7075 alloy, respectively. Five indentations are performed on each sample at well distributed and enough spaced points to prevent any effect of indentations on each other, and a mean value is given with an error less than 5 Hv.

Alloy	Si	Fe	Cu	Mn	Mg	Cr	Zn	Ti	Al
2024	0.5	0.5	4.2	0.6	1.8	0.1	0.25	0.1	Bal.
7075	0.4	0.5	1.6	0.3	2.3	0.18	5.5	0.2	Bal.

Table 1 Chemical compositions of 2024 and 7075 alloys (mass fraction, %)

3-Artificial Neural Network (ANN)

Bourquin et al. and Agatonovic-Kustrin and Beresford[2-11] described the basic theories of ANN model. Artificial neural networks offer an alternative procedure to tackle complex problems, and are applied in different applications. The most popular type of neural network is Multi- Layer Feed Forward (MLFF). A schematic diagram of typical MLFF neural-network architecture is shown in Fig. 1. The network usually includes an input layer, some hidden layers and an output layer. Usually knowledge is stored as a set of Connection weights. A neural network is trained to map a set of input data by iterative adjustment of the weights. Information from inputs is fed forward through the network to optimize the weights between neurons. Optimization of the weights is made by backward propagation of the error during training or learning phase. The ANN reads the input and output values in the training data set and changes the value of the weighted links to reduce the difference between the predicted and target (experimental) values. The error in prediction is minimized across many training cycles (iteration or epoch)

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until network reaches specified level of accuracy. A complete round of forward–backward passes and weight adjustments using all input–output pairs in the data set is called an epoch or iteration. In this study, we focused on the learning situation known as supervised learning, in which a set of input/output data patterns is available. Thus, the ANN has to be trained to produce the desired output .

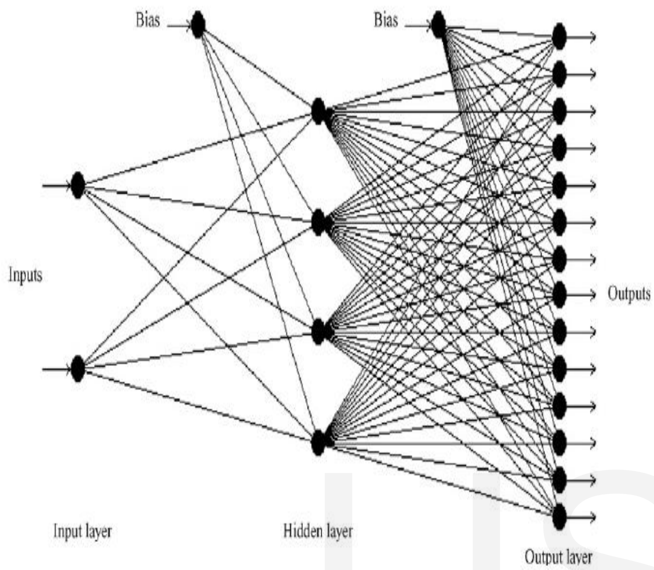


Fig.(1). Schematic representation of a multilayer feedforward network consisting of two inputs, one hidden layer with four neurons and 14 outputs.

4 ANN model for microhardness

Microhardness of 2024 and 7075 aluminum alloy can be simulated at different temperatures using ANN. Author choose to internally model the problem with five individual neural networks trained separately using experimental data, The first and second ANN for 2024 alloy, third, fourth and fifth for 7075 alloy. The first and second ANN were configured to have aging time, load (200 g), cold-rolled (at 170 ^{o}C and190 ^{o}C respectively) as inputs while the output was microharness . Third , fourth and fifth ANN were configured to have aging time, load(300 g) , cold-rolled (at 130 ^{o}C , 150 ^{o}C and170 ^{o}C respectively) as inputs while the output was microharness . Fig.(2) represent a block diagram of the first microhardness ANN based modeling.

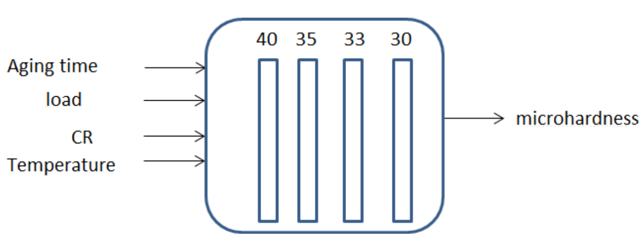


Fig. (2) Block diagram of the first microhardness ANN model.

4 Results and discussion

The proposed ANN models were applied to simulate the microhardness. By employing the above mentioned proposed models with different values of the ANN parameters we have obtained different numbers of hidden neurons for the ANN models. The results obtained for the five models are discussed in the following: The first ANN having four hidden layers of 40 ,35 , 33 and 30 neurons as shown in Fig.2 ,second network :45, 44, 36 and 40 neurons,third network:55,26,30 and 26 neurons ,fourth network : 44, 60, 30, 28 neurons, and finally fifth network: 30, 20, 30, 20 neurons respectively with one neuron in the output layer. Network performance was evaluated by plotting the ANN model output against the experimental data and analyzing the percentage error between the simulation results and the experimental data Fig.(3). In the training process 500 epochs was found to be sufficient, Fig. (3), with respect to the minimum mean sum square error (MSE) of $4.39x10^{-8}$ for all networks, the function which describes the nonlinear relationship is given in appendix. The simulation results from the trained neural network and the experimental data (target) are shown in Figs. 4 and 5. Results of hardness based ANN showed almost exact fitting to the experimental which is not usually the case with other conventional theoretical techniques. This gives the ANN the provision of wide usage in modeling of solid state physics.

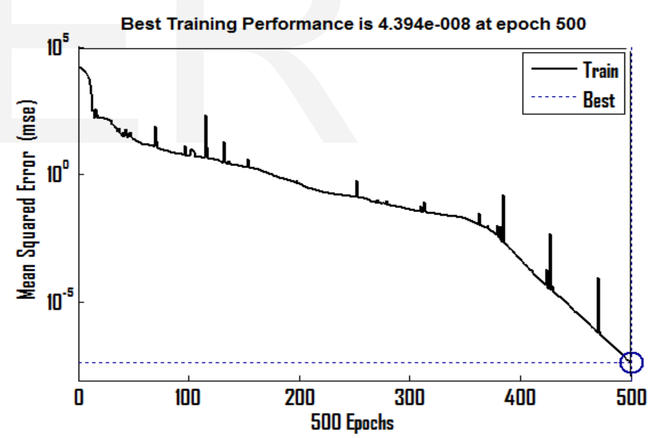
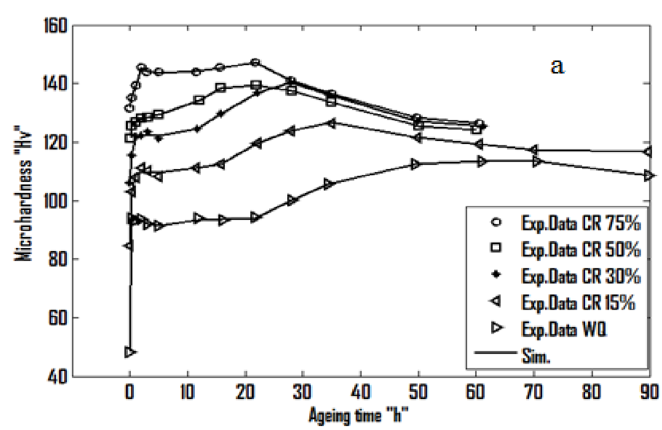


Fig. (3) performance for microhardness using ANN model, where epochs are the number of training.



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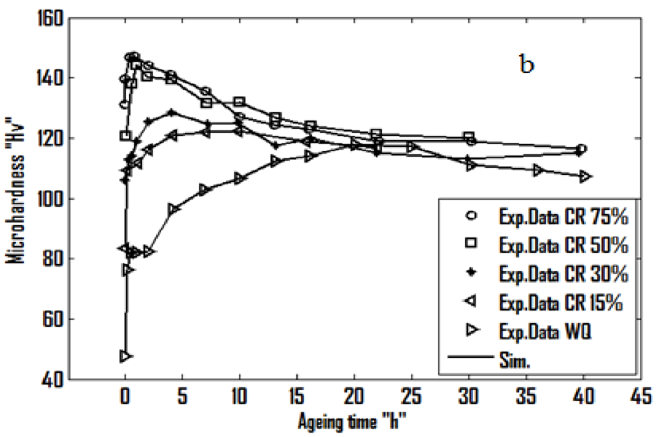
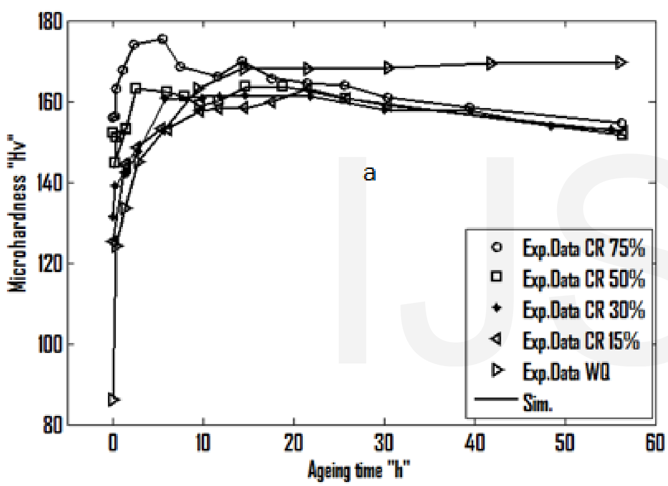
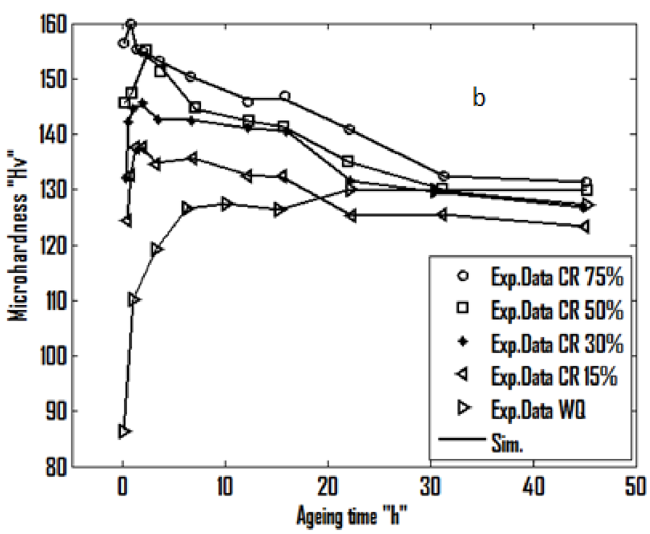


Fig.4 hardness simulation of the 2024 alloy at (a)170^{o}C and (b)190^{o}C





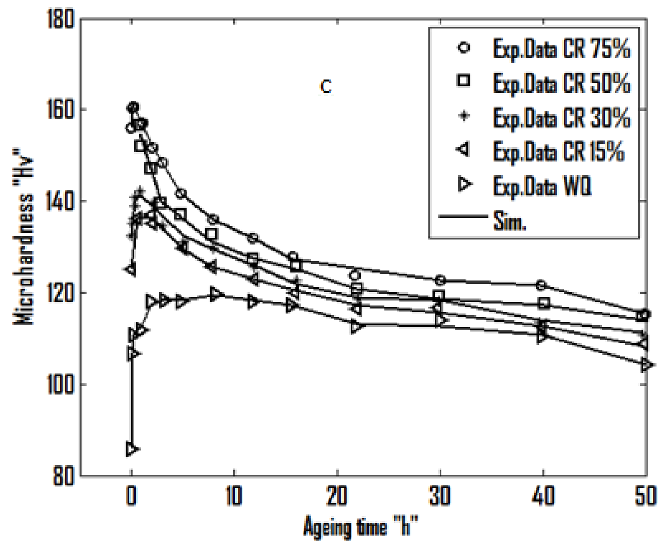


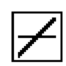
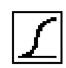
Fig.5 Hardness simulation of the 7075 alloy at (a)130^{o}C , (b)150^{o}C and (c)170^{o}C

Appendix

The equation which describes hardness is given by:

Hardness= pure line [net.LW{5,4}logsig (net.LW {4,3} logsig(net.LW{3,2}logsig(net.LW{2,1}logsig(net.IW{1,1}T+ net.B{1})+ net.B{2})+ net.B{3})+ net.B{4})+ net.B{1}]

Where

Pureline  , logsig 

T is the input
net.IW {1, 1}is linked weights between the input layer and first hidden layer,
net.LW {2, 1} is linked weights between first and second hidden layer.
net.LW {3, 2} is linked weights between the second and third hidden layer,
net.LW {4, 3} is linked weights between the third and fourth hidden layer,
net.LW {5, 4} is linked weights between the fourth and output layer,
net. B{1}: the bias of the first hidden layer,
net. B{2}: the bias of the second hidden layer,
net. B{3}: the bias of the third hidden layer,
net. B{4}: the bias of the third hidden layer,and
net. B{5}: the bias of the output layer.

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