Prediction of Irradiation Damage by Artificial Neural Network for Austenitic Stainless Steels

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1. Introduction

The internal structures of pressurized water reactors (PWR) located close to the reactor core are used to support the fuel assemblies, to maintain the alignment between assemblies and the control bars and to canalize the primary water. In general these internal structures consist of baffle plates in solution annealed (SA) 304 stainless steel and baffle bolts in cold worked (CW) 316 stainless steel. These components undergo a large neutron flux at temperatures between 280 and 380°C.

Well-controlled irradiation-assisted stress corrosion cracking (IASCC) data from properly irradiated, and properly characterized, materials are sorely lacking due to the experimental difficulties and financial limitations related to working with highly activated materials.

In this work, we tried to apply the artificial neural network (ANN) approach, predicted the susceptibility to an IASCC for an austenitic stainless steel SA 304 and CW 316. *G.S. Was* and *J.-P. Massoud* experimental data are used. Because there is fewer experimental data, we need to prediction for radiation damage under the internal structure of PWR. Besides, we compared experimental data with prediction data by the artificial neural network.

2. Prediction Model and Results

2.1 Artificial Neuron Network (ANN)

The ANN performs fundamentally like a human brain. The cell body in the human neuron receives incoming impulses via dendrites (receiver) by means of chemical processes. If the number of incoming impulses exceeds a certain threshold value the neuron will discharge it off to other neurons through its synapses, which determines the impulse frequency to be fired off.

Therefore, processing units or neurons of an ANN consist of three main components; synaptic weights connecting the nodes, the summation function within the node and the transfer function. Synaptic weights characterise themselves with their strength (value) which corresponds to the importance of the information coming from each neuron. In other words, the information is encoded in these strength-weights.

The summation function is used to calculate a total input signal by multiplying their synaptic weights and summing up all the products.

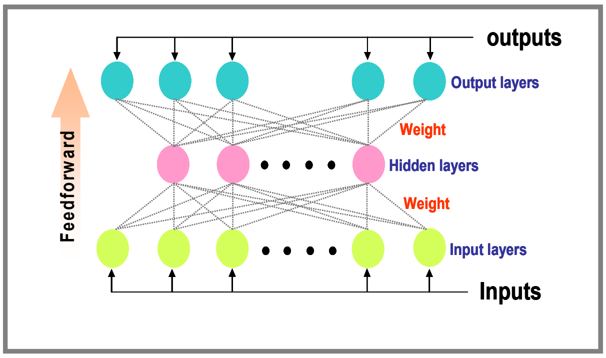

Figure 1. Scheme of Multi-Layer Perceptron (MLP).

2.2 Multi-Layer Perceptron Model

The Multi-layer perceptron (MLP) is the most widely used type of neural network (Figure 1). Multi-layer perceptrons are feedforward neural networks trained with a standard backpropagation algorithm. They are supervised networks so they require a desired response to be trained. They learn how to transform input data into a desired response, so they are widely used for a pattern classification. With one or two hidden layers, they can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems.

2.3 Experimental Data and Prediction Method

G.S. Was [1,2] and *J.-P. Massoud* [3] used austenitic stainless steel irradiated in the EBR-II, BOR-60 and OSIRIS reactors. These steels were irradiated with 1 MeV protons to doses between 1 ~ 40 dpa at 300 ~ 400°C both with or without a 15 appm helium pre-implanted at ~100°C.

The artificial neural network code NeuroShell Predictor was used to analyse the data and two different training performances are investigated:

- Input layers : temperature, dose.
- Output layers : dislocation loop size, dislocation loop density.
- Training strategy : genetic (combines a genetic algorithm with statistical estimator)

2.4 Prediction of Dislocation Loop size

For the PWR internal structures constructed of solution annealed 304 plates and cold-worked bolts, it is therefore difficult to measured their dislocation loop characteristics at PWR relevant temperatures based only on a fast reactor experience. According to *G.S. Was* and

J.-P. Massoud experimental data, the data of dislocation loop characteristics is not existed at 360°C. So, we predicted the susceptibility to IASCC for an austenitic stainless steel at 360°C.

Figure 2 shows that the comparison between the predicted and measured dislocation loop size for an austenitic stainless steel SA 304 and CW 316. The value for R-squared ranges from 0 to 1. The closer the value is to 1, the better the net is able to make predictions. The net is not able to make good predictions if the value is near 0. The R-squared value of SA 304 was 0.852921, and in case of CW 316 was 0.674923. And the error bars of data were 15.2 and 16.8 percent. The reasons for irradiation damage generated from the point defects created during irradiation. However, the material of CW 316 already has point defects before radiation. Therefore, R-squared values of CW 316 lower than SA 304 by radiation damage. On the other hand, the error rate was higher. The results of the prediction are listed in Table 1.

Figure 3 shows that the relative importance of the input variables as predicted by the neural network. In case of SA 304 material, the dose is significantly better than the temperature in the prediction of a dislocation loop size. However, the material of CW 316, which was predicted the temperature is important better than the dose in the neural network.

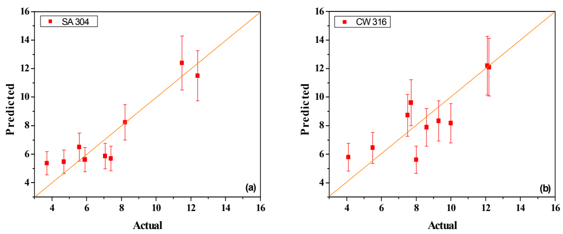

Figure 2. Comparison between the predicted and measured dislocation loop size at 360°C.

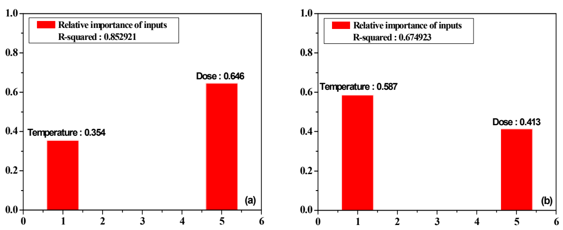

Figure 3. The relative importance of the inputs using the MLP model.

Table 1. The prediction of the dislocation loop size and density for an austenitic stainless steel SA 304 and CW 316.

Material	Temperature (°C)	Dose (dpa)	Dislocation loop size (nm)	Dislocation loop density (10^{22} m^{-3})
SA 304	360	1	5.30821	5.840002
		3	6.58899	6.400621
		5	8.01956	3.9247
		8	11.65091	3.081838
		10	12.23358	3.218955
		13	12.38342	3.294482
		15	12.38497	3.299244
		20	12.38504	3.300009
CW 316	360	1	5.30821	3.217652
		3	9.79457	3.217675
		5	11.91714	3.217697
		8	12.10407	3.217731
		10	12.10959	3.217753
		13	12.11351	3.217787
		15	12.11414	3.217809
		20	12.11437	3.217865

3. Conclusion

The artificial neural network was used to analysis a radiation damage. Neural networks have the ability to learn patterns and trends in datasets with several variables and can effectively use an interpolation to make prediction for cases when there are no data. Base on experimental data of a radiation damage as *G.S. Was* and *J.-P. Massoud*, we tried to apply the artificial neural network (ANN) approach. The neural network used two input parameters: temperature, dose. Validation of the prediction gave a good agreement.

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