Artificial Neural Network Prediction Model for Impact Energy of Thermal Aged Cast Stainless Steel

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ABSTRACT

Impact energy prediction of thermal aged cast stainless steel from impact test was studied using artificial neural network (ANN) modeling. Impact energy data for specimens from eleven cast stainless steel alloys at different aging times and temperatures, were used to evaluate possible artificial neural network architecture for prediction impact energy. These data are taken from Argonne National Laboratories (ANL) in USA that involved impact test results of cast stainless steel after aging between 200 and 400^{o}C for up to 30000 hour. The ANN model exhibited excellent comparison with experimental results of ANL i.e. correlation coefficient (R=0.9451) and mean square error (MSE=$1.2*10^{-5}$). Since a large number of variables were used during training the ANN model, a reliable and useful predictor for impact energy in thermal aged cast stainless steel was provided.

نموذج الشبكات العصبية الاصطناعية التنبؤي لطاقة الصدمة للصلب المسبوك المقاوم للصدأ المعتق حرارياً

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الخلاصة

تم دراسة تنبؤ طاقة الصدمة من خلال اختبار الصدمة للصلب المسبوك المقاوم للصدأ باستخدام نموذج الشبكات العصبية الاصطناعية. استخدمت بيانات طاقة الصدمة لعينات من احد عشر سبيكة من الصلب المسبوك المقاوم للصدأ عند أزمان ودرجات حرارة تعتيق مختلفة لتقييم هندسية الشبكات العصبية الصناعية لتنبؤ طاقة الصدمة. تم الحصول على هذه البيانات من مختبرات آركون الامريكية والتي تتضمن نتائج اختبار الصدمة للصلب المسبوك المقاوم للصدأ بعد التعتيق عند درجات حرارة بين 200 و 400 ^{o}م ولازمان تجاوزات 30000 ساعة. اظهر نموذج الشبكة العصبية الاصطناعية مقارنة ممتازة مع النتائج العملية لمختبرات آركون الامريكية أي ان معامل تصحيح = 0.9451 ومتوسط مربع الخطأ = $1.2*10^{-5}$. ان نموذج الشبكات العصبية الاصطناعية المستخدم يعتبر اكثر وثوقية في تخمين الصلب المسبوك المقاوم للصدأ المعتق حراريا حيث كان هنالك عدد كبير من المتغيرات المستخدمة في تدريب الشبكة العصبية الاصطناعية.

1. Introduction

In recent years much research has been devoted to the examination of the properties of steels destined for long time service at high temperature. Many papers which describe the problems of exploitation of these kinds of steels have been published in 1997 and 2003 [1-2]. As a result of long time service at high temperature, the structure of steel shows some degradation effects. These effects cause a weakening of the mechanical properties of steel. Most power plant installations have failed while engaging at room temperature. Increasing knowledge of the fracture process of steel at room temperature has a significant importance for the safe exploitation of constructions made of these materials. At the present time several tests are being used with an aim to examine the degree of structure degradation of steel during service [3].

Cast stainless steels are used extensively in the nuclear industry for valve bodies, pump castings, and primary coolant piping [4]. Charpy-impact tests were conducted by ANL on several cast stainless steel alloys that were thermally aged up to 30000 hour at temperatures between 200 and 400^{o}C (392 and 752^{o}F).The aim of the present research was to obtain impact energy data to predict the degree of toughness loss suffered by cast stainless steel components during normal and extended service life of reactors using ANN modeling.

Neural computing is a relatively new field of artificial intelligence (AI), which tries to mimic the structure and operation of biological neural systems, such as the human brain, by creating an Artificial Neural Network on a computer. These ANN are modelling techniques that are especially useful to address problems where solutions are not clearly formulated or where the relationships between inputs and outputs are not sufficiently known. ANN have the ability to learn by example. Patterns in a series of input and output values of example cases are recognized. This acquired 'knowledge' can then be used by the ANN to predict unknown output values for a given set of input values. Alternatively, ANN can also be used for classification. In this case, the ANN output is a discrete category to which the item described by the input values belongs. ANNs are composed of simple interconnected elements called processing elements (PEs) or artificial neurons that act as microprocessors. Each PE has an input and an output side. The connections are on the input side corresponding to the dendrites of the biological original and provide the input from other PEs. The connections on the output side correspond to the axon and transmit the output. Synapses are mimicked by providing connection weights between the various PEs and transfer functions or thresholds within the PEs. The activation of the PE results from the sum of the weighted inputs and can be negative, zero, or positive. This is due to the synaptic weights, which represent excitatory synapses when positive (*wi*.0) or inhibitory ones when negative (*wi*,0). The PEs output is computed by applying the transfer function to the activation, which as a result of the synaptic weights, can be negative, zero, or positive. The type of transfer function to be used depends on the type of ANN to be designed[5].

For the last few years, the authors have been using various ANN modelling techniques in materials science and engineering fields including effect of heat treatment on mechanical properties in MIM alloy [6], analysis of stress ratio effects on fatigue propagation in a sintered duplex steel [7], low cycle fatigue life of nitrogen-alloyed 316L stainless steel [8], assessment of ultimate strength of plates with pitting corrosion [9], and effect of different environmental parameters on pitting behavior of AISI type 316L stainless steel: [10]. The authors found that ANN can be effectively used to develop models to analyze and predict mechanical properties of materials.

2. Material Characterization

Material was obtained from various experimental alloys of CF-3, CF-8, and CF-8M (ASTM specification A351 and A451) cast stainless steels. 208 experimental specimens were obtained in the form of keel blocks approximately 180 mm long and 120 mm high, with a thickness range that tapered from 90 to 30 mm. The composition was varied to provide different concentrations of nickel, chromium, carbon, and nitrogen in the material; and ferrite content in the range of 3 to 30% in the microstructure. The chemical compositions of cast stainless steel used for the present research were listed in Table 1 [4].

3. Neural Network Modeling

ANNs are computing systems composed of highly interconnected, but very simple, processing elements (or neurons) that process data using the ANN's response to external inputs. The primary characteristics of ANN models are: massive parallelism, non-linearity, processing by multiple layers of neurons, and, finally, dynamic feedback among neurons [11]. Due to their parallel structure, which is inspired by the parallelism of the human brain, ANNs can be used for a range of multivariable nonlinear applications for which an accurate analytical solution is very difficult to obtain.

The neural network approach usually follows three steps: preparation of the data from the database, design of the ANN, and training of the ANN. In the training step the training functions, the training algorithms and the parameters of the network are chosen, and then the testing of the trained network is performed. As a result, the trained ANN can be used for predictions.

3.1 Preparation of the data

Input parameters are very important in neural network modelling. The selection of these input parameters is based on the physical background of the process to be investigated, but mostly it is conditioned by the available database. For this study, the following input parameters were used: aging temperature, aging time, P%, Si%, Mn%, Cr%, Mo%, S%, Ni%, N%, and C%. The output of the ANN was impact energy. To obtain better training results, all the ANN inputs were scaled to match the range of the first hidden layer's transfer function. For the hyperbolic transfer function used in our investigation, the range lay between -1 and 1.

3.2 Design of the neural network

When designing ANNs, it is very important to match the neural architecture to the problem. For this study the most widely used class of feed-forward neural networks, the multi-layer perceptrons was used [12]. Currently, there is no analytical way of defining the network structure as a function of the complexity of the investigated problem [12]. The structure must be manually selected using a trial-and-error process.

ANNs with one or two hidden layers and an adequate number of hidden neurons are sufficient to model any solution surface of practical interest [13]. ANNs with three or more hidden layers are much more difficult and time-consuming to train and demand huge databases [12]. In the present study two hidden layers were found to be sufficient.

The number of hidden neurons (nodes) depends on the nature of the investigated problem. There are various methods to determine the number of hidden neurons but none can be applied generally. As a result, an adequate number is usually determined on the basis of a selection algorithm, which begins with very simple ANNs (with only a few hidden neurons) and then increases in complexity by adding hidden neurons until the optimum network architecture is reached. In the present model there are 10 neurons in the first hidden layer and 5 neurons in the second hidden layer.

The transfer function is also one of the important features of ANNs. On the basis of testing and research in similar areas the most accurate predictions were obtained with a hyperbolic transfer function:

$$f(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \quad \ldots\ldots(1)$$

3.3 Training of the neural network

During the training procedure of present model, the database was randomly divided into two subsets before each training: 188 of the data was used for the training set, and 20 of the data was used for the test set. During the training process, the network weights are continuously adjusted till the difference between the predicted output and experimental value is minimized, i.e. the error function defined as the sum of squares of the difference between predicted and experimental value on all the data reaches a set limit or the number of predetermined training operations are completed. A critical factor in developing a robust model is the numerical optimization technique applied for minimizing the error. Neural network functions depend non-linearly on their weights and so the minimization of the corresponding error function requires the use of iterative non-linear optimization algorithms. These algorithms make use of the derivatives of the error function with respect to the weights of the network.

Resilient backpropagation algorithm is the optimization technique employed in building of present model. After completing the training process, the model was tested using another batch (set) of data which has not been used in the training set.

The following statistical parameters of significance are calculated at the end of the training and testing calculations:

1. *Correlation coefficient* (*R*): is a measure of how the actual and predicted values correlate to each other. The goal is to maximize the value of *R*.
2. *Mean square error* (MSE): is a statistical measure of the differences between the values of the outputs in the training set and the output values the network is predicting. The goal is to minimize the value of MSE.

In the present model, the value of correlation coefficient reached to 0.9451 and mean square error reached to $1.2*10^{-5}$.

4. Results and Discussion

The present artificial neural network modelling was used to predict the impact energy of cast stainless steel under the effect of thermal aging. The sets of data used to train and test the proposed network were taken from the results of ANL laboratories. The architecture of neural network for this model is given in Figure 1. It consists of eleven nodes in the input layer with two hidden layers were chosen, the first hidden layer has ten nodes, and the second hidden layer has 5 nodes. The output layer has one node i.e. impact energy. The decision function used for both of first hidden layer and second hidden layer was (*tansig*), and for the output layer is (*purelin*). The results of impact energy predicted by the present model were shown to be agreed well against experimental values, i.e. correlation coefficient, R=0.9451 and MSE=$1.2*10^{-5}$ as shown in Figure 2.

The effect of thermal aging time on impact energy of different cast stainless steel alloys are shown in Figure 3. Impact energy decreased with increasing thermal aging time. As the thermal aging time increased, the fracture toughness will decrease as a result of decreasing impact energy resulted from Charpy-impact test [14].

The effect of thermal aging temperature on impact energy of the present ANN model at different aging time for different cast stainless steel alloys are shown in Figures 4-8. The results indicated that impact energy decreased with increasing thermal aging temperature. Thermal aging of cast stainless steel between 200 and 400^{o}C causes an increase in hardness and tensile strength and a decrease in ductility, Charpy-impact energy, and fracture toughness of the material [4]. Also, between 0 and 200^{o}C, the behaviour of impact energy is linear. This mean that there is no effect to thermal aging between 0 and 200^{o}C.

5. Conclusions

The most important conclusions that can be drawn from the present research are as follow:

1. Increase of thermal aging time and temperature resulted in decrease in impact energy for cast stainless steel alloys.
2. Thermal aging of cast stainless steel is sensitive between 200 to 400^{o}C.
3. ANN model was very effective in prediction of impact energy of cast stainless steel. The results were found to be agreed well with that obtained from ANL laboratory tests.

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Table 1: The chemical composition in wt.% for cast stainless steel alloys [4]

Cast Stainless Steel	Mn%	Si %	P %	S %	Mo%	Cr %	Ni %	N %	C %
47 Grade CF-3	0.60	1.06	0.007	0.006	0.59	19.81	10.63	0.028	0.018
51 Grade CF-3	0.63	0.86	0.014	0.005	0.32	20.13	9.06	0.058	0.010
52 Grade CF-3	0.57	0.92	0.012	0.005	0.35	19.49	9.40	0.052	0.009
56 Grade CF-8	0.57	1.05	0.007	0.007	0.34	19.65	9.28	0.030	0.066
59 Grade CF-8	0.60	1.08	0.008	0.007	0.32	20.33	9.34	0.045	0.062
60 Grade CF-8	0.67	0.95	0.008	0.006	0.31	21.05	8.34	0.058	0.064
61 Grade CF-8	0.65	1.01	0.007	0.007	0.32	20.65	8.86	0.080	0.054
63 Grade CF-8M	0.61	0.58	0.007	0.006	2.57	19.37	11.85	0.031	0.055
64 Grade CF-8M	0.60	0.63	0.006	0.005	2.46	20.76	9.40	0.038	0.038
65 Grade CF-8M	0.50	0.48	0.012	0.007	2.57	20.78	9.63	0.064	0.049
66 Grade CF-8M	0.60	0.49	0.012	0.007	2.39	19.45	9.28	0.029	0.047

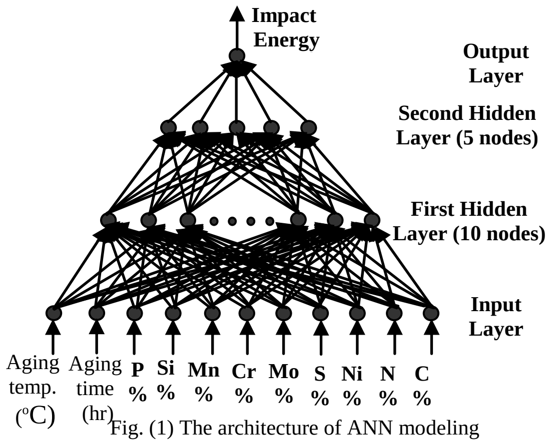

Fig. (1) The architecture of ANN modeling

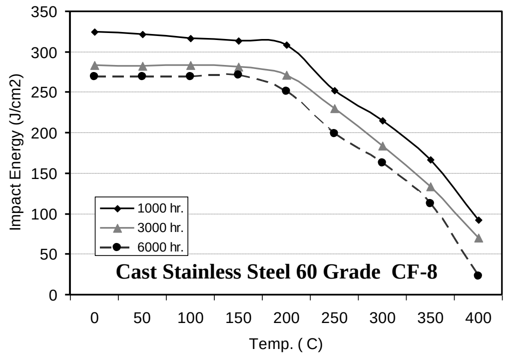

Fig.(5) Effect of thermal aging temperature on the impact energy at different aging time

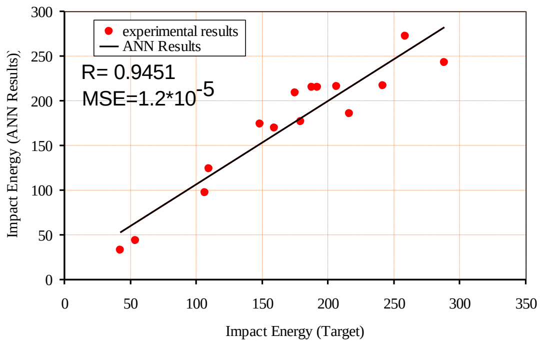

Fig.(2) Comparison between ANN Results and Target Results using Resiliant Backpropagation Algorithm

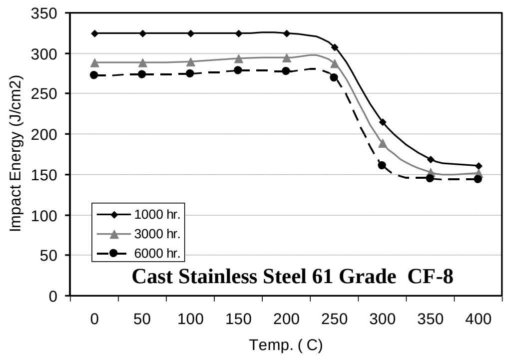

Fig.(6) Effect of thermal aging temperature on the impact energy at different aging time

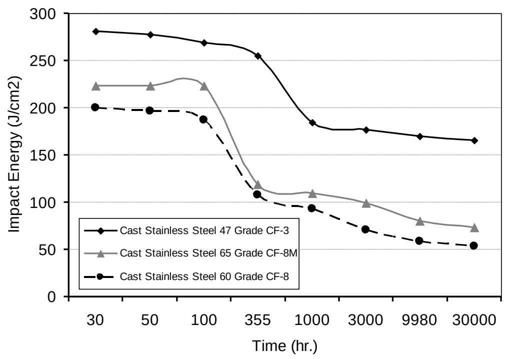

Fig.(3) Effect of thermal aging time on the impact energy for different cast stainless steel alloys

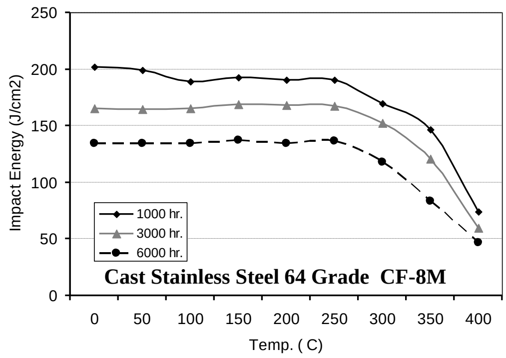

Fig.(7) Effect of thermal aging temperature on the impact energy at different aging time

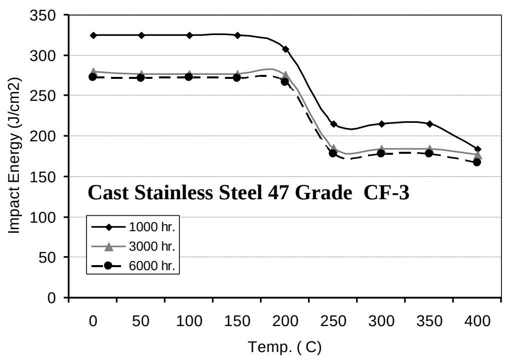

Fig.(4) Effect of thermal aging temperature on the impact energy at different aging time

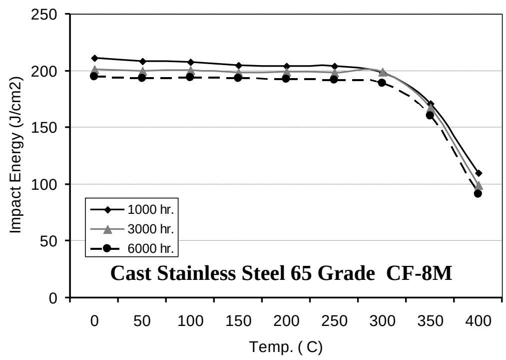

Fig.(8) Effect of thermal aging temperature on the impact energy at different aging time o

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Cast Stainless Steel 65 Grade CF-8M

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