Tensile-Property Characterization of Thermally Aged Cast Stainless Steels using Neural Networks.

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Abstract

The effect of thermal aging on tensile properties of cast stainless steels during service in light water reactors has been evaluated and recorded by the Argonne National Laboratory.

Tensile data for several experimental and commercial heats of cast stainless steel (CF-8M) are presented for predicting the change in tensile flow and yield stresses and engineering stress-strain curve as a function of time and temperature of service in the light water reactors using Neural Networks.

Thermal aging increase the tensile strength of this type of steel. The result and correlation described by this work may be used for assessing thermal embitterment of cast stainless steel components.

استعمال طريقة الشبكات العصبية الصناعية لوصف خاصية الشد للصلب ألسبائكي تحت تأثير الحرارة لفترات زمنية طويلة.

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الملخص:

تأثير الحرارة بمرور الزمن على خواص الشد والاجهادات الناتجة عنها في الصلب ألسبائكي المستخدم في مفاعلات الماء الخفيف قد تمت دراستها والحصول على نتائجها العملية عن طريق جهاز تماثلي في مختبرات اركون الدولية .

اختبارات الشد أجريت على عينات من الصلب السبائكي لعدد من درجات الحرارة العملية والمختبرية .

في هذا البحث قمنا باستخدام تقنية الشبكات العصبية لتقييم ووصف التغير الحاصل في خواص الشد والاجهادات التي يتعرض لها هذا النوع من الصلب ألسبائكي في مفاعلات الماء الخفيف .تم الاعتماد على البيانات المتوفرة من الجانب العملي لتدريب البرنامج والحصول على أفضل شبكة عصبية تعطي نتائج تقترب من التطابق مع النتائج العملية .

اعتمادا على الشبكة العصبية التي تم اعتمادها نتيجة لإعطائها أفضل نسبة خطأ وطريقه تمثيل واقتراب للهدف ، قمنا بوصف تأثير مرور الزمن (الشيخوخة) والحرارة على اجهادات الخضوع والانفعال للصلب ألسبائكي ،اعتمادا على درجتين لحرارة الغرفة (25,290) مئوي.

إن مرور الزمن والحرارة المستخدمة لذلك وجد بأنها تزيد من مقاومة الشد للصلب ألسبائكي واجهادات الانفعال والخضوع.

إن هذه النتائج مفيدة جدا في مجال تصميم هذه التطبيقات وكذلك تعطي مؤشر عملي مفيد لمعرفة العمر العملي قبل الدخول بمرحلة الخطر.

Introduction

Cast duplex stainless steel used in light water reactor (LWR) systems for primary pressure-boundary components are susceptible to thermal embitterment at reactor operating temperature.
Thermal aging of cast stainless steel at these temperatures causes an increase in hardness and tensile strength and decrease in ductility, impact strength and fracture toughness of the material.
Investigation at Argonne National Laboratory has shown that the thermal embitterment of cast stainless steel component may occur within the reactor design lifetime of 40 yr. [1]
This report presents tensile-property data on several heats of cast stainless steel aged up to 58000 h at temperature between 290C° and 450C°.
The kinetics of thermal embitterment depends on both material and aging parameters. [2]
A neural network is a non-linear system consisting of a large number of highly interconnected processing units, nodes or artificial neurons. Each input signal is multiplied by the associated weight value and summed at a neuron. The result is put through activation function to generate a level of activity for the neuron. This activity is the output of the neuron. When the weight value at each link and the connection pattern are determined, the neural network is trained. This process is accomplished by learning from the training set and by applying for certain learning rule. The trained network can be used to generalize for those inputs that are not included in the training set [3].
The first structural engineering applications of neural network go back only to the end of 1980s [4]. Since then, a wide range of applications has emerged.
These applications have shown the robustness of the neural network in solving complex mechanics and engineering problems and its promising future development. With a history traced to the early 1940s, and two periods of major increases in research activities in the early 1960s and after the mid-1980s, Artificial Neural Networks (ANN) have now evolved to be a mature branch in the computational science and engineering.[3] They have found numerous applications in science and engineering, from biological and medical sciences, to information technologies such as artificial intelligence, pattern recognition, signal processing. In the field of structural engineering, there have been a lot of attempts and researches making use of Neural Network (NN) to improve efficiency or to capture relations in complex analysis or design problems.
Hajela et al. 1991 [5] used Back propagation Neural Network (BPNN) to represent the force-displacement relationship in static structural analysis. Such models provided computational efficient capabilities for reanalysis and appeared to be well suited for application in numerical optimum design.
Adeli and Hung 1994 [6] developed an adaptive conjugate gradient learning algorithm for training a multilayer neural network and applied it to structural engineering. The problem of arbitrary trial and error selection of the learning and momentum ratios encountered in the momentum back propagation algorithm was circumvented in the new adaptive algorithm. Kany and Yoon 1994 [7] described the configuring and training of neural network for truss design application and explored the possible roles for neural network in structural

design problems. Zeng 1995 [8] mapped a structural analysis problem onto continuous Hopfield neural network by means of the connection weights represented by the coefficient of the stiffness matrix and the nodal loads of bar, beam and triangular elements as the inputs to the network.

Abdalla and Stavroulakis 1995 [9] applied neural network (NN) to represent experimental data to model the behavior of semi-rigid steel structure connections, which are related to some highly nonlinear effect such as local plasticization etc.

Mukherjee et al. 1996 [10] mapped the relationship between the slenderness ration, the modulus of elasticity and the buckling load for columns.

Arsian and Hajela 1997 [11] described an approach for a multilevel decomposition-based design optimization. This approach allowed for a more precise non-linear representation of the coupling as opposed to linear representation based on optimal problem parameter sensitivity. The effectiveness of the approach was demonstrated through the application to two structure optimization problems.

Hajela 1998 [12] has applied the binary states Hopfield neural network to the optimization of a truss structure. This optimization assignment was based on a particular member being assigned to a special position so as to reduce the overall shape distortion and minimize the member pre-loads. The value of the design variable was unity when the member is assigned to position *i* and zero otherwise. Lu 2000, [13] used a two layered back propagation neural network to predict the local and distortional behavior of cold-formed. Steel compression members.

After training, the generalization of the neural network was tested by patterns not included in the training patterns.

Artificial neural networks to predict the effect of thermal aging on the tensile properties of cast stainless steel.

(ANNs) are model-free estimators that perform robust multidimensional, nonlinear reactor mapping [6], the most commonly used ANN is the standard back propagation network in which every layer is linked or connected to the immediately previous layer.

The relationships between the parameters being modeled and the actual behavior of these variables in the real world must be correlated as precisely as possible. However, in most cases this is not possible, and several approximations and simplification are often made at various stages.

When dealing with sparse, noisy, or incomplete data [8].

In addition, conventional methods lack generalization, fail to incorporate statistical and systematic fluctuations, and in most cases are limited to finite state spaces.

Tensile property at our study is not a very difficult to model. Beside of a closely nonlinear.

Therefore a finite number of parameters that need to be accurately defined if such systems are to be properly characteristics.

In this paper , we give an over all describe to the characterization of the mechanical behavior after thermal aging , on the cast stainless steel depending on time or temperature , and also approach to material design in which the use of neural networks was one stage in a process that also made use of genetic algorithms to accurately predict and optimization.

Rearrange the data and classified on the groups depending on the time of aging with stresses for the different temperatures, and the temperature of aging with the stresses for all the aging time.

Separate the data and take an average to these groups.

The database that we used selected carefully so as to include all range of temperature and the time for all the cast stainless steel used in the (L.W.R) applications.

Two-hidden layer back propagation neural network has been used to predict the behavior. The effects of the Parameters, such as the number of nodes in the input layer, output layer and hidden layer, the pre-process (normalization) of the training patterns, the weight-factors initialization and the selection of the learning rate and momentum coefficient, on the behavior of the neural network have been checked.

Provide the (ANNs) with a three parameter as an input data (test temperature, aging temperatures, and aging time), on the same form we feed the neural network with the target representing by the yield and ultimate stresses.

After that we take a mean and standard deviation for all the input and the target output.

Experimental work:-

Tensile test were conducted at (ANL) and at the material engineering associates (MEA).The orientation and location of the mechanical test specimens from pipe sections, slabs, and KRB pump cover plate are shown in Fig. (1&2).[1]

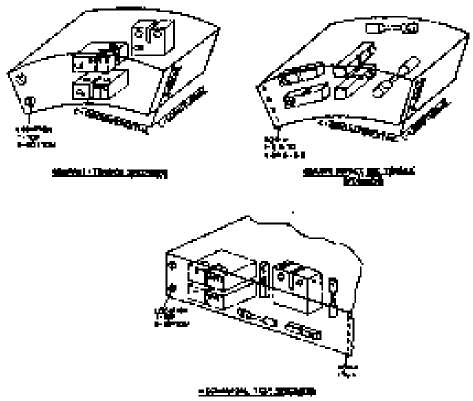

Figure (1). Orientation and location of the mechanical-test specimens taken from (a) and (b) pipe sections and (c) slabs Figure

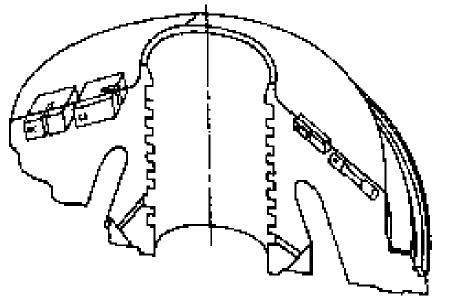

Figure (2). Orientation and location of the mechanical-test specimens taken from KRB pump cover plate

The specimen blanks from the experimental and commercial heats were aged at (290,320,350,400&450 C°) for times up to 58000 h , tensile test at ANL were performed according to ASTM specification E8 in an Instron tensile test machine with a maximum loading capacity of 90KN, cylindrical specimen with a diameter of 5 mm, and a gauge length of 20.3mm were used for all the tests [1] .

Tensile test were conducted at room temperature and 290 C°, on the five experimental heats (290-450 C°)up to 58000 h .The results from the tests used as a data to the neural networks .

Rearrange the data and classified on the groups depending on the time of aging and the temperature of aging with the stresses, and then separate the data and take an average to these groups.

The database used was selected carefully so as to include all range of temperatures and the time for cast stainless steel used in the (L.W.R.).

Provide the (ANNs) with a three parameters as input data Test temperatures, aging temperatures, and the aging time, on the same form feed the net with the target representing by the yield and ultimate stresses after that we take a mean and standard deviation for all the input and the target output.

NEURAL NETWORKS:

The neural networks used on this study include the standard back propagation network with one hidden layer, and with two hidden layer, as a result we depend on the two hidden layer net, because of this network provide a quick training to those that provide excellent generalization.

The advantages of more hidden layers are that different activation functions can be selected.

The important step was the design of the neural network, as we say above, we depend on the two hidden layer network, from these number of hidden we choose the best collection of node depending on the factor R [3 13 5 2].As shown in Fig.(3)

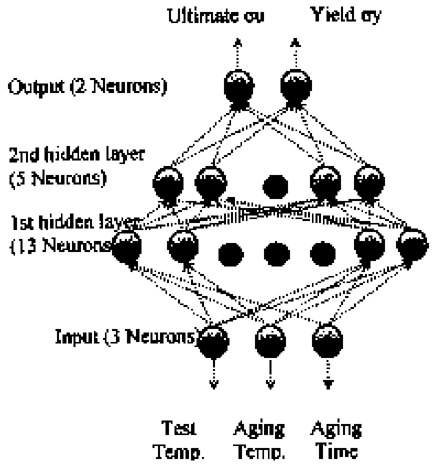

Fig. (3) The structure of the proposed NN model

The activation function used to create correlation between the input and the 1st hidden layer and between the 1st and 2nd hidden layers was a (tansig) function, and a (purelin) function between the hidden layer and the output.

There are an eight different activation functions were used, as below

$f(x) = \dfrac{1}{1+e^{-x}}$ (Standard logistic)

$f(x) = x$ (Linear)

$f(x) = \tanh(x)$ (Hyperbolic tanh)

$f(x) = \tanh(1.5x)$

$f(x) = \sin(x)$

$f(x) = \dfrac{2}{1+e^{-x}} - 1$ (Symmetric logistic)

$f(x) = e^{-x^2}$ (Gaussian)

$f(x) = 1 - e^{-x^2}$ (Gaussian compliment)

While the most commonly used activation is logistics, in many cases other function or combinations of functions are known to perform better.

On the training method, the most important criterion for successful network training and optimization is accurate generalization. Care must be taken to prevent the memorization of input data.

An evaluation set is created either from the training data or from a separate set of data with known output.

Then this will used to check the accuracy of the trained network. The process of selecting the final network, and the training optimization involved covers a number of steps. The correlation coefficient r^2 is a statistical indicator usually applied to multiple regression analysis. As shown in Fig. (4)

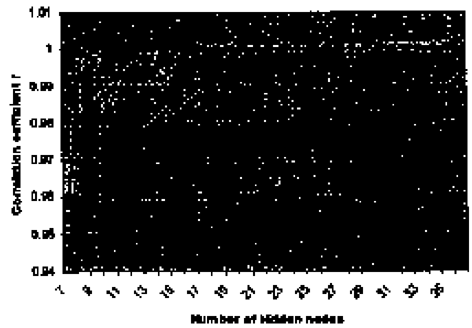

Fig. 4. Error plots for variation of number of hidden nodes in a double hidden layer back propagation neural network.

Figure (4) tended to flatten out after 15 nodes, suggestion some statistical fluctuation when using more than 15 nodes, this may indicate that the (near) optimum number of nodes for

accurately defining the given problem was reached.
If compares the accuracy of the model to the accuracy of a trivial bench mark model.
A perfect fit would result in R^2 value of one, a very poor fit less than zero.
In this study we depend on the (trainscg) as a training function and as a result get R^2=0.9738. As shown in Fig.(5)

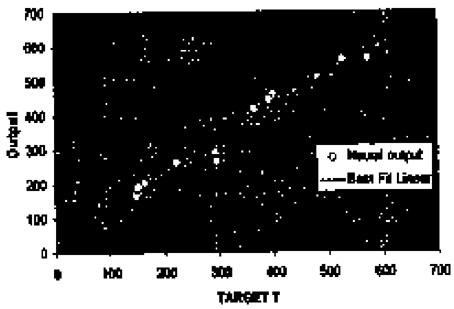

Fig.(5)Actual versus predicted output when final model is applied.

Take a 50 shows on the iteration steps, with 20000 epochs (epochs meaning the time to reach the target) to reach the goal which is equal to 1.e-6.
After choose and check our parameters the neural network do a simulation between the target and the network output and take a mean and standard deviation to the output.
Finally got a best line between the target and the neural network output.

RESULT&DISSCUSION:

There are several possible networks. In the end, one network with a given set of parameters must be selected to make prediction.
This involves a considerable a mount of training with all network types for all possible parameter value combinations.
Here select one network from a double network architecture that used for our final prediction, we select network that train quickly and provide acceptable results as compared to the best network found.
The result of tensile properties of cast stainless steel indicate that the increase in yield stress due to thermal aging in much lower than the increase in ultimate stress.
From the best (ANNs) found in this work to describe the effect of thermal aging on the cast stainless steel properties. We present a procedure and correlation for predicting the change in the tensile yield and ultimate stresses and engineering stress-strain curve of cast stainless steel components that due to thermal aging service in LWRs at 280-330C°.
The correlation describe in this paper may be used to assess thermal embitterment of cast stainless steel components.
The estimated tensile properties may be used as input to a structural analysis code. Such as leak before break, analysis of nuclear power plant piping or for performing fitness for service evaluations of safety related components. In support of plant life extension and license renewal.
As a result we have a clear describe to the effect of aging temperature (the application temperatures) on the different aging time at both the R.T.(25,290C°) as shown in Figs.(6 to 13) for all the aging time respected in this work the yield and ultimate stresses increase with increase the aging temperature, and this increasing be clear after the temperature 200C°, and for all these curves the ultimate increase more than the yield increase. Beside of these results there are a clear increase in the ultimate and yield stresses when the test occurs at a 290C° instead of at 25C°.
On the other hand, when we take the effect of the aging time for all the temperatures and at the room temperature dependence here, as shown in Figs. (14 to 19) we can find that the yield and ultimate stresses increase with

increasing the aging time for all aging temperature and this phenomena be clear after the (30000h) aging time until reaching the expected life (58000h) aging time.

After this time we still have an increase on the stresses for the temperature from (0-320 C°). At 320C° we have a decrease in the stresses when reaching the (60000h) in work.

This behavior be clear with increasing the aging time and aging temperature up to (60000h).

These results give a clear describe to the age of the cast stainless steel work in the LWR applications and the effect of the thermal aging on the stress and the ultimate of this type of steel.

Conclusions:

We show how neural networks can be successfully used to predict the properties of the cast stainless steel under a thermal aging condition.

We have that the structure-property relationships in cast stainless steel used in LWR can be captured effectively be neural networks.

In addition we can use networks to show the desired properties, and the fine range to the safety work.

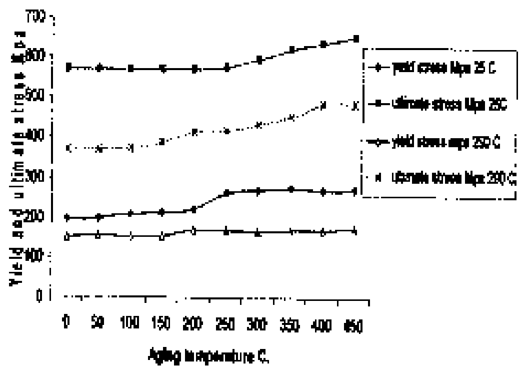

Fig. (6)Show the effect of the aging temperatures on the yield and ultimate stresses at the aging time t=10000 h. for the test temp.T=25C° &T=290C°

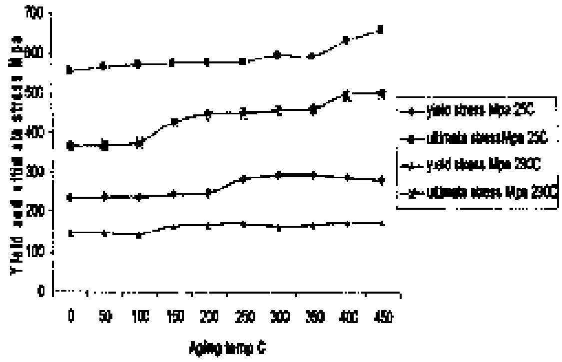

Fig.(7)Show the effect of the aging temperatures on the yield and ultimate stresses at the aging time t=2570 h.for the test temp.T=25C° &T=290C°

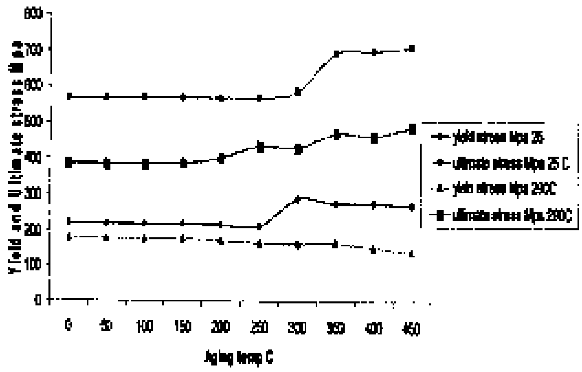

Fig.(8)Show the effect of the aging temperatures on the yield and ultimate stresses at the aging time t=30000 h.for the test temp.T=25C° &T=290C°

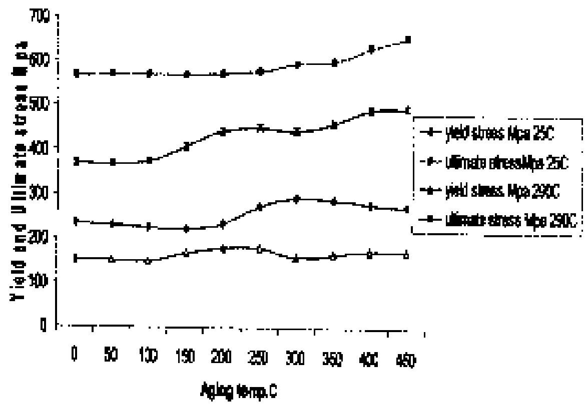

Fig.(9)Show the effect of the aging temperatures on the yield and ultimate stresses at the aging time t=5780 h.for the test temp.T=25C° &T=290C°

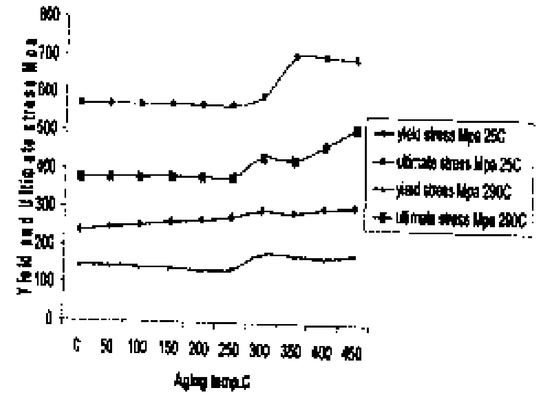

Fig.(10)Show the effect of the aging temperatures on the yield and ultimate stresses at the aging time t=55000 h. for the test temp.T=25C° &T=290C°

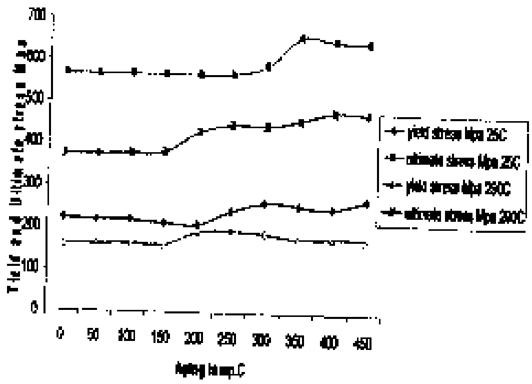

Fig.(11)Show the effect of the aging temperatures on the yield and ultimate stresses at the aging time t=18000 h.for the test temp.T=25C° &T=290C°

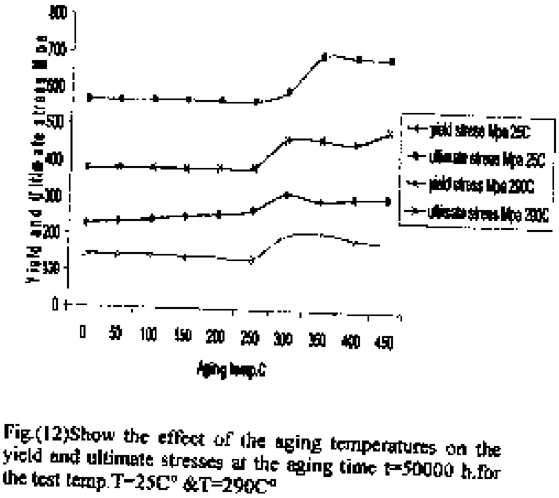

Fig.(12)Show the effect of the aging temperatures on the yield and ultimate stresses at the aging time t=50000 h.for the test temp.T=25C° &T=290C°

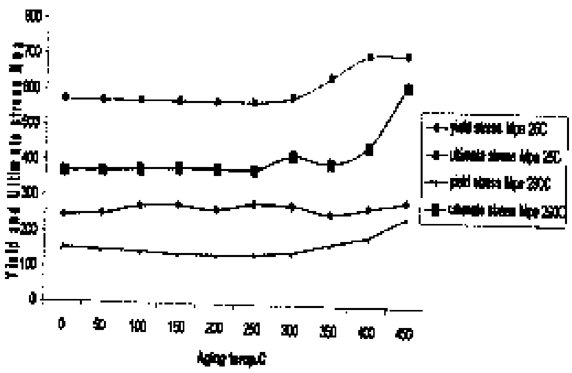

Fig.(13)Show the effect of the aging temperatures on the yield and ultimate stresses at the aging time t=68000 h.for the test temp.T=25C° &T=290C°

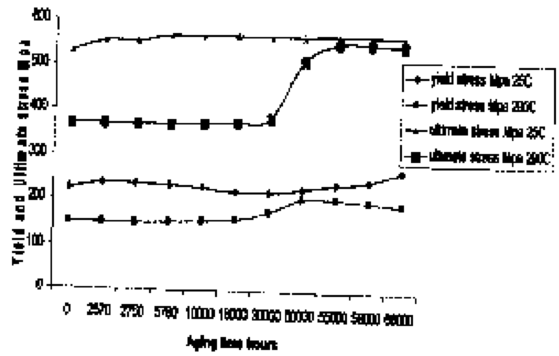

Fig.(14)show the effect of the aging time on the yield and ultimate stress on the aging temperature T=0 C° at the test temperature T= 25C° and T=290C°.

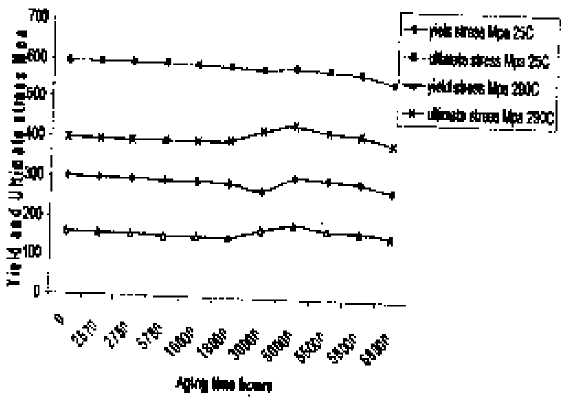

Fig.(15)show the effect of the aging time on the yield and ultimate stress on the aging temperature T=290 C° at the test temperature T= 25C° and T=290C°.

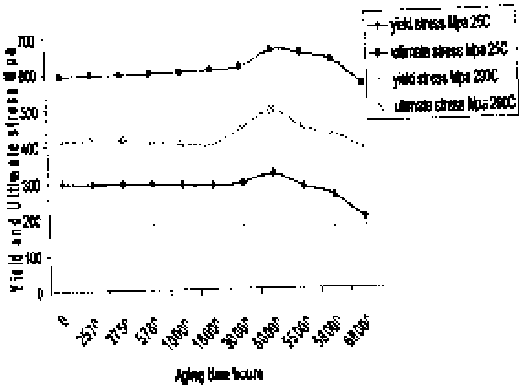

Fig (16)show the effect of the aging time on the yield and ultimate stress on the aging temperature T=320 C° at the test temperature T= 25C° and T=290C°.

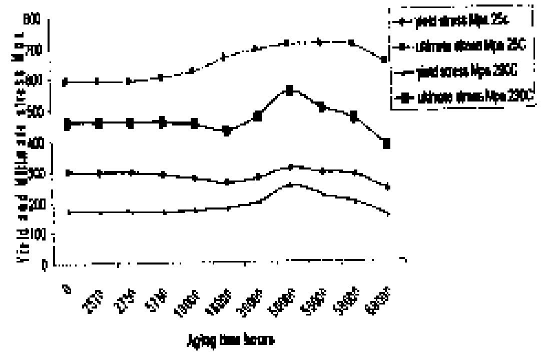

Fig.(17)show the effect of the aging time on the yield and ultimate stress on the aging temperature T=350 C° at the test temperature T= 25C° and T=290C°.

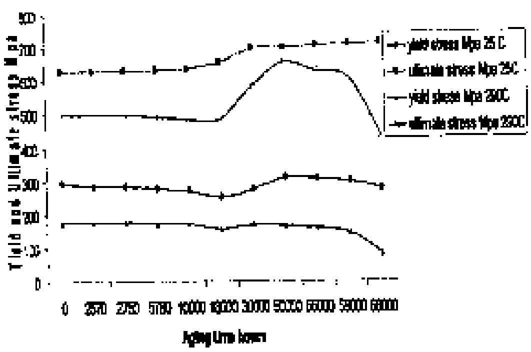

Fig.(18)show the effect of the aging time on the yield and ultimate stress on the aging temperature T=400 C° at the test temperature T= 25C° and T=290C°.

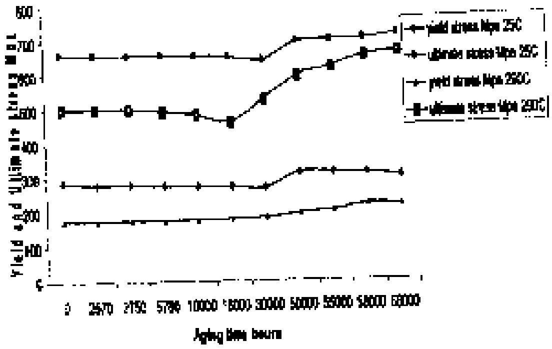

Fig.(19)show the effect of the aging time on the yield and ultimate stress on the aging temperature T=450 C° at the test temperature T= 25C° and T=290C°.

References:-

1-W.F. Michaud, P.T. Toben, W.K. Soppet, O.K. Chopra "Tensile-Property Characterization of Thermally Aged Cast Stainless Steels" U.S. Nuclear Regulatory Commission Office of Nuclear Regulatory Research Washington, DC 20555-0001 .pp(256) 1994.

2-O. K. Chopra and H. M. Chung, "Effect of Low–Temperature Aging on the Mechanical Properties of Cast Stainless Steels," in *Properties of Stainless Steels in Elevated–Temperature Service*, M. Prager, ed., MPC Vol. 26, PVP Vol. 132, ASME,
New York, pp. 79–105 (1988).

3-RAFIL MAHMOOD LAFTAH(M.Sc. Mech. Eng.)2007 Buckling Behavior of Stiffened Plate Panels Using Artificial Neural Network

4-O. K. Chopra, "Thermal Aging of Cast Stainless Steels: Mechanisms and Predictions," in *Fatigue, Degradation, and Fracture – 1990*, W. H. Bamford, C. Becht, S. Bhandari, J. D. Gilman, L. A. James, and M. Prager, eds., MPC

Vol. 30, PVP Vol. 195, ASME, New York, pp. 193-214 (1990)

5-Hajela et al, P. and Berke, L., "Neurobiological Computational Models in Structural Analysis and Design", Computers & Structures, Vol. 41, No. 4, pp. 657-667, (1991).

6-Adeli, H. and Hung, S.L., "An Adaptive Conjugate Gradient Learning Algorithm for Efficient Training of Neural Networks", Applied Mathematics and Computation, Vol.62, pp. 81-102, (1994).

7-Kang, H.T. and Yoon, C. J., "Neural Network Approaches to Aid Simple Truss Design Problems", Microcomputer in Civil Engineering, Vol. 9, pp. 211-218, (1994).

8-Zeng, P., "Artificial Neural Network Computing in Structural Engineering", Developments in Neural Network and Evolutionary Computing for Civil and Structural Engineering, Edinburgh, UK, pp. 37-50, (1995).

9-Abdalla, K. M. and Stavroulakis, G. E., "A Backpropagation Neural Network Model for Semi-Rigid Steel Connections", Microcomputers in Civil Engineering, Vol. 10, pp. 77-87, (1995).

10-Mukherjee, A. Deshpande, J.M. and Anmala, J., "Prediction of Buckling Load of Columns Using Artificial Neural Networks", Journal of Structural Engineering, Vol. 122, No. 11, pp.1385-1387, (1996).

11-Arsian, M.A. and Hajela, P., "Counterpropagation Neural Networks in Decompostion Based Optimal Design", Computers and Structures, Vol. 65, No. 5, pp. 641-650, (1997).

12-Hajela, P., "Neural Networks-Applications in Modeling and Design of Structural Systems", Neural Networks in Mechanics of Structures and Materials, Udine, October 19-23, (1998).

13-Lu, W., "Neural Network Model for Distortional Buckling Behaviour of Cold-Formed Steel Compression Members", Ph.D. Thesis, Helsinki University of Technology, (2000).

14-N. K. Roy, D. P. Landau, and W. D. Potter, "Polymer property prediction and optimization using neural networks ," IEEE transaction on neural network, Vol.17 ,No. 4 July 2006.

15-L. Rutkowski, "Generalized regression neural networks in time varying environment," *IEEE Trans. Neural Netw.*, vol. 15, no. 3, pp. 576–596, May 2004.