PREDICTING THE AXIAL LOAD CAPACITY OF STEEL COLUMNS IN FIRE USING ARTIFICIAL NEURAL NETWORKS

Dr. Ahmed Ajel [1], Dr. Hayder Mahdi [2], Dr. Luay M. Abass [3]
[1] Lecturer, Department of Structure and Water Resources Engineering, faculty of Engineering, Kufa University, Najaf, Iraq, ahmeda.almachtumi@uokufa.edu.iq.
[2] Lecturer, Department of Structure and Water Resources, faculty of Engineering, Kufa University, Najaf, Iraq, hayderm.almusawi@uokufa.edu.iq.
[3] Lecturer, Department of Structure and Water Resources Engineering, faculty of Engineering, Kufa University, Najaf, Iraq, luay.albothabhak@uokufa.edu.iq.
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ABSTRACT

The ability to reasonably predict the response of steel structures under fire effects is of great importance in structural fire safety design. This paper presents neural networks prediction of axial load capacity for steel columns in fire. An algorithm of back propagation neural network with the log-sigmoid activation function is adopted because of its precision and results enhancement of foretelling. The legitimacy of the technique is tried by contrasting and distributed test information on steel columns at surrounding and elevated heat. The examinations demonstrate such technique gives great correlation with test result. Parametric studies have been done to evaluate the impacts of cross sectional shape, slenderness ratios and eccentricity of loading on the carrying capacity of steel columns under fire. The slim sections of steel columns with slenderness ratio domain (100-140) react distinctively by showing an abundantly decreased rate of loss in strength within the temperature domain (20°C - 300°C). This domain diminishes further with expanding slenderness ratios, and for middle columns with slenderness ratio domain (40-80), is like that of stumpy columns however at decreased buckling stress. Be that as it may, in this scope of (L/R) ratios the lessening in stress with expanding temperature is regular and demonstrates no sudden drop, because of the collaboration amongst buckling and yielding. On other hand, the eccentricity of loading on the carrying capacity of steel columns under fire shows that the slender column, (slenderness ratio) greater than 120, the column demonstrates a diminishing impact of used eccentricity of loadings with expanding slenderness ratios. This might be as a consequence of more impelled thermal bowing that is straightforwardly relative to the column length. And the load-eccentricity characteristics of the intermediate column, (slenderness ratio) domain (20 – 60), are schemed at increasing temperature gradient. It is fascinating to observe that the eccentricity of the limit of maximum column load capacity slightly effected with temperature gradient. It is trusted that the important data gave in this work will be helpful in giving a superior comprehension on the genuine behavior of steel sections in fire and a great step in improving the method of design.

Keywords: steel column, axial load, Fire, artificial neural network, slenderness ratio, Mat lab software.

أستنباط قابلية التحمل المحورية للأعمدة الحديدية المعرضة للحريق بواسطة الشبكات العصبية الاصطناعية

(1) الدكتور أحمد عاجل علي /جامعة الكوفة /كلية الهندسة
(2) الدكتور حيدر مهدي عبد الجواد /جامعة الكوفة /كلية الهندسة
(3) الدكتور لؤي محمد عباس /جامعة الكوفة /كلية الهندسة

القدرة على التنبؤ بشكل معقول لسلوك المنشآت الحديدية تحت آثار الحرائق تعتبر ذات أهمية كبيرة في التصميم الإنشائي الآمن تجاه الحرائق. يعرض هذا البحث التنبؤ باستخدام تقنية الشبكات العصبية للحمولة المحورية للأعمدة الحديدية تحت تأثير الحريق. تم اعتماد خوارزمية الشبكة العصبية ذات التلقين العكسي للمعلومات مع دالة تنشيط (لوغاريتمية - سينية) بسبب أنها دقيقة وعززت الاقتراب من النتائج المتنبأ بها. ولتحقق من دقة الطريقة تم اختبار تقنية الشبكة العصبية بمقارنة نتائجها مع نتائج الفحوصات المختبرية والمعروضة لدى الباحثين سابقين والخاصة بالأعمدة الحديدية تحت تأثير درجات متغيرة وعالية. المقارنات بينت أن هذه الطريقة تعطي ارتباط جيد مع نتائج الفحوصات العملية. وقد أجريت دراسات على تغيير المدخلات المؤثرة على الأعمدة الحديدية لتقييم تأثير شكل المقطع العرضي , نسب النحافة وكذلك لامركزية التحميل على قابلية تحملها تحت تأثير الحريق. بينت الدراسة تأثير درجات الحرارة عل المقاطع النحيفة للأعمدة الحديدية والتي تمتلك معامل نحافة يتراوح ما بين (100- 140) والذي أظهر ردة فعل متميزة في خسارة القابلية في التحمل في نطاق درجات الحرارة ما بين (20 – 300) درجة مئوية وتستمر هذه الخسارة بالتزايد بشكل مضطرد بازدياد معامل النحافة للعمود, أما الاعمدة ذات المقاطع المتوسطة والتي تمتلك معامل نحافة ما بين (40- 80) تكون خساراتها واضحة في إجهادات الانبعاج وهي بذلك تمتلك خاصية عدم الفشل المفاجئ تحت تأثير زيادة درجة الحرارة ويرجع ذلك لخاصية التعاون في حفظ التوازن ما بين الانبعاج للعمود وخضوع مادة الحديد له. ومن الدراسة لتأثير عدم مركزية الاحمال أوضحت الدراسة التأثير المحدود لعدم مركزية الأحمال على العمود الحديدي والذي يملك (مقطع جيد) بمعامل نحافة يزيد عن 120 ويرجع ذلك الى الانتشار القسري للحرارة على طول ارتفاع العمود الحديدي وبذلك يهمش تأثيرها بشكل نسبي. أما بالنسبة للأعمدة الحديدية التي تمتلك مقاطع بنسبة نحافة ما بين (20- 60) فأن تأثير عدم مركزية الاحمال عليها يكون واضح وأكثر تطرفا. ومما تقدم فأن الباحثين يأملون أن هذه المعلومات المستنتجة في هذا البحث ربما ستكون مفيدة لتوفير فهم أفضل لسلوك الاعمدة تحت تأثير الحريق وكذلك خطوة مهمة في طريق تطوير طريقة التصميم.

1. INTRODUCTION

Research on the behavior of structures under fire conditions started in the late nineteenth century, motivated by setbacks of structures on account of fundamental breakdown brought on by fires. Starting now and into the foreseeable future, fire planning investigation has turned out to be reliably. In the midst of the latest decades fire building diagram has become in a general sense, and the execution of steel sections in fire hazardous conditions is one of the basic fields of moral and experimental study.
Because of the high cost of full-scale fire tests and size difficulties of existing heaters, and in addition to the impenetrability to fire test of a stack bearing segment is ordinarily limited these studies rely. Therefore, there are no possible results of evaluating the test results truly.
The late efforts have been made to modernize the outline procedure utilizing moral neural systems as they can gain from accessible tests amid preparing process .Artificial neural system is another innovation rose up to simulating of human brain and has been effectively connected in various fields of building. The results obtained from ANN analyses using the software, Mat lab are generally in reasonable agreement with experimental results.

2. THE BEHAVIOUR OF STEEL COLUMNS IN FIRE

Fire can be critical to the structural safety of the building. When a fire occurs in a building, the increase in temperature due to the fire can lead to a large reduction in strength and stiffness of the structural members. It can also result in large thermally induced forces and deformations in structural members. These effects can lead to collapse of buildings in fire. While there have been significant advances in the understanding of structural response to fire in recent years, there are still many aspects of structure-fire behavior that are not well understood and require further research.
In the case of a building fire elevated temperatures have two main effects on a steel structure: Steel suffers a loss of strength and stiffness with increasing temperatures and the almost linear elastic,

perfectly plastic stress-strain relationship of steel carbon material at surrounding temperature becomes distinctly nonlinear.

Global and local buckling of a steel column is induced by large deformations due to applied load to the element. The loss of stiffness and strength and the nonlinear stress strain relationship of carbon steel at elevated temperatures results in a much lower resistance of the steel section than at ambient temperature.

Experimental tests have given key data on structures under fire action and advances on computational assets have prompted the improvement of numerical strategies fit for reproducing their conduct. The work reported in this paper is intended to contribute to an improved perception of the response of steel columns to fire by using Neural Network Modeling.

3. NEURAL NETWORK MODELING BACKGROUND

Artificial Neural Networks (ANN) are widely used to approximate complex systems that are difficult to model using conventional modeling techniques such as mathematical modeling (Shahin et al. , 2001)[12], (Neural networks, 2004)[7] , (Ashour et al., 2004)[2]. They applied in several civil engineering problems structural, geotechnical, management etc. (Haytham ,2005)[6].

An ANN is a get together (system) of an extensive number of exceptionally associated preparing units, the alleged hubs or neurons. The neurons are associated by unidirectional correspondence channels (associations or connections). The quality of the associations between the neurons is spoken to by numerical qualities which typically are called weights. Information is put away as a gathering of weights. Every neuron has an initiation esteem that is a component of the whole of inputs got from different hubs through the weighted connections (Ashour et al., 2004) [2], (Kirkegaard et al., 1993) [7].

Additionally ANN can be characterized as a type of counterfeit consciousness, which by method for their engineering, endeavor to reenact the organic structure of the human brain and connected neuron units system (Shahin et al. , 2001) [12], (Shahin, et al., 2002) [13].

4. EXPERIMENTAL DATABASE

The experimental test information embraced in the present study relies on the database compiled by Pauli et al. (2012) [10] and Uppfeldt (2012) [14]. A sub-database comprising of a sum of 62 columns test was made out of the 118 experimental tests in the premier database; **Table 1** summarizes the properties of the selected sub-database. The accompanying criteria were utilized as a part of creating the sub-database utilized as a part of this study:

- The test column is a hollow steel section.
- The failure of the test column as reported is due to fire and axial force (by changing the steel section – slenderness ratio, surrounding temperature gradient, and effect of eccentricity of loading with thermal gradient) .
- The range of test temperature is (20 -764 °C).
- The slenderness ratio, L/r, between (7.5-74).

Table 2 summarizes the ranges of the parameters in the selected database.

5. NEURAL NETWORK DESIGN AND TRAINING

To train the ANN models, first, the full training data file is randomly split into testing and training data sets. The multilayer feed forward and back-propagation technique is used to develop and train the NN model of this study where the sigmoid transform function adopted.

A decent expectation for these cases is a definitive confirmation test for the ANN models. These tests must be connected for (input and output) reaction inside the domain of training phase. Preprocessing of data sets by scaling was completed to upgrade the preparation procedure of the neural system. At that point, to keep away from the slight velocity of learning close to the end

focuses particularly of the output range because of the property of the sigmoid capacity, in this manner, the input and output sets were scaled between the interims (0.1 to 0.9).
The back-propagation learning algorithm was employed for learning in the MATLAB program (Demuth, et al., 2006) [3]. Every train of the network comprised of one disregard the whole 82 training information sets. The 12 testing information sets were utilized to screen the training progress. Distinctive training capacities accessible in MATLAB system were tested for the present application.
The scaled conjugate gradient (SCG) techniques built in MATLAB ended up being proficient preparing capacity, and along these lines, was utilized to develop the neural network model. This preparation capacity is one of the conjugate gradient algorithms that begin preparing via seeking in the steepest drop bearing (negative of the gradient) on the primary cycle. The network architecture is acquired by recognizing the quantity of hidden layers and the quantity of neuron units in every hidden layer. The system learns by contrasting its yield for every example and an objective chose yield for that example, after that the procedure of computing the error and propagating an error work in reverse through the neural system is finished. To utilize the trained neural network, new values for the info parameters are displayed to the network. The network then ascertains the neuron yields utilizing the current weight values created in the preparation procedure.

6. ARCHITECTURE OF NN MODEL

Distinctive ANN architecture exists, the surely understood are (Rumelhart et al., 1986) [10], (Eberhart et al., 1990) [4]: Contestant learning NN, Boltzmann machine, Hop-field network, and Back propagation (multi-layered) network. The last sort obtains its denomination from the method it learns, by back-propagating the errors seen at the yield nodes (Abbes, 2006) [1].
A multilayered feed-forward NN with a back-propagation algorithm was embraced at present study. The ANN was developed using the popular MATLAB software package (Abbes, B., 2006) [1].
A regular case of back-propagating system of network architecture is appeared in **Figure. 2**, the preparing units are masterminded in multi - layers in this neural network model. Each NN model has an input layer, an output layer, and various hidden layers. The last register muddled relationship amongst examples, and the spread happens in a feed-forward manner, from the input layer to the output layer. Connected with every linkage between two neurons is a numerical quality W_{ij}, which speaks to the heaviness of that association (Ghaboussi et al., 1991) [5]: W_{ij} weight of association among units i and j. These ones weights are altered amid the preparation of the neural system in an iterative procedure. At the point when the iterative procedure has met, the accumulation of connected weights catches and stores the data present in the case utilized as a part of neural network training. To train the ANN models, at the beginning the whole experimental info document was isolated into training and testing information sets. The network model was constructed. The model has nine input parameters and one output parameter.
The reason behind this is to think about the criticalness of parameter on steel column capacity in fire. The models has two hidden layers with fifteen nodes each, and yield layer with single output neuron giving axial load capacity of steel column. Since the sigmoid function is utilized as exchange function, however the inputs and in addition the output result are scaled-down in the scope of (0.1–0.9). The meeting of the models in training depends on diminishing the error of resilience for mean squared (SSE) error amid the preparation cycles and observing the by and large the execution of the trained NNs by looking at the outputs. **Figure (5)** was illustrated the minimum error could be issued by selected architecture (10-15-15-1). The architecture of the developed ANN model and its properties are shown in **Table (3)**.

7. RESULTS AND DISCUSSION

The load-bearing capacity of tested columns relies on upon the mechanical properties of the material, the geometry of the cross-section and column effective length. The predictions of the selected ANN model as compared to the experimental values are illustrated in Figures 4-6 for the choosing training and testing data. The coefficient of correlation (R) was equaled to 0.998, and 0.997 for both training and testing data set, respectively. The accuracy of the predicted ANN values of the axial capacity for steel columns subjected to fire is shown in **Figures (7-10)** for the selected experimental series (S1, S2, S4, and S6); the comparison shows that the predicted ANN values and experiments are in good agreement.

8. PARAMETRIC STUDY

One of the upsides of neural network models is that parametric studies can be effectively done by just differing one information parameter and all other info parameters are set to consistent qualities. Through parametric studies, it can confirm the execution of model in reproducing the physical conduct of steel column under the impact of fire because of the variety in a specific parameter values. The impact of different parameters on load carrying capacity of columns under fire was investigated, such as column cross section and gross geometric slenderness ratios, and load eccentricity. Temperature is a major parameter influencing the structural action of a steel column in fire. The impact of the different column shapes at elevated and at ambient temperatures on the ultimate strength of column decrease of both strength and stiffness with increasing temperatures was analyzed.

8.1 Effect of Slenderness Ratio with Thermal Gradient

Figures (12-15) demonstrates the linkage between critical stress, σ_{cr}, and slenderness ratio for expanding temperature. The peak stress is non-dimensional with respect to normal temperature yield stress, σ_y.

- At 300 C° a comparative curve is acquired yet the critical stress is obviously diminished contrasted and the encompassing temperature situation. This diminishment is around 20% for slenderness ratios until 80 however get to be insignificant for slenderness ratios more noticeable than around 120.
- At temperatures (T > 200 C°) the curves own oneself frame however still the peak stress diminishes with expanding temperature because of mellowing of the material that is anticipated well by ANN model. For slenderness ratios greater than 120 there exists a decent estimation to the peak stress where loss of rigidity is obvious whereas in the least slenderness ratios district the loss of ferocity commands the behavior. Plainly for all slenderness ratios the impact of buckling is imperative.

The same data in **Figures (12-15)** given in **Figure (16-19)** as the non-dimensional ratio (σ_{cr} / σ_y) versus temperature. The cross-sectional capacity decreases with increasing cross-sectional slenderness ratios and serves as an upper boundary of the load-bearing capacity of a column. It is seen that to a great degree stumpy columns lose strength quality a tiny bit at a time as the temperature greater than 400° C. The lowering in the buckling stress gets the chance to be brisk as the temperature augments further.

- The reaction of middle columns, ($40 \geq L/R \leq 80$), is like that of stumpy columns however at decreased buckling stress. Be that as it may, in this scope of (L/R) ratios the lessening in stress with expanding temperature is regular and demonstrates no sudden drop, because of the collaboration amongst buckling and yielding.
- The slim sections of steel columns, ($100 \geq L/R \leq 140$), react distinctively by showing an abundantly decreased rate of loss in strength within the temperature domain (20°C ≤ T ≤ 300°C). This domain diminishes further with expanding slenderness ratios. The Euler buckling for slender column is obviously more critical, and the impact of material stiffness is in this way more purported.
- At temperatures greater than 300° C the axial bearing capacity starts to lessen all the more quickly.

The cross-sectional capacity decreases with increasing cross-sectional slenderness ratios and serves as an upper boundary of the load-bearing capacity of a column.

8.2 Effect of Eccentricity of Loading with Thermal Gradient

The relationship between thermal tendency and loading eccentricity is examined in this part for series 1. Temperature tendency tempts eccentricity as a consequence of the movement in the neutral axis and this connected with eccentricity of loading may have a few critical impacts on the conduct of a column in fire. Along these lines the purpose of utilization of the used eccentricity impacts its impact on the reaction of the columns.

For more slender column, $L/R \geq 120$, column demonstrates a diminishing impact of used eccentricity of loadings with expanding slenderness ratios. This might be as a consequence of more impelled thermal bowing that is straightforwardly relative to the column length.

The load-eccentricity characteristics of the intermediate column, $20 \leq L/R \geq 60$, are schemed at increasing temperature gradient. It is fascinating to observe that the eccentricity of the limit of maximum column load capacity slightly effected with temperature gradient.

9. CONCLUSIONS

In this study, the ANN model was developed to predict the axial load capacity of steel columns in fire. A back-propagation artificial neural network (BPANN) was used. The measured experimental rates are compared with the axial load capacity calculated from ANN model. A parametric study was carried out to explain the effects of various parameters on the behavior of axial load capacity of steel column. From this study it can be concluded the following:

- The ANN model is active and valid to simulate the behavior of axial load capacity of steel columns in fire, the ANN predictions are accurate provided that the input data are within the ranges used for training the NN.

- ANN algorithm is a powerful and economical apparatus for completing parametric study among a few parameters that influence physical marvel in engineering as showed for the instance of axial load capacity of steel columns in fire.
- From parametric study the thermal gradient, slenderness ratio and initial imperfection are the major factors effect on the axial load capacity of steel columns in fire.

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Table 1: Experimental Database

Specimen	Temperatures	B	H (mm)	t (mm)	L (mm)	Strain Rate	e mm	Fy (MPa)	Fu (MPa)	Ex10^3	Ultimate Load KN
Series 1,Pauli et al.(2012)											
SHS200_Stub_20C	20	200	200	5	600	0.1	0	355	510	210	1815
SHS200_Stub_20C	20	200	200	5	600	0.1	0	355	510	210	1658
SHS200_Stub_400C	400	200	200	5	600	0.1	0	355	510	210	969
SHS200_Stub_550C	550	200	200	5	600	0.1	0	355	510	210	687
SHS200_Stub_550Css	550	200	200	5	600	0.01	0	355	510	210	542
SHS200_Stub_700C	700	200	200	5	600	0.1	0	355	510	210	201
Series 2,Pauli et al.(2012)											
SHS100_Stub_20C	20	100	100	4	300	0.1	0	355	510	210	628

SHS100_Stub_400C	400	100	100	4	300	0.1	0	355	510	210	628
SHS100_Stub_550C	550	100	100	4	300	0.1	0	355	510	210	361
SHS100_Stub_550Css	550	100	100	4	300	0.01	0	355	510	210	286
SHS100_Stub_700C	700	100	100	4	300	0.1	0	355	510	210	103
SHS100_Stub_700Css	700	100	100	4	300	0.01	0	355	510	210	71
Series 3,Pauli et al.(2012)											
SHS100_SL_20C	20	100	100	4	1980	0.1	0	355	510	210	490
SHS100_SL_400C	400	100	100	4	1980	0.1	0	355	510	210	354
SHS100_SL_550C	550	100	100	4	1980	0.1	0	355	510	210	227
SHS100_SL_550Css	550	100	100	4	1980	0.01	0	355	510	210	215
SHS100_SL_700C	700	100	100	4	1980	0.1	0	355	510	210	77
Series 4,Pauli et al.(2012)											
SHS160_Stub_20C	20	160	160	5	480	0.1	0	355	510	210	1225
SHS160_Stub_400C	400	160	160	5	480	0.1	0	355	510	210	795
SHS160_Stub_550C	550	160	160	5	480	0.1	0	355	510	210	468
SHS160_Stub_550Cs	550	160	160	5	480	0.02	0	355	510	210	403
SHS160_Stub_550Css	550	160	160	5	480	0.01	0	355	510	210	364
SHS160_Stub_700C	700	160	160	5	480	0.1	0	355	510	210	138
SHS160_Stub_700Cs	700	160	160	5	480	0.02	0	355	510	210	88
Series 5,Pauli et al.(2012)											
SHS160_SL_20C	20	160	160	5	1840	0.1	0	355	510	210	1089
SHS160_SL_400C	400	160	160	5	1840	0.1	0	355	510	210	760
SHS160_SL_550C	550	160	160	5	1840	0.1	0	355	510	210	467
SHS160_SL_550Cs	550	160	160	5	1840	0.02	0	355	510	210	428
SHS160_SL_700C	700	160	160	5	1840	0.1	0	355	510	210	130
SHS160_SL_700Cs	700	160	160	5	1840	0.02	0	355	510	210	98
Series 6,Pauli et al.(2012)											
RHS120_Stub_20C	20	120	60	3.6	360	0.1	0	355	510	210	483
RHS120_Stub_20C_z10	20	120	60	3.6	360	0.1	10	355	510	210	356
RHS120_Stub_20C_z50	20	120	60	3.6	360	0.1	50	355	510	210	161
RHS120_Stub_400C	400	120	60	3.6	360	0.1	0	355	510	210	408
RHS120_Stub_400C_z10	400	120	60	3.6	360	0.1	10	355	510	210	280
RHS120_Stub_400C_z50	400	120	60	3.6	360	0.1	50	355	510	210	133
RHS120_Stub_550C	550	120	60	3.6	360	0.1	0	355	510	210	257
RHS120_Stub_550C_z10	550	120	60	3.6	360	0.1	10	355	510	210	205
RHS120_Stub_550C_z50	550	120	60	3.6	360	0.1	50	355	510	210	87
RHS120_Stub_700C	700	120	60	3.6	360	0.1	0	355	510	210	74
Series 7,Pauli et al.(2012)											
RHS120_M_550C_z0	550	120	60	3.6	850	0.1	0	355	510	210	226
RHS120_M_550C_z30	550	120	60	3.6	850	0.1	30	355	510	210	96
RHS120_SL_20C_z0	20	120	60	3.6	1840	0.1	0	355	510	210	348
RHS120_SL_20C_z10	20	120	60	3.6	1840	0.1	10	355	510	210	211
RHS120_SL_20C_z50	20	120	60	3.6	1840	0.1	50	355	510	210	102
RHS120_SL_400C_z0	400	120	60	3.6	1840	0.1	0	355	510	210	242
RHS120_SL_400C_z10	400	120	60	3.6	1840	0.1	10	355	510	210	139
RHS120_SL_400C_z50	400	120	60	3.6	1840	0.1	50	355	510	210	73
RHS120_SL_550C_z0	550	120	60	3.6	1840	0.1	0	355	510	210	186
RHS120_SL_550C_z10	550	120	60	3.6	1840	0.1	10	355	510	210	111
RHS120_SL_550C_z50	550	120	60	3.6	1840	0.1	50	355	510	210	49

RHS120_SL_700C_z0	700	120	60	3.6	1840	0.1	0	355	510	210	71
Series A, Uppfeldt (2012)											
A11	609	200	200	5	900	0.1	0	314	510	210	694
A12	685	200	200	5	900	0.1	0	314	510	210	567
A13	20	200	200	5	900	0.1	0	314	510	210	1129
A15	764	200	200	5	900	0.1	0	314	510	210	463
A16	20	200	200	5	900	0.1	0	314	510	210	1118
Series B, Uppfeldt (2012)											
B11	676	150	150	3	900	0.1	0	363	510	210	203
B13	20	150	150	3	900	0.1	0	363	510	210	398
B14	720	150	150	3	900	0.1	0	363	510	210	165
B15	588	150	150	3	900	0.1	0	363	510	210	248
B16	20	150	150	3	900	0.1	0	363	510	210	393

Table 2: Range of Input Parameters in Database

Input parameter	Ranges	
	Minimum	Maximum
Temperatures, °C	20	764
B, mm	100	200
H, mm	60	200
t, mm	3	5
L, mm	300	1980
Strain Rate	0.01	0.1
e, mm	0	50
Fu, MPa	314	363

Table 3: Architecture of the developed model and its properties

ANN Used Model	
Training algorithm used	Back probation algorithm
Architecture	10-15-15-1
Performance function in terms of SSE	0.01
Learning Algorithm	Learn gdm
Activation Function	Logsig- Logsig-purelin
Number of epochs required for training	5000

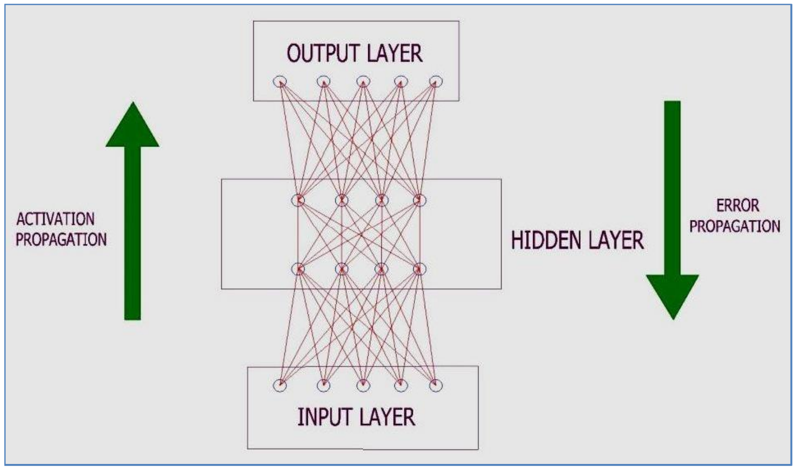


Figure 1: Back-propagation technique of neural network.

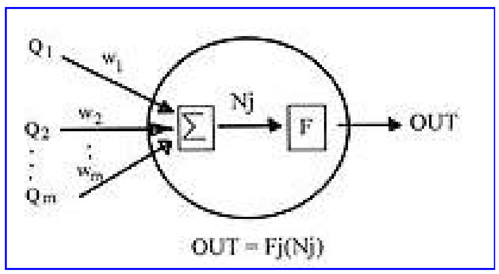


Figure 2: The schematic representation of network processing within an artificial neuron.

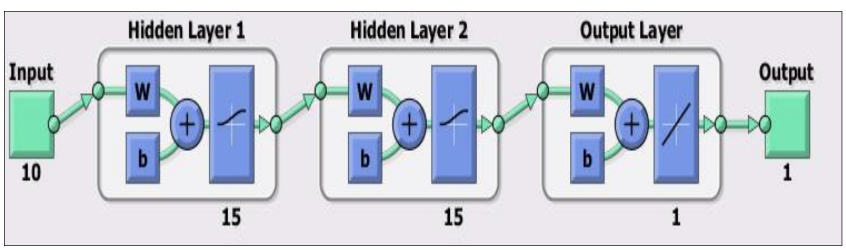


Figure 3: ANN Architecture.

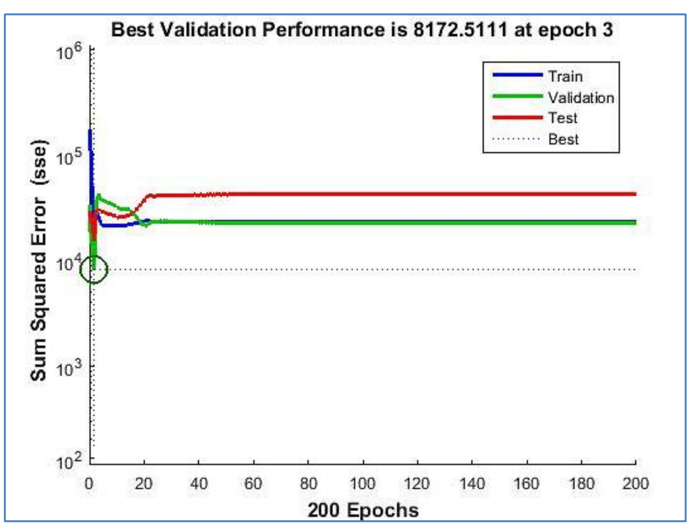
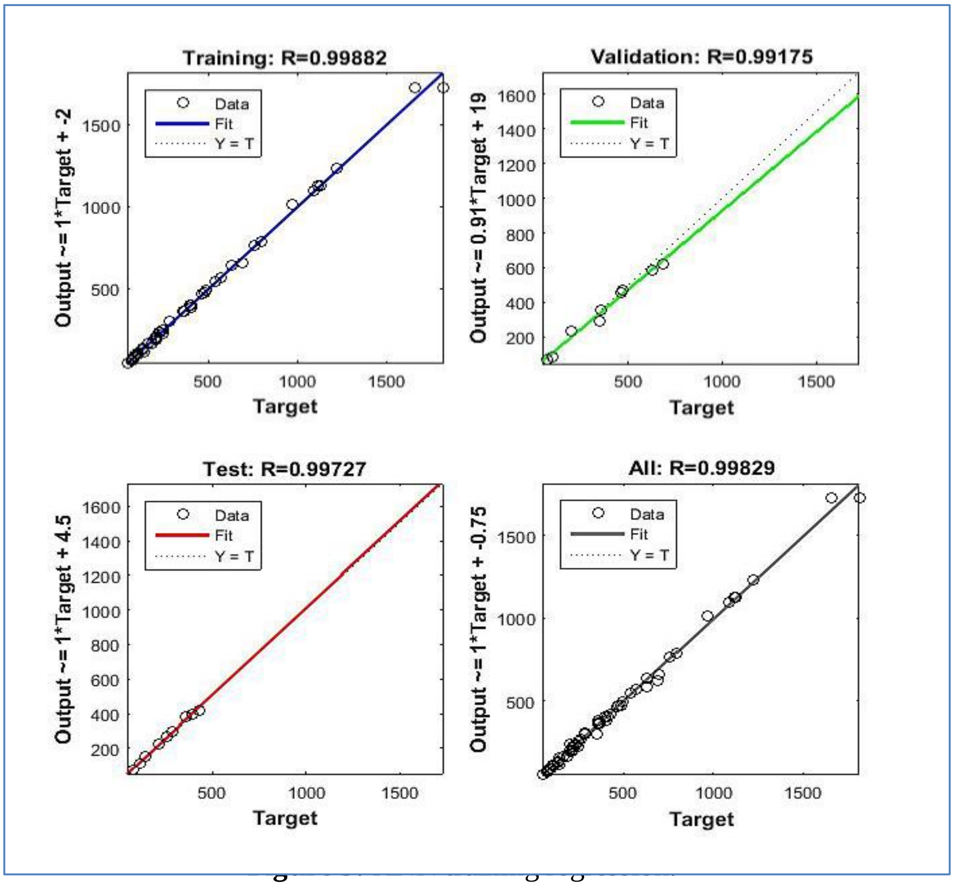


Figure 4: ANN training performance.



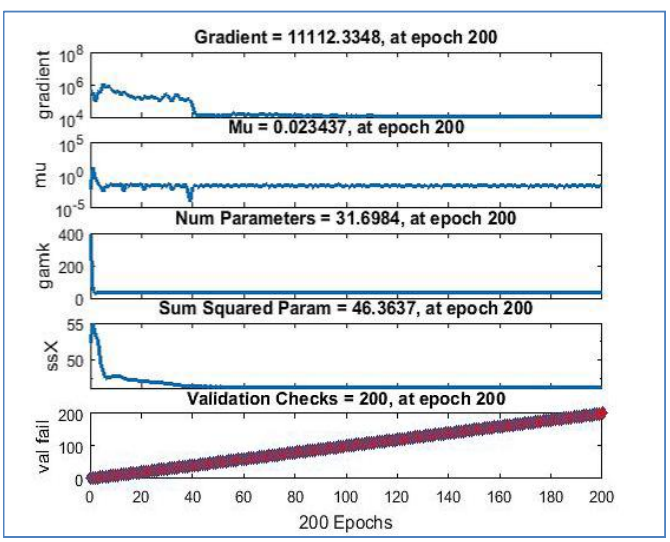


Figure 6: ANN training states.

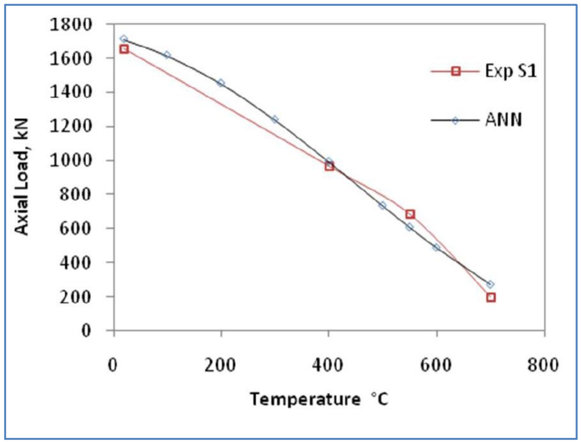


Figure 7: Comparison of results from ANN-model and experiments for series S1.

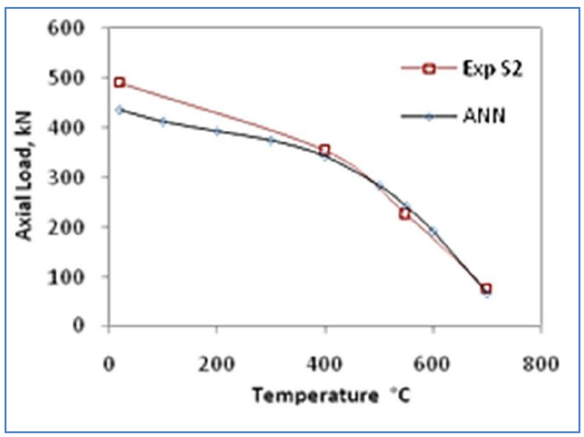


Figure 8: Comparison of results from ANN-model and experiments for series S2.

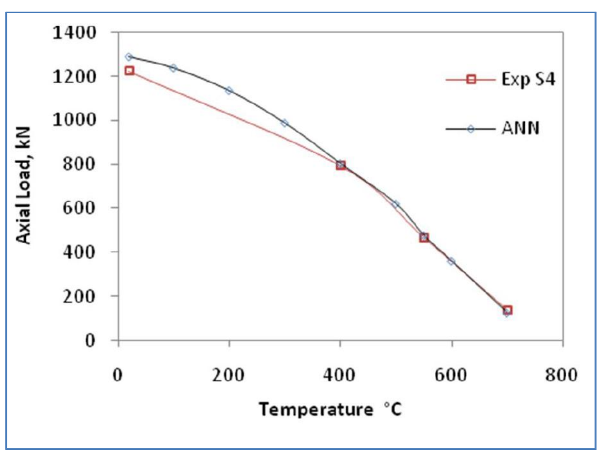


Figure 9: Comparison of results from ANN-model and experiments for series S4.

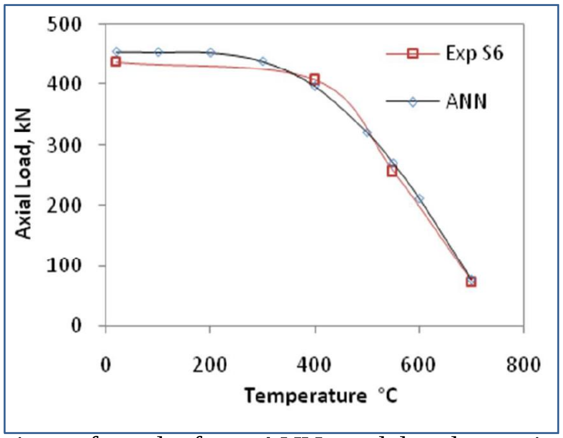


Figure 10: Comparison of results from ANN-model and experiments for series S6.

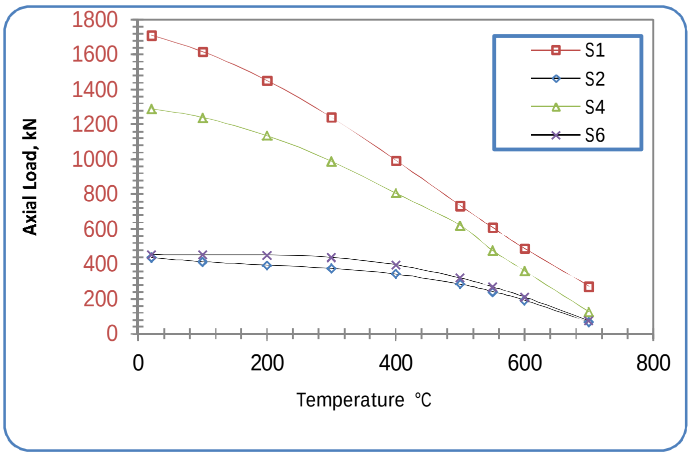


Figure 11: ANN-model results for series (S1, S2, S4, and S6) at different temperature.

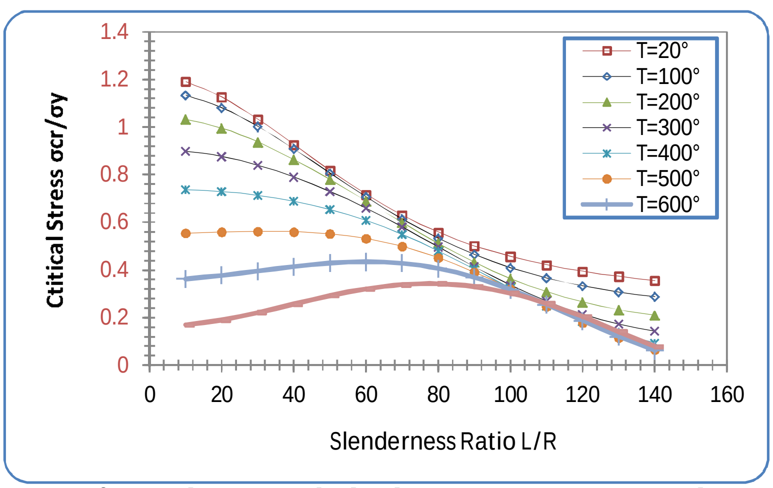


Figure 12: Variation of critical stress with slenderness ration at increased temperature for series 1.

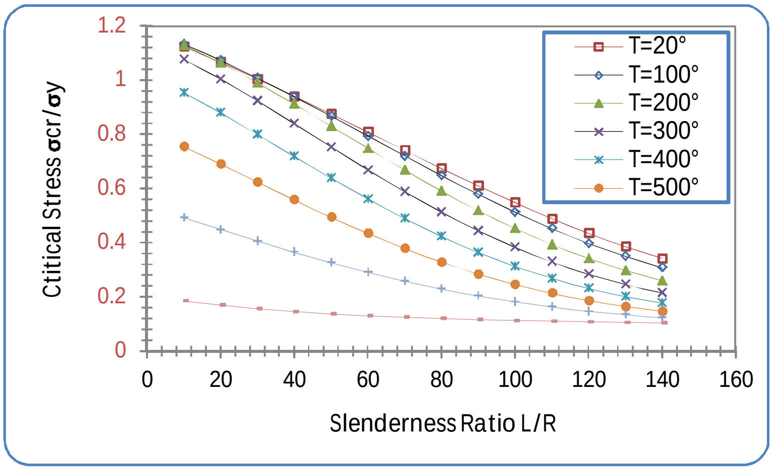


Figure 13: Variation of critical stress with slenderness ration at increased temperature for series 2.

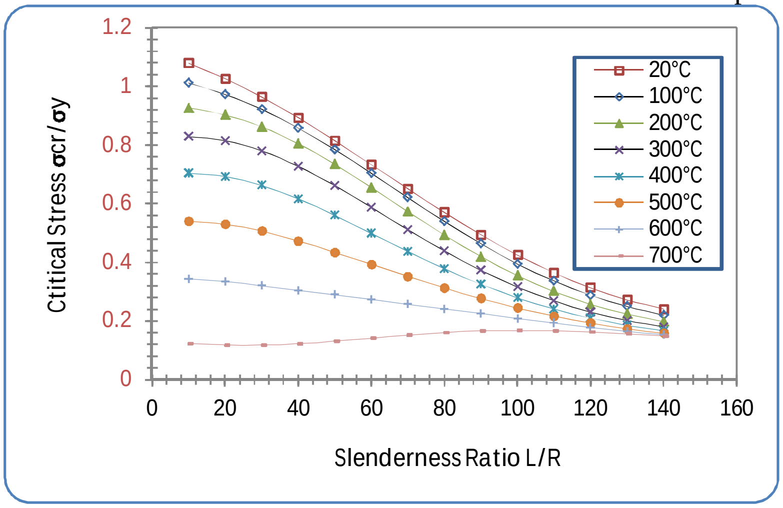


Figure 14: Variation of critical stress with slenderness ration at increased temperature for series 4.

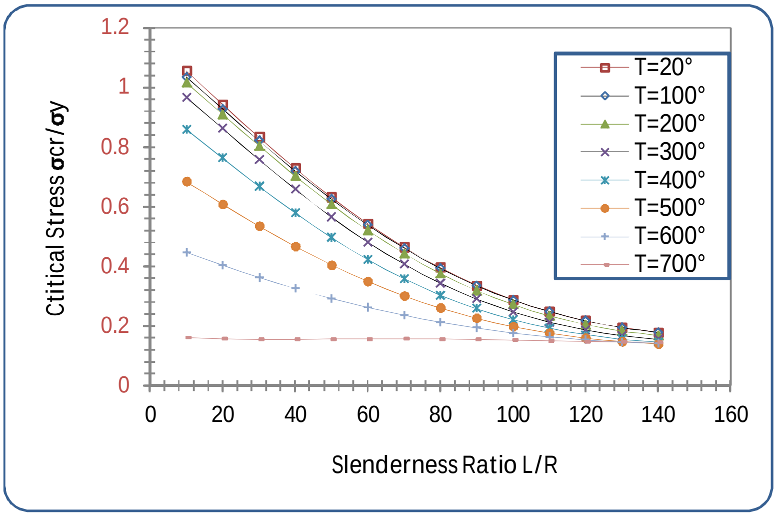


Figure 15: Variation of critical stress with slenderness ration at increased temperature for series 6.

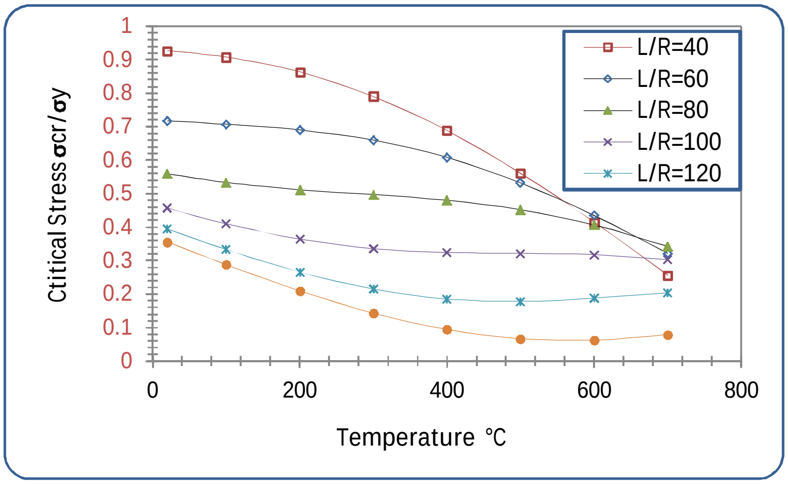


Figure 16: Variation of critical stress with temperature for series 1.

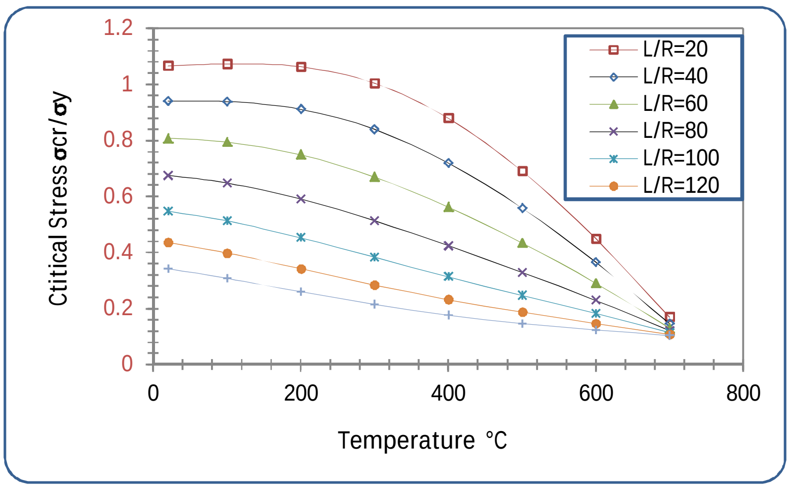


Figure 17: Variation of critical stress with temperature for series 2.

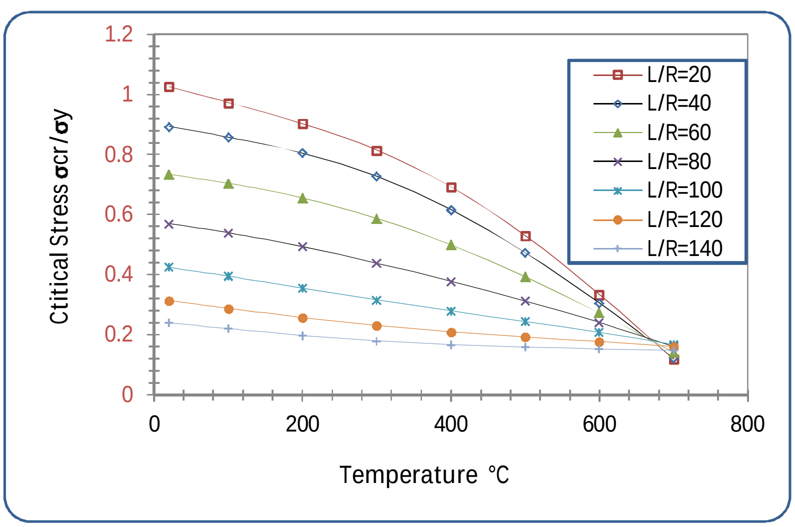


Figure 18: Variation of critical stress with temperature for series 4.

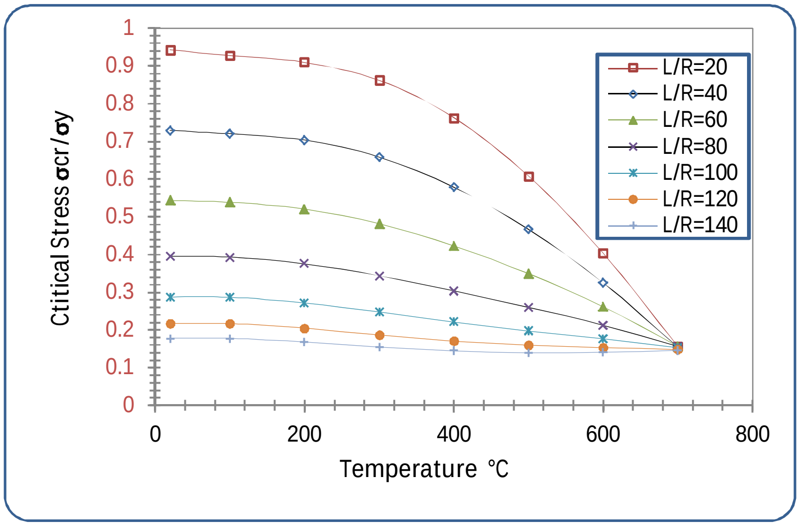


Figure 19: Variation of critical stress with temperature for series 6.