

# Predicting the mechanical behavior of steel frames exposed to elevated temperatures using artificial neural networks

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**Abstract:** - The structural behavior fire-resistant steel is essential; fire-resistant steel is proven to have higher strength at elevated temperature than that of conventional steel. Also, the requirement of fire protection in the fire-resisting steel can be relaxed as compared with conventional steel structures. However, the design criteria for the application of the fire-resisting steel in steel columns are still limited. Experimental approach into the analysis of fire-resistant steel frames is costly and expensive. Such analyses aim at evaluating the variations of the ultimate strength of steel frames due to the reduction effects on strength resulting in the increasing temperature. An alternative approach to model the mechanical behaviour of steel frames when exposed to fire at high temperatures is presented in this work. The concept is based on a series of stress-strain curves obtained experimentally at various temperature levels. An artificial neural network (ANN) is employed to predict the stress-strain curve under such condition. The numerical results obtained from ANNs of stress levels for the material were compared with the experimental data. A New model for reduction factor is introduced and compared with other models. Using ANN was found to be an efficient tool for modelling the material properties of steel frames for high temperature applications.

**Key-Words:** - Material models, artificial neural networks, fire-resistant steel, fire load, stress strain curves, strength of materials, elevated temperature.

## 1 Introduction

It is well known that the strength of engineering materials decrease with the increase of their temperature. Steel, which is incombustible, can absorb a significant amount of thermal energy when exposed to elevated temperatures such in the case of a fire. It will, nevertheless, recover its strength after cooling to ambient temperature. The behaviour of steel at high temperatures, as when subjected to a fire, is of a prime concern to many researchers and a vast number of researchers investigated this particular subject in great depth particularly Fire Resistance Steel (FRS).

Fire resistance steel (FRS) means steels that are basically thermo-mechanically treated (TMT) to perform much better structurally under fire than the ordinary steel and these type of steels have the ferrite-pearlite microstructure

of ordinary structural steels but the presence of Molybdenum and Chromium stabilizes the microstructure. And the fire rating of steel are expressed in units of time 1/2, 1,2,3,4 hours etc. Fire testing methods performance of any system varies depending on the heating consideration to which it is exposed.

Experimental evaluation of mechanical properties of FRS, namely ultimate strength, usually requires complex experimental work, experts and special equipment. It also requires extensive experimental setup which would be time consuming and will result is high costs [1].

## 2 Artificial Neural Networks

In the past few years, ANNs have been extensively used for many different industrial applications such as control, prediction, pattern

recognition, classification, material modelling, speech and vision. ANNs have been trained to solve nonlinear and complex problems that are not exactly modelled mathematically [2].

ANNs eliminate the limitations of the classical approaches by extracting the desired information using the input data [3]. Applying ANN to a system needs sufficient input and output data instead of a mathematical equation. Furthermore, it can continuously re-train for new data during in operation, thus it can adapt to changing of the system. Another merit of ANNs is that it can be used to deal with the complications related to incomplete and loose input data [4,5].

This study aims at evaluating stress-strain curves depending on ANNs by using experimental data from a previous research work [6]. Furthermore, this work evaluates the variation between experimental data and the resulted data from ANNs, and shows the importance of ANNs to verify the experimental data and the accuracy of the results.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. An ANN can be configured for a specific application, such as pattern recognition or data classification, through a learning process. Two phases in all NN application exist: the phase of learning or training and the phase of test. Once trained the model with the type of selected learning, the phase of test is followed, in which the representative features of the inputs, called training patterns, are processed. After calculated the weights of the network, the values of the last layer neurons, they are compared with the wished output to state the suitability of the design [7]. ANNs have different layers, interconnected through a complex network. A typical feedforward ANN is depicted in Fig. 1, with  $m$  inputs and  $p$  outputs, and each circle representing a single neuron. The name feedforward implies that the flow is one way and there are not feedback paths between neurons. The output of each neuron from one layer is an input to each neuron of the next layer [8].

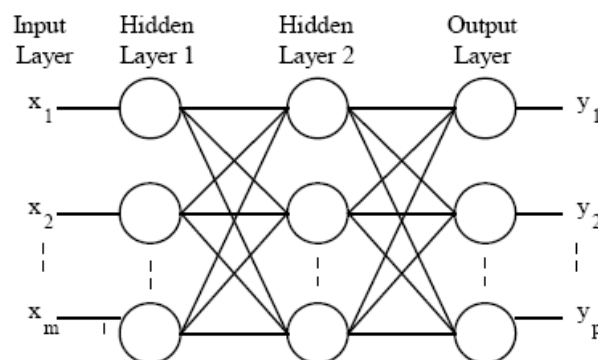


Figure 1: A typical ANN structure

In order to select a good Neural Network configuration, there are several factors to take into consideration. The major points of interest regarding the ANN topology selection are related to (1) network design, (2) training and (3) some practical considerations. A Multilayer Perceptron (MLP) was used in this work.

An MLP is a network of simple neurons called perceptrons. The basic concept of a single perceptron was introduced by Rosenblatt in 1958 [15]. The perceptron computes a single output from multiple real-valued inputs by forming a linear combination according to its input weights and then possibly putting the output through some nonlinear activation function. 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 pattern classification. MLP can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems. The most NN applications involve MLPs [7].

### 3 Fire resistance Steel Investigations

Steel properties at elevated temperature were the focus of a number of research studies particularly experimentally [6, 9, 10, and 11]. The effect of width-thickness ratios, slenderness ratio and residual stress on the performance of fire-resistant steel was investigated [6] for a series of fire resistance steel columns loaded to their ultimate stress at specified temperature. In the same work, researcher evaluated the variations of the ultimate strength of steel columns due to different width-to-thickness

ratios under specific elevated temperature and investigated the reduction effects on column strength resulting in increasing temperature and finally established design guidelines of steel columns using fire resisting steel.

An investigation into the deterioration of mechanical properties of light gauge cold-formed steels, tensile test coupon tests was carried out [9] to determine the mechanical properties of these steels made of both low- and high-strength steels and thicknesses of 0.6, 0.8 and 0.95 mm at temperatures ranging from 20 to 800 °C. It was reported that the currently available reduction factors are unsafe in the fire safety design of cold-formed steel structures [9].

A few researchers employed the ANN modelling technique to predict the mechanical properties in various applications [10] an Artificial Neural Network (ANN) was used to analysis steel frames subjected to fire in plastic range. The study was based on a series of stress strain curve obtained experimentally for various temperature levels. This study was carried out for steel of strength 35.5 kN/cm<sup>2</sup> and heating rate 10°C/min. Input data to the ANN was strain and temperature. Stress was output. A non-linear analysis of steel frames subjected to fire was presented but the resulted were limited to a steel strength of 35.5 kN/cm<sup>2</sup> and heating rate of 10 °C/min.

Another research work considered the effect of changing heating rate on parameters characterizing steel behaviour under fire [11]. Two structural steel grades were used for the study. Heating rate and stress level were used for the input, while deformations versus time relation and strength profiles were output. Metallographic analysis was carried out to analyse data after strength tests.

A neural network model to predict mechanical properties of dual phase steel at high temperature was developed in a different research work [12]. Martensitic morphology, marten site volume fraction range of deformation temperature and pre-strain percentage as input data. Yield strength and tensile strength were the output.

The effectiveness of three back-propagation artificial neural network models that predict the

impact toughness of quenched and tempered pressure vessel steel exposed to multiple post weld heat treatment cycles was reported [6], the hardness of simulated heat affected zone in pipeline and tap fitting steels after in-service welding and the hot ductility and hot strength of various micro-alloyed steels over the temperature range for strand or slab straightening in continuous casting process. Predicted and actual values of each model were well matched.

#### 4 Material Model

The material model was constructed by an artificial neural network (ANN) on the basis of experimental data [6]. The structural behavior of stub columns using fire-resistant steel has been investigated experimentally under uniform fire load where fire-resistant steel was proven to have higher strength at elevated temperature than that of conventional steel. The main purpose of the reported experimental studies was to evaluate the variations of the ultimate strength of steel columns due to different width-to-thickness ratios under specified elevated temperature; in addition, to investigate the reduction effects on column strength resulting in the increasing temperature; and finally, to establish the design guidelines of steel columns using fire-resisting steel [6].

Several types of ANN geometries exist. A review of different ANNs is widely available and given in the literature [10,11 from ref 3]. The multi-layer feed-forward network is usually chosen if a functional approximation is sought. Since it is our aim to approximate the strain–stress relation, the multilayer feed-forward network trained by supervised learning was chosen in this work.

In this work, the designed neural network is meant to estimate stress ( $\sigma$ ) while strain ( $\epsilon$ ) and temperature  $T$  were used as input data. A total of 320 input output pairs were used. Those were divided into three sets: training, validation and testing sets.

A neural network has to be configured such that the application of a set of inputs produces (either 'direct' or via a relaxation process) the desired set of outputs. Various methods to set the strengths of the connections exist. One way

is to set the weights explicitly, using a priori knowledge. Another way is to 'train' the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule [13]. Supervised learning or Associative learning in which the network is trained by providing it with input and matching output patterns. These input-output pairs can be provided by an external teacher, or by the system which contains the neural network (self-supervised).

Unsupervised learning or Self-organisation in which an (output) unit is trained to respond to clusters of pattern within the input. In this paradigm the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather the system must develop its own representation of the input stimuli. Last method of training is the Reinforcement Learning. This type of learning may be considered as an intermediate form of the above two types of learning. Here the learning machine does some action on the environment and gets a feedback response from the environment. The learning system grades its action good (rewarding) or bad (punishable) based on the environmental response and accordingly adjusts its parameters. Generally, parameter adjustment is continued until an equilibrium state occurs, following which there will be no more changes in its parameters. The self-organizing neural learning may be categorized under this type of learning.

The validation set is used after the neural network has been training to assess the performance of the trained neural network. The validation set is similar to the training set but not equal. Many practitioners of Neural Networks forget to validate the trained neural network using the validation set. A mistake which can be made with artificial neural networks is to use the validation data set for training. The network would learn for the training data and incorporate it into its strategy to achieve perfect accuracy. However, with a different data set the network may not perform well at all, even if they are similar. More

problematic is that there would be no way of telling whether the network is performing well.

The purpose of these two sets (the training set and the validation set) is to assess how well the neural network will behave with other sets during simulation. As a general rule, the training set must include all different training cases. This will guarantee that the neural network will behave similar with the validation set and the training set. In some real life problems, however, it is not possible to include all cases in the training sets.

To assess the quality of the behavior of an artificial neural network the mean squared error (MSE) is typically used for comparison purposes. It is computed between the actual network output and the desired output (also known as target). Typically, the number of hidden neurons can be increased to reduce the MSE. However, this must be done with caution as over-fitting may occur. It is very easy to commit over-fitting, as many tools to simulate neural networks do not caution the user when this happens. If the MSE obtained during training is much smaller than the MSE obtained during validation, over-fitting has been for sure committed; in this case the training and the neural network are useless.

The neural network performance is tested with a testing set which is not part of the training set. The testing set can be seen as the representative cases of the general phenomenon, stress-strain data in this research. If the network performs well on the testing set, it can be expected to perform well on the general case, as well. Cross-validation methods can also be used to avoid overlearning. In cross-validation, we switch the places of the training set and the testing set and compare the performance of the resulting networks.

Based on the previous understanding of the training, testing and validation sets, different sizes of learning and testing sets were attempted.

As a final conclusion of those attempts, 65% (240) pairs were used for training, 20% (64) for validation, and 5% (16) for testing. Table 1 shows sample inputs and targets used throughout the modelling process.

Many calculations with different geometries of neural networks were carried out. The final solution was calculated with the geometry 2-1-20-1 which means there was one hidden layer that included (20) neurons as shown in Fig. 2.

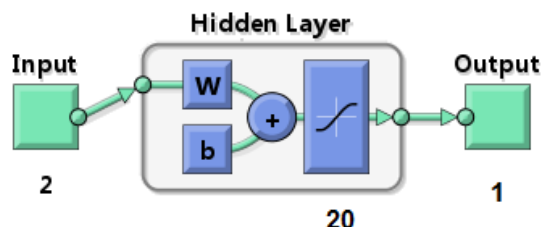


Figure 2: Neural Network geometry

The material model, later used in the mechanical analysis, was constructed by the ANN on the basis of experimental data [6]. The neural network was meant to estimate stress, while strain and temperature were used as input data. The calculation was carried out for steel. Different sizes of learning and testing sets were tried; however the results did not differ considerably.

The relative error allowed was set to 0.05, which is a relatively low value in an ANN training procedure. Many calculations with different geometries of neural networks were carried out.

The efficiency of the learning procedure was explored where actual and calculated values belonging to the testing set are compared. In this case, the coefficient of correlation was very high:  $R = 0.99974$ . The training performance is illustrated in Fig. 3.

A feed-forward procedure was used to train the algorithm. The strain and temperature were used as inputs; stress was the output of neural network model.

The consensus between the calculated values obtained by the ANN and the experimental ones is very good along the entire stress-strain curve for all temperature levels.

However, some difficulties appear within the course of modelling the properties of steel at elevated temperatures by the ANN. Values of the yield points of particular stress-strain curves were under predicted because of the shape of the stress-strain curve itself and since those points are not explicitly defined by the

curve shape. This problem was overcome by manually evaluating those points using a slope method using the experimentally obtained stress-strain relations. Furthermore, due to the regressions used in the ANN, the approximations for the stress-strain relations below the yield limit exhibited a certain deviations from a linear shape, which has also been reported in an earlier research work [10].

Knowing that an ideal linear relationship exists between stress and strain below this yield region, a linear regression based on actual experimental data has been used to cover this range. This is a valid approach for most metals and where the behaviour is governed by Hooks law. The approach used in this work can predict data for up to 2% strain (which is the range of experimental data). Predictions beyond this level of strain cannot be validated due to the lack of experimental data. However, strain hardening approach can be used with reasonable precision to extend the existing predictions beyond the availability of experimental data. Predictions obtained for the various temperatures ( $T = 20\text{ }^{\circ}\text{C}$  to  $700\text{ }^{\circ}\text{C}$ ) are shown in Figs. 4a-h. The figures show the “raw” ANN predictions which somewhat underestimate or overestimate the experimental data. The differences are quite minimal and one can remain confident that the accuracy of predictions is quite acceptable. Fig. 5 shows the final ANN results for the whole temperature range used in this study.

The predictions in their current form (strain-versus stress) are very useful. However, researchers in the related fields (i.e. structures) would be more interested in using a strength reduction factor rather than raw data.

## 5 Reduction Factor

All researchers interested in studying material properties at high temperature deal with a term called reduction factor ( $K_d$ ). Reduction factor denotes the ratio between the value of a property at interested temperature to the value of this property at room temperature, this term gives a good understanding on the effect of elevated temperature on the material properties.

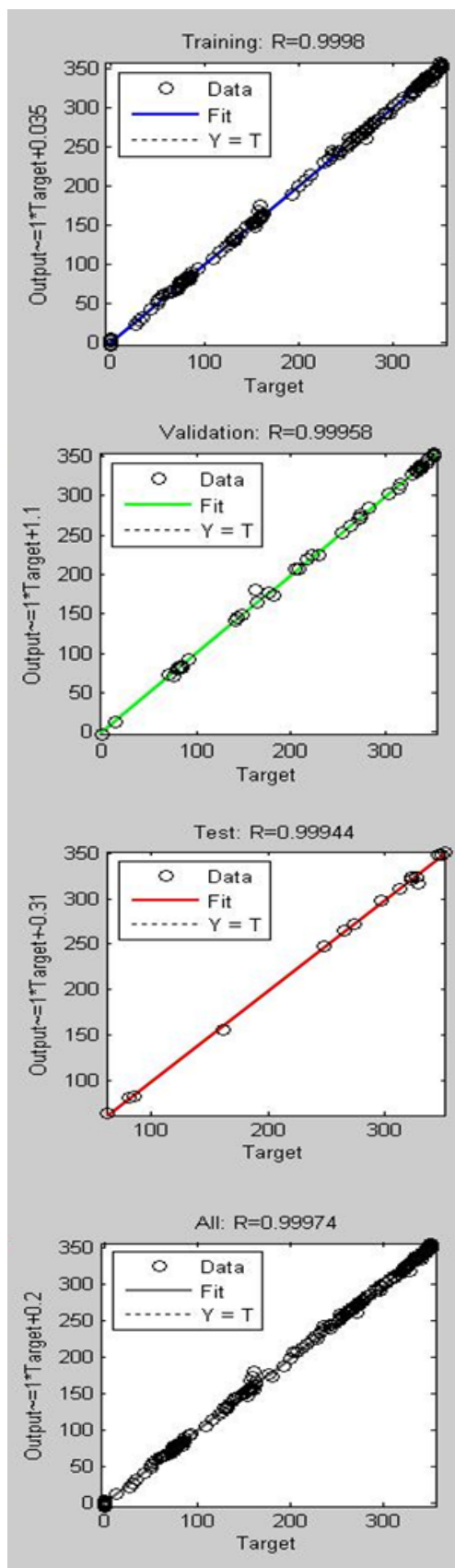


Figure 3: ANN training performance

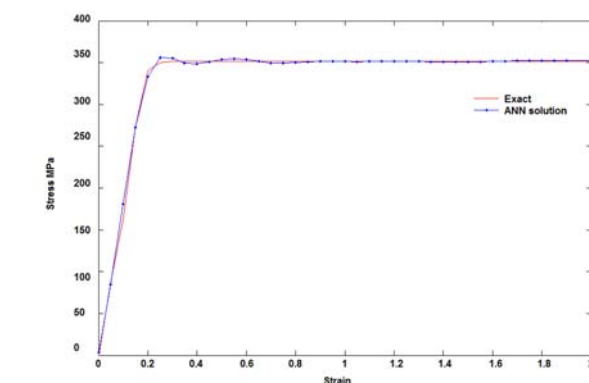
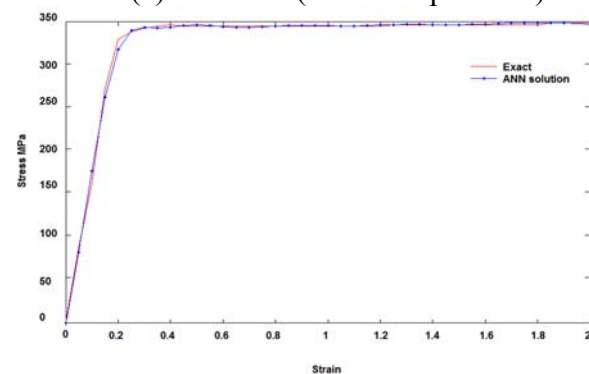
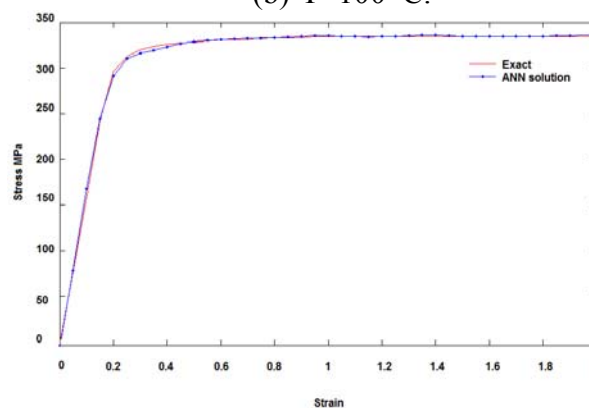
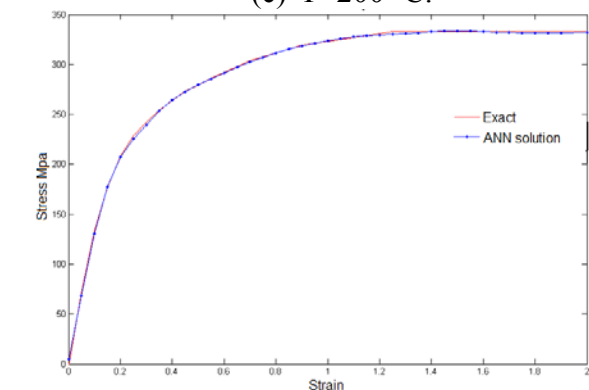
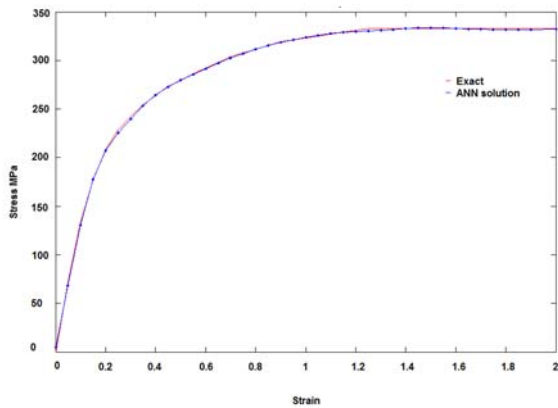
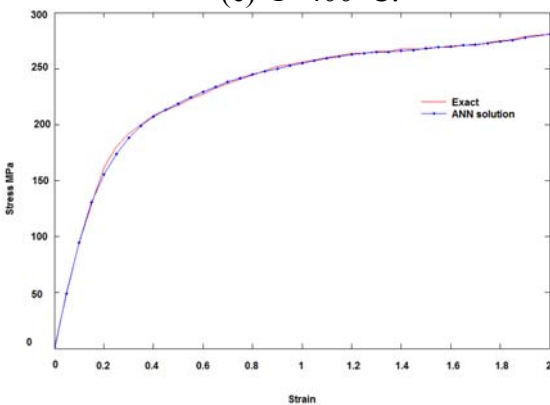
(a)  $T=20\text{ }^{\circ}\text{C}$  (room temperature).(b)  $T=100\text{ }^{\circ}\text{C}$ .(c)  $T=200\text{ }^{\circ}\text{C}$ .(d)  $T=300\text{ }^{\circ}\text{C}$ .

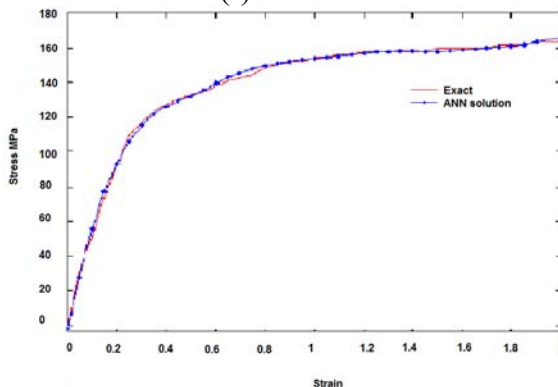
Figure 4: stress-strain curve from actual experimental data and ANN predictions



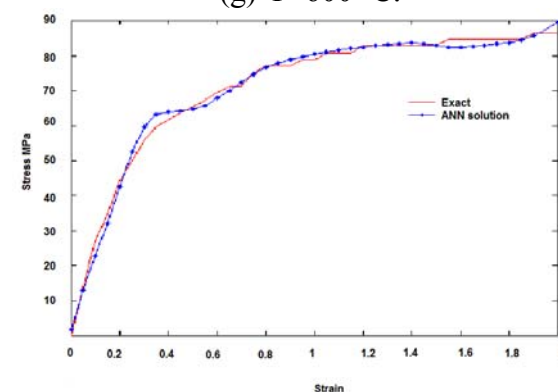
(e) T=400 °C.



(f) T=500 °C.



(g) T=600 °C.



(h) T=700 °C.

Figure 4 (cont.): stress-strain curve from actual experimental data and ANN predictions

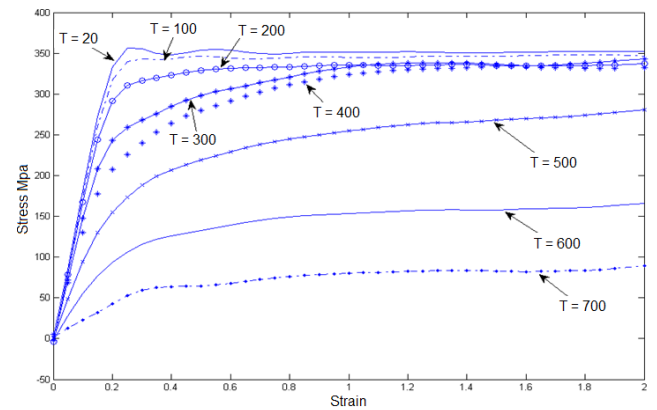


Figure 5: ANN stress-strain curves at elevated temperature

Many researchers stated models on the behaviour of material properties at a certain temperature experimentally or by using ANN models, these models come in mathematical formulae or tabular ones, pervious verified models [9, 10, 14, 15 and 16] stated the mathematical relationship for the reduction factor as:

$$K_d = 1.876 \times 10^{-11} T^{3.98} - 1.91 \times 10^{-8} T^3 + 3.625 \times 10^{-6} T^{1.996} + 10^{-4} T + 0.99 \quad (1)$$

In this work, the reduction factor is obtained from the ANN model; The data is acquired by comparing the strength value (in this case the ultimate strength of the selected steel) to that extracted from the ANN predictions. The final values are shown in Table 2 together with comparisons to previous reduction factor models. Fig. 6 shows a graphical representation of the ANN reduction factor and also shows a comparison with previous experimentally obtained data from previous research works.

Designers use the reduction factor in the form represented by equation (1). In this work, curve fitting was undertaken to obtain a reduction factor calculated from ANN results. Matlab was used to fit the data and it resulted in a polynomial from of the 6<sup>th</sup> degree, giving the best fit to the data. The reduction factor as function of temperature is:

$$K_d = 2 \times 10^{-16} T^6 - 4 \times 10^{-13} T^5 + 3 \times 10^{-10} T^4 - 10^{-7} T^3 + 10^{-5} T^2 - 1.3 \times 10^{-3} T + 1.0209 \quad (2)$$



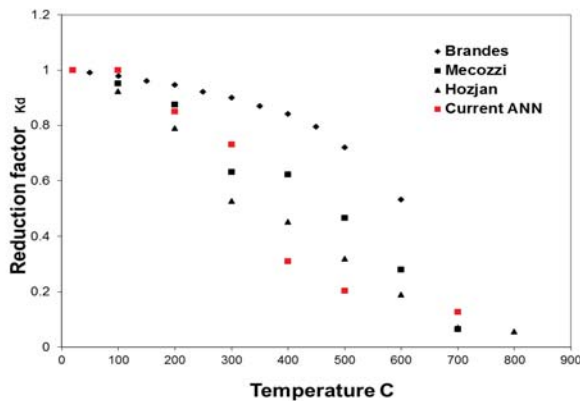


Figure 6: reduction factors at elevated temperature

Fig. 6 clearly indicates the closeness of the extracted reduction factors from this work compared to previous research works. Predictions beyond the available experimental data cannot be used without verification.

## 6 Conclusion

This paper predicted the stress at elevated temperature using an artificial neural network. A feed forward network was used, in which strain and temperature were treated as inputs while stress was the output. Temperature range from 20 up to 700 °C was investigated to predict the stress-strain curves at these temperatures. As a result, reduction factors were calculated, and thus a new reduction factor model was generated as an outcome and then compared with other factors obtained experimentally and numerically by ANN from previous research studies. The generated reduction factor model was shown to be an excellent correlation to the experimental data and proved that the adopted ANN approach was efficient and accurate. Furthermore, the suggested reduction factors were represented in polynomial form and thus enabling the use of the equation for simple calculations and to extend the data within and beyond the given experimental data.

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Table 1: Sample inputs and targets  
(a) T = 20 °C

Strain, ( $\epsilon$ )	Stress, ( $\sigma$ )
0	0
0.05	86.54
0.1	161.69
0.15	273.08
0.2	340.38
0.25	350
0.3	351.92
0.35	351.92
0.4	351.92
0.45	351.92
0.5	351.92
0.55	351.92
0.6	351.92
0.65	351.92
0.7	351.92
0.75	351.92
0.8	351.92
0.85	351.92
0.9	351.92
0.95	351.92
1	351.92
1.05	351.92
1.1	351.92
20	1.8
20	1.85
20	1.9
20	2

Table 1: Sample inputs and targets (Cont.)

(b)  $T = 100\text{ }^{\circ}\text{C}$ 

Strain, ( $\epsilon$ )	Stress, ( $\sigma$ )
0	0
0.05	84.62
0.1	159.62
0.15	271.15
0.2	328.85
0.25	338.15
0.3	342.31
0.35	344.23
0.4	346.15
0.45	344.23
0.5	344.23
0.55	344.23
0.6	344.23
1	344.23
1.05	344.23
1.1	344.23
1.15	344.23
1.2	344.23
1.25	346.15
1.3	346.15
1.35	346.15
1.4	346.15
1.45	346.15
1.5	346.15
1.55	346.15
1.6	346.15
1.65	346.15
1.7	346.15
1.75	346.15
1.8	346.15
1.85	348.07
1.9	348.07
2	348.07

(c)  $T = 200\text{ }^{\circ}\text{C}$ 

Strain, ( $\epsilon$ )	Stress, ( $\sigma$ )
0	0
0.05	75.93
0.1	157.41

Table 2: Reduction factor

T $^{\circ}\text{C}$	Model			
	Brandes [2]	Hozjan [3]	Mecozzi [8]	ANN [this work]
20	1	1	1	1
50	0.99			
100	0.98	0.922	1	0.951
150	0.96			
200	0.945	0.789	0.849	0.874
250	0.92			
300	0.9	0.526	0.63	0.73
350	0.87			
400	0.84	0.452	0.31	0.622
450	0.795			
500	0.72	0.319	0.203	0.466
600	0.53	0.189		0.28
700		0.07	0.064	0.127
800		0.056		