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# MODELING OF TEMPERING CURVES OF ALLOY STEELS BY MEANS OF NEURAL NETWORKS[1]

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**Abstract**

The tempering process aims to get the microstructures that lead to service mechanical properties and to promote the relaxation of the residual stresses generated during quenching. The goal of this work is to predict the effect of tempering time and tempering temperature on hardness by means of neural networks (NN). Five types of steels, SAE 4140, SAE 4340, SAE 5160, SAE 6150 and SAE 52100, were tempered in different conditions. The inputs of the NN were the chemical composition, the tempering time and tempering temperature, while hardness was the output. The selected temperatures were 100, 150, 200, 250, 300, 400, 500, 600 and 700ºC. The time on each temperature was 10s, 90s, 900s, 3600s, 9000s and 86400s. It was tested many architectures, until find the best one that fitted the data. To evaluate this NN there were calculated the correlation coefficient (R value) and the performance function value. The NN selected was that one with lower performance function and the value of R nearest to 1.

**Key words:** Tempering; Modeling; Hardness; Neural networks.

## MODELAGEM DAS CURVAS DE REVENIMENTO DE AÇOS LIGA POR MEIO DE REDES NEURAIS

**Resumo**

O processo de revenimento visa alcançar microestruturas que resultem em propriedades mecânicas utilizáveis e promover o alívio das tensões residuais originadas durante a têmpera. O objetivo deste trabalho é predizer o efeito do tempo e da temperatura de revenimento na dureza por redes neurais (RN). Cinco tipos de aço, SAE 4140, SAE 4340, SAE 5160, SAE 6150 e SAE 52100, foram revenidos em diferentes condições. As entradas da rede foram a composição química, o tempo e a temperatura de revenimento, enquanto a saída foi a dureza. As temperaturas selecionadas foram 100, 150, 200, 250, 300, 400, 500, 600 e 700ºC. O tempo em cada temperatura foi de 10s, 90s, 900s, 3600s, 9000s e 86400s. Foram testadas diversas arquiteturas até encontrar a que melhor ajustava os dados. Para avaliar a rede foram calculados o coeficiente de correlação (valor R) e o valor para a função de desempenho. A RN escolhida foi aquela com menor valor para função de desempenho e valor de R próximo a 1.

**Palavras-chave**: Revenimento; Modelagem; Dureza; Redes neurais.

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# 1 INTRODUCTION

During tempering of quenched steels, changes on microstructure are produced over a wide range, resulting in corresponding changes in mechanical properties. The tempering process is dependent of the relation time-temperature. An inappropriate selection of these process parameters affects temper embrittlement, non-optimal stress relief, hardness, tensile strength, yield strength and transformation of retained austenite.

This relation has been already reported by Hollomon and Jaffe in 1945,[1] when they noticed that the same hardness could be reached by different time-temperature histories. In this work they have obtained a relation between hardness ($H$) and a tempering parameter, as follows on Eq.(1):

$$f\,(H)=f\,[\,T\,(\,c+\log t)] \qquad (1)$$

where $c$ is a constant, $T$ is the absolute temperature and $t$ is the time.

As they had worked only with plain carbon steels, many authors had suggested that this model do not fit well all types of steel, a review of the development of the tempering parameters development has been reported by Canale, et al.[2] Grange and Baughman[3] suggested $c$=18 for all carbon steels. Nehrenberg[4] used $c$=20, and developed tempering curves for a series of stainless steels. An example of the use of neural networks to the same proposal was made by Filetin et al.[5] who worked with tool steels. The aim of this work is to calculate hardness for five alloyed steels, tempered in different conditions of time and temperature by means of neural networks.

Heat treatment of materials is a fundamental metallurgical process, which involves very complex and nonlinear phenomena. In this way, physical models are difficult or impossible to obtain. In such cases neural networks seems to be a powerful tool. Neural networks can be defined as a general method of regression analysis in which a flexible non-linear function is fitted to experimental data.[6]

# 2 MATERIALS AND METHODS

## 2.1 Experimental Procedure

The samples were austenitized at 850ºC, and quenched in a mineral oil. Three specimens were tempered at each specified time and temperature, and cooled in air. The selected temperatures were 100, 150, 200, 250, 300, 400, 500, 600 and 700ºC. During tempering process the furnace temperature varied ±10ºC. The time on each temperature was 10s, 90s, 900s, 3600s, 9000s and 86400s. It was generated about 225 different conditions. Table 1 shows the chemical composition of five types of steel used in this work.

**Table 1.** Chemical composition of steels

| Steel | %C | %Mn | %P | %S | %Si | %Ni | %Cr | %Mo |
|---|---|---|---|---|---|---|---|---|
| SAE 4140 | 0.41 | 0.88 | 0.016 | 0.018 | 0.23 | - | 1.02 | 0.22 |
| SAE 4340 | 0.39 | 0.75 | 0.019 | 0.016 | 0.26 | 1.74 | 0.79 | 0.26 |
| SAE 5160 | 0.62 | 0.88 | 0.012 | 0.018 | 0.22 | - | 0.79 | - |
| SAE 6150 | 0.51 | 0.81 | 0.021 | 0.014 | 0.28 | - | 0.98 | - |
| SAE 52100 | 1.02 | 0.40 | 0.017 | 0.014 | 0.23 | - | 1.42 | - |

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Five hardness measurements were collected using a LECO RT-240 durometer, with a load of 150kgf. Figures 1 to 5 show the results obtained for SAE 4140, SAE 4340, SAE 5160, SAE 6150 and SAE 52100 steels, respectively.

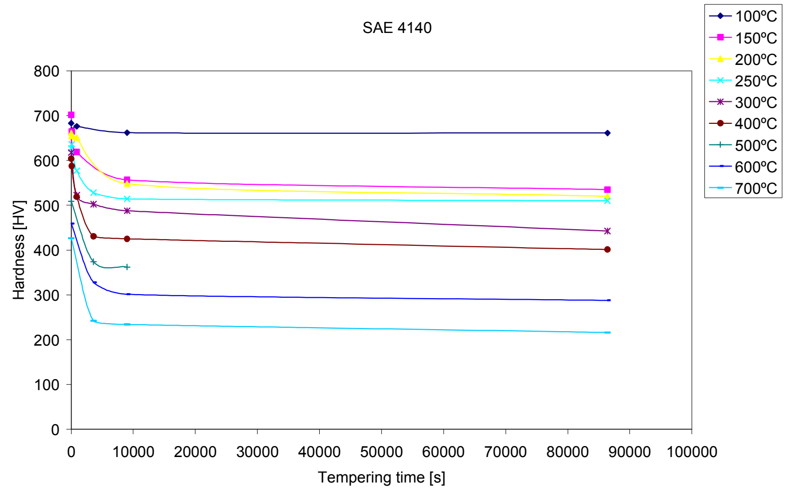


**Figure 1.** Measured hardness for SAE 4140 steel tempered in different conditions.

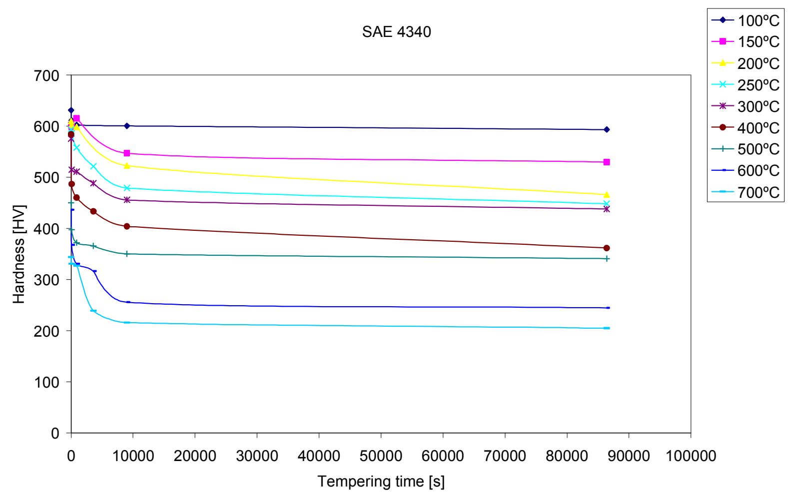


**Figure 2.** Measured hardness for SAE 4340 steel tempered in different conditions.

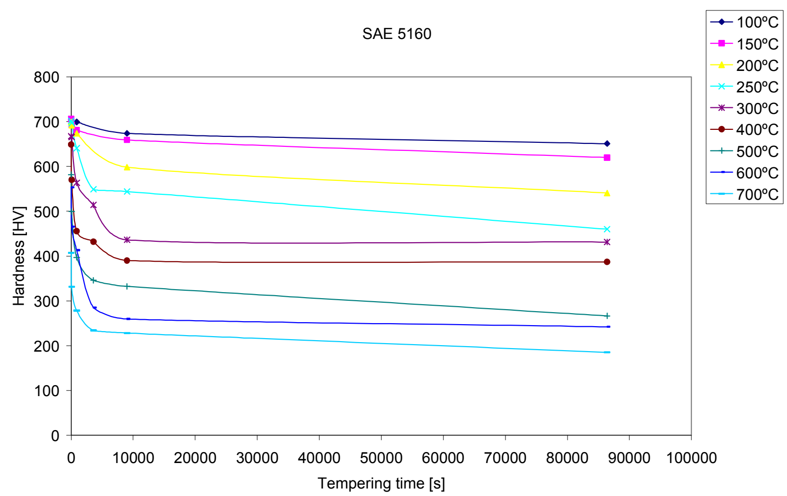


**Figure 3.** Measured hardness for SAE 5160 steel tempered in different conditions.

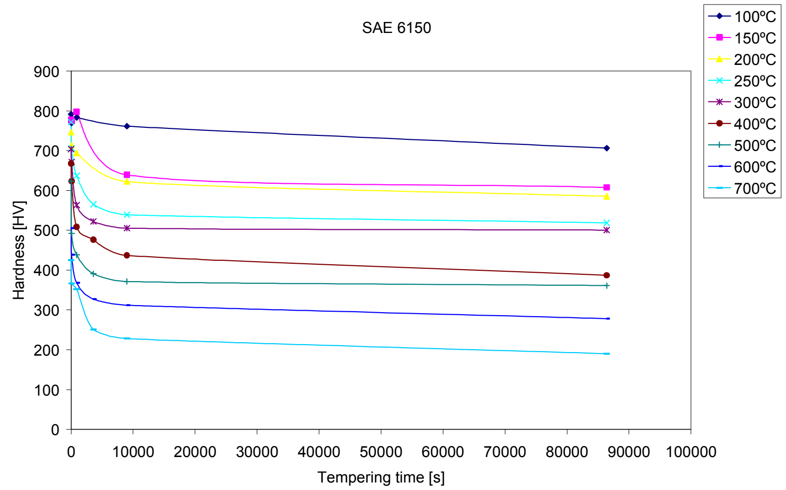


**Figure 4.** Measured hardness for SAE 6150 steel tempered in different conditions.

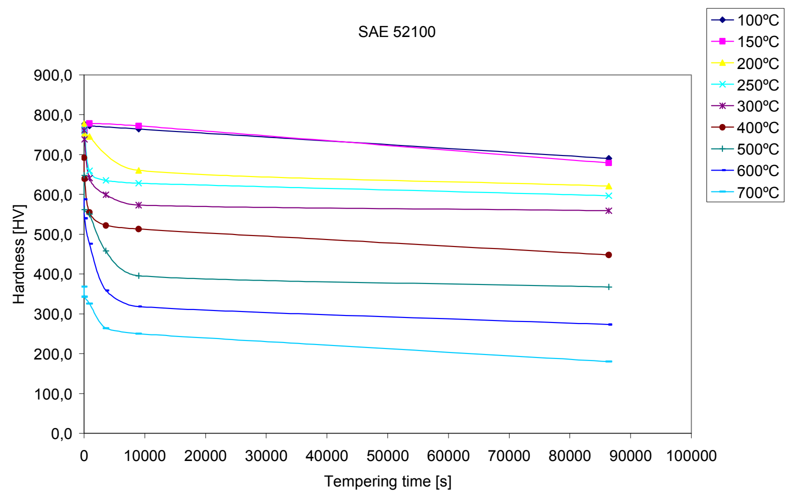


**Figure 5.** Measured hardness for SAE 52100 steel tempered in different conditions.

## 2.2 Neural Networks

A feed forward network was built with chemical composition, tempering temperature and time on temperature as inputs and hardness as output. The activation function was set as a tangent hyperbolic function as shown in Eq. (2) in the hidden layers, while a linear function was used for the output layer as shown in Eq. (3):

$$h_i = \tanh\left(\sum w_{ij} x_j + \theta_i\right) \tag{2}$$

$$y = \sum w_i h_j + \theta_i \tag{3}$$

where $x_j$ are the inputs and $w_{ij}$ are the weights, which define the neural network. The biases $\theta_i$ are treated internally as weights associated with a constant input set to unity.

To train the neural network was used the MATLAB function *trainbr*, which consists in a modified Levenberg-Marquart training algorithm. Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that at the end of training the resulting network has good generalization qualities.[7]

Many network architectures were tested until to find the best configuration. It was verified that a neural network with three hidden layers with four neurons, was that one that promoted the best fit for the output layer. The neural network had 10 inputs and just the hardness as output. The performance was measured according to the sum of squared errors (*SSE*), given by Eq. (4):

$$SSE = \sum_{i=1}^{n} w_i (y_i - \hat{y}_i)^2 \quad (4)$$

The correlation coefficient is a measure of the correlation (linear dependence) between two variables *x* and *y*, giving a value between +1 and −1 inclusive. It is widely used in the sciences as a measure of the strength of linear dependence between two variables. It was developed by Karl Pearson and can be calculated by Eq. (5):

$$R = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2}} \quad (5)$$

where $\bar{x}$ is the mean value of *x* series and $\bar{y}$ is the mean value of *y* series.

The data set was obtained experimentally as shown on section 2.1, and completed with the database used by Grange and Baughman.[3] This set was divided between a training set and a test set. The training set was composed of 511 conditions and the test set of 57 samples picked out randomly from training set. The range, mean and standard deviation of input data are listed on Table 2.

**Table2.** Input data

| Input variables | Min. | Max. | Mean | Standard deviation |
|---|---|---|---|---|
| Temperature [ºC] | 99 | 703 | 382.7 | 196.3 |
| Time [s] | 10 | 86400 | 20075 | 33684 |
| %C | 0.39 | 1.02 | 0.597 | 0.232 |
| %Mn | 0.4 | 0.88 | 0.739 | 0.180 |
| %P | 0.012 | 0.021 | 0.017 | 0.003 |
| %S | 0.014 | 0.018 | 0.016 | 0.002 |
| %Si | 0.22 | 0.28 | 0.244 | 0.023 |
| %Ni | 0 | 1.74 | 0.361 | 0.707 |
| %Cr | 0.79 | 1.42 | 0.99 | 0.235 |
| %Mo | 0 | 0.26 | 0.0914 | 0.118 |

## 3 RESULTS AND DISCUSSION

After the training section the final error obtained by the modified performance function, given by Eq. (4), was equal to 10 HV. Figures 6 and 7 shows the measured and calculated hardness obtained for training and test data set respectively. To evaluate this neural network there were calculated the correlation coefficient (R value), a straight line and the equation obtained for the best linear fit for the data.

For the training set the value of R was 0.99 and 0.974 for the test set. These values indicate that the selected NN had a good generalization.

Figure 8 brings a comparison of part of calculated and measured data used to test the network. These data correspond to that obtained from section 2.1. It is also possible to observe the effect of time and tempering temperature on hardness.

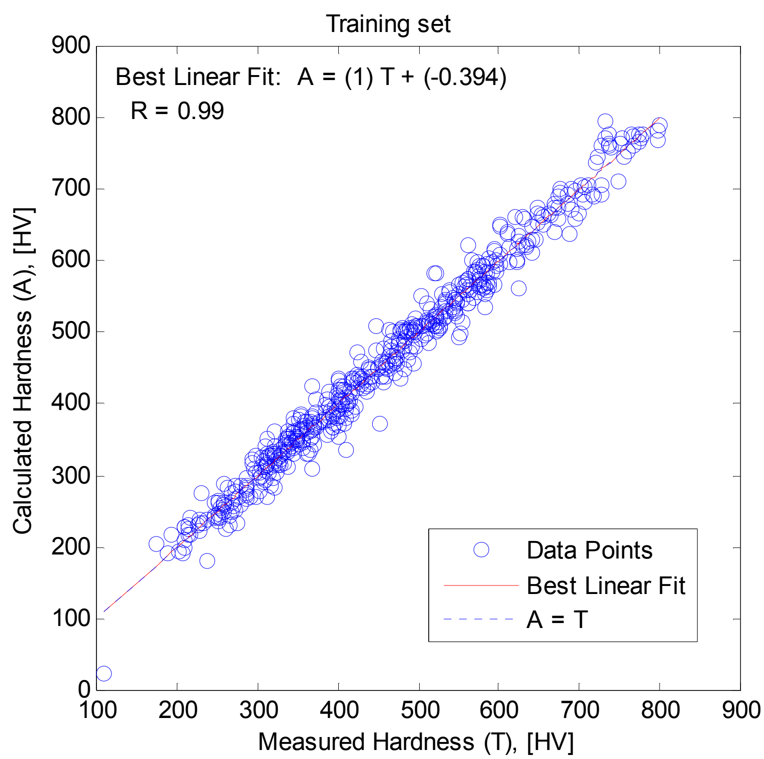


**Figure 6.** Predicted hardness by the neural network versus experimental values for training data set.

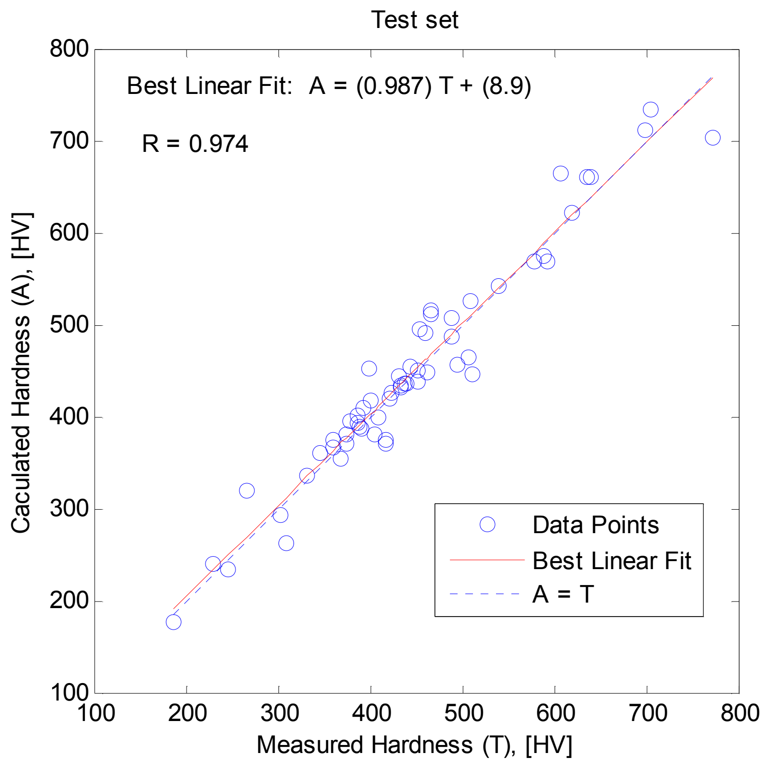


**Figure 7.** Predicted hardness by the neural network versus experimental values for test data set.

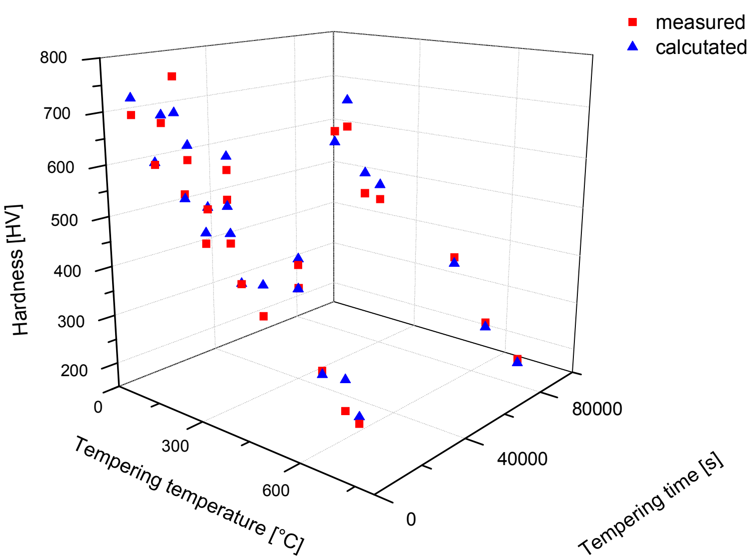


**Figure 8.** Comparison of measured and calculated data and the effect of time and tempering temperature on hardness.

## 5 CONCLUSION

As can be verified neural networks are a powerful tool to predict mechanical properties of steels. This work was an attempt to model five types of steel, and results obtained in here encourage more investigations in this area. It could be inserted to this NN other steels enlarging its predictive capacity. The great potential

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of using neural networks is the economic benefits that it can provide for the industry, because it can reduce the necessity of expensive experimental investigation of steels on its mechanical properties.

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