UNIVERSITY OF ŽILINA
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# SEMDOK 2024

## 27th International Seminar of Ph.D. Students

under the auspices of
prof. Dr. Ing. Milan Sága
Dean of the Faculty of Mechanical Engineering of the University of Žilina

MATERIALS SCIENCE MASTERS

**Western Tatras - Zuberec, Slovak Republic**
**February 5 – February 7, 2024**

Žilinská univerzita / EDIS – Publishing Centre of the University of Žilina

ISBN 978-80-554-2076-9

# PREDICTING THE YIELD STRESS AND TENSILE STRENGTH OF TWO STAINLESS STEELS USING ARTIFICIAL INTELLIGENCE

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## 1. Introduction

In modern industry, regarding conventional engineering (mechanical, civil etc.), steel still represents the most applied material. One of the reasons for that is significantly lower steel price compared to other metal materials (e.g. Al and Ti). However, one of the greatest setbacks is proneness to corrosion on parts' surfaces. That setback was eliminated by introduction of the stainless steels, which are resistant to corrosion (minimum of 12 % of Cr dissolved in solid steel solution). Industry nowadays has at its disposal several thousands of stainless steels, each carefully engineered to meet specific requirements. Besides Cr, the addition of other chemical elements, like Ni, Mo, V etc., is present in those steels. Stainless steels with adequate addition of Ni in literature are often referred as austenitic stainless steels. They keep the austenitic structure at room temperatures since Ni expands the region of stable austenite in the Fe-$Fe_3C$ diagram, [1].

The Artificial Neural Networks (ANN) are created from Artificial Neural Cells (Artificial neuron), whose model was created looking upon the biological neural cells (bio-neurons). The working principle of bio-neurons is that all the signals received on dendrites are summed in neurons' body. If a sum of all signal values exceeds the critical value, the signal is sent through axon to further layers and cells. The working principle of artificial neurons is quite similar. The difference between the two is that in the case of artificial cells, numbers' values are used instead of signals. The working principle is that if the value of a number received from other cells, multiplied by the value of weight coefficient, and added to a bias value, exceeds some critical value, the transfer function (e.g., sigmoidal, or linear) is activated and it sends the obtained value to the next layer, [2].

The neural network's ability to predict some value is based on its training, which means that an adequate set of data is supplied to the network. Each data set has two parts, input, and output. For each input there is a known output. Based on that, the ANN arranges weight and bias values so that the input data, after summing and multiplying through ANN, gives already known output. The ANN is considered as the better if the error between the known and calculated output is lower, [3].

The ANNs were applied in solving different problems, e.g., to recognize steel type based on its chemical composition [4], to model structure and properties of new steel grades [5] or to predict steels hardenability [6].

In this paper are presented the results of predicting the two mechanical properties of austenitic stainless steels, X5CrNi18-10 (AISI 304), X5CrNiMo17-12-2 (AISI 316), using the Artificial Neural Networks and they are compared to already known values. Input and output data for training artificial neurons were created using *Cambridge Education Software Edu Pack 2010 (CES EDU PACK 2010)*. For the two considered steels' properties, the two input and two output data sets were needed. In both cases, properties were predicted based on chemical composition of steels, so the input set in both cases was common. Each output set consisted of values of investigated property for other stainless steels. In this case, mentioned properties of 57 other stainless steels were at disposal in the used software, so the output data sets were created using those. Separate networks with different parameters were used for the two properties. The complete properties prediction process was conducted in Mathworks Matlab software, using its neural network module.

## 2. Predicting the yield stress values of austenitic stainless steels

A special neural network was created in Mathworks Matlab software, with the input data set based on chemical composition of 57 other stainless steels found in *CES Edu Pack 2010*. The output data set was based on the yield stress values of those steels, the chemical composition of which formed the input data.

The first (input) layer consisted of 18 neurons, each representing one element from chemical composition. The second layer had 10 neurons. This value is software default number of neurons for the second layer, and it could be changed, but for this purpose it provided the adequate precision, so it was not changed. The number of neurons in the third (output) layer is equal to the number of properties predicted by the neural network. In this case that number is one, as only the yield stress value is predicted. The chosen activation function between the layers was sigmoidal tan function. The Bayesian Regularization algorithm was chosen as the training algorithm. The structure of described network is presented in Fig. 1, and the training parameters are given in Tab. 1.

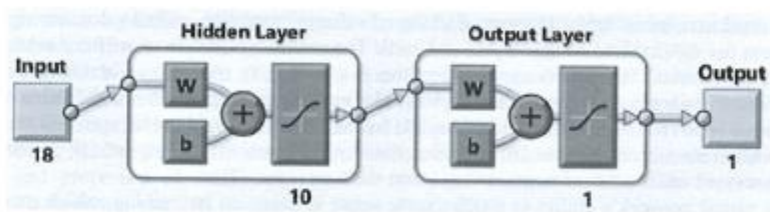


*Fig. 1 Structure of the neural network for predicting the yield stress values*

The created network was trained using parameters given in Tab. 1. Application of given parameters resulted in regression displayed in Fig. 2. Values of the yield stress, obtained by entering the chemical composition values of steels X5CrNi18-10 and X5CrNi17-12-2, are presented in Tab. 2.

*Tab. 1 Values of parameters used for the network training*

| Parameter | Value |
|---|---|
| Max. number of epochs | 1000 |
| Time | Infinite |
| Goal | 0 |
| Min gradient | 0.0000001 |
| Max. number of fails | 0 |
| Initial momentum value | 0.005 |
| Incline momentum | 0.1 |
| Decline momentum | 10 |
| Max. momentum value | 10000000000 |

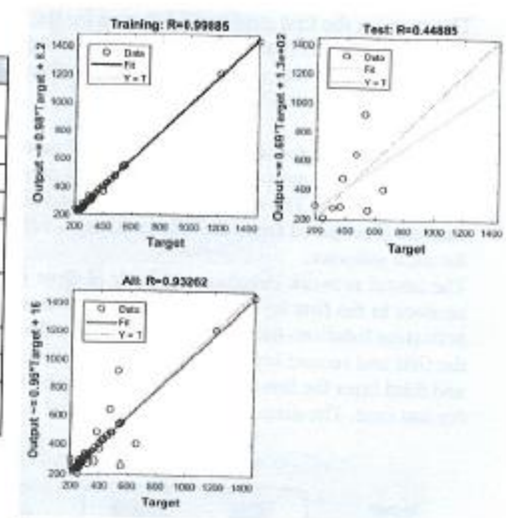


*Fig. 2 Display of obtained regression values r = 0.933*

*Tab. 2 Values of obtained yield stress, [MPa]*

| Steel | X5CrNi18-10 | X5CrNiMo17-12-2 |
|---|---|---|
| CES EDU PACK 2010 | 258 | 240 |
| ANN | 247.5739 | 228.3207 |

Obtained results are displayed in Fig. 3. For steel X5CrNi18-10 obtained value for the yield stress is 247.57 [MPa], which is 11 [MPa] smaller than the value found in the CES software. As for the steel X5CrNiMo17-12-2, the obtained value is 228.3207 [MPa], i.e., for 12 [MPa] smaller.

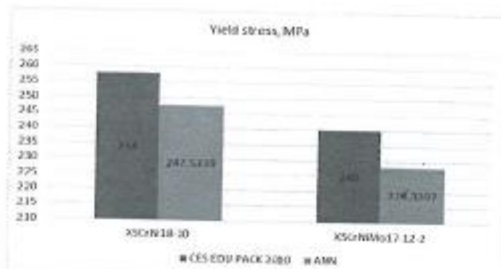


*Fig. 3 Graphic display of obtained yield stress values*

The error for the first steel is 4.04 %, and for the second is a little bigger, 4.87 %. As error values for both steels are lower than 5 %, it could be concluded that results obtained by the ANN are close to real values and that this ANN could be used when predicting yield stress values of other austenitic stainless steels.

### 3. Predicting the tensile strength values of austenitic stainless steels

A special neural network was prepared for predicting the tensile strength values of the considered steels. The input data set is the same as for the yield stress predicting. The output data set is prepared from the tensile strength values for other stainless steels available in the used software.

The neural network structure was built of three layers. As in the first case, the number of neurons in the first layer is equal to wt % of elements in chemical composition. Different activation functions between the layers were selected with respect to the first case. Between the first and second layer, the tan sigmoidal function was chosen, and between the second and third layer the linear function was used. The Levenberg-Marquardt algorithm was used for this case. The described structure of neural network is presented in Fig. 4.

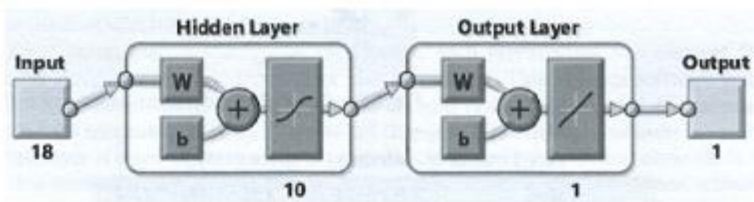


*Fig. 4 Structure of neural network for predicting the tensile strength values*

Created network was trained using parameters given in Tab. 3. Application of given parameters resulted with regression displayed in Fig. 5. Entering the chemical composition values for steels X5CrNi18-10 and X5CrNi17-12-2 values of tensile strength were obtained, given in Tab. 4.

***Tab. 3** Value of parameters used for network training*

| *Parameter* | *Value* |
|---|---|
| ***Max. number of epochs*** | 1000 |
| ***Time*** | Infinite |
| ***Goal*** | 0 |
| ***Min gradient*** | 0.0000001 |
| ***Max. number of fails*** | 6 |
| ***Initial momentum value*** | 0.001 |
| ***Incline momentum*** | 0.1 |
| ***Decline momentum*** | 10 |
| ***Max. momentum value*** | 10000000000 |

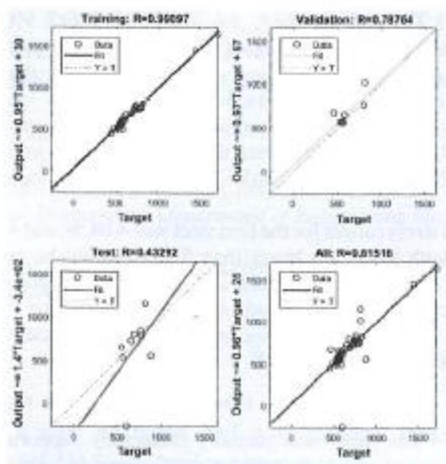

*Fig. 5 Display of obtained regression values r = 0.815*

***Tab. 4** Values of obtained tensile strength, [MPa]*

| *Steel* | *X5CrNi18-10* | *X5CrNiMo17-12-2* |
|---|---|---|
| CES EDU PACK 2010 | 565 | 570 |
| ANN | 549.7284 | 571.825 |

The tensile strength values from the CES software and values obtained by ANN are shown in Fig. 6. For steel X5CrNi18-10 the tensile strength value is 549.7284 [MPa], which is almost 17 [MPa] less than the experimentally obtained one, while for the steel X5CrNiMo17-12-2, the obtained value is almost 2 [MPa] bigger. The error value for the first steel is 2.7 %, and for the second is approximately 0.32 %. In this case, the error values are negligible, so this ANN is suitable for predicting the tensile strength values of other austenitic stainless steels, as well.

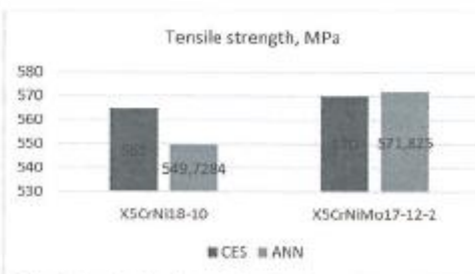


*Fig. 6 Graphic display of obtained tensile strength values*

## 4. Conclusions

The subject of this research was to investigate if the ANN could predict the yield stress and tensile strength values of austenitic stainless steels. Data sets for the ANNs were created from the CES EDU PACK 2010 software. The input data consisted of chemical composition of mentioned steels and the output data sets were created for their investigated properties. After the data sets were prepared, the neural networks were created and trained. Two steels X5CrNi18-10 and X5CrNiMo17-12-2 were used to validate results obtained from the ANN.

The error for the yield stress results for the first steel was 4.04 %, and 4.87 % for the second. As error values for both steels are lower than 5 %, it could be concluded that results obtained by the ANN are close to real values, i.e., the ANN is suitable for predicting values of this mechanical property for the austenitic steels. The error value for the tensile strength for the first steel was 2.7 %, and for the second 0.32 %. In this case, the error values were negligible, so this ANN is suitable, as well.

***Acknowledgment***

Research presented in this paper was partially financially supported by the project of Operational Programme Integrated Infrastructure "Support of research and development capacities to generate advanced software tools designed to increase the resilience of economic entities against excessive volatility of the energy commodity market", ITMS2014+ code 313011BUK9, co-funded by European Regional Development Fund, and by the project TR35024 of the Ministry of Education, Science and Technological Development of Republic of Serbia.

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