Available online at www.sciencedirect.com

ScienceDirect

Procedia Structural Integrity 68 (2025) 839–844

Structural Integrity Procedia

www.elsevier.com/locate/procedia

European Conference on Fracture - ECF24

A new artificial neural network model for predicting fatigue limit and fracture toughness values of some stainless steels

Dj. Ivković[a], D. Arsić[a]*, A. Sedmak[b], D. Adamović[a], V. Mandić[a], M. Delić[a], A. Mitrović[b]

[a]*Faculty of Engineering, University of Kragujevac, Sestre Janjić 6, 34000 Kragujevac, Serbia*
[b]*Facuty of Mechanical Engineering, University of Belgrade, Kraljice Marije 16, 11120 Belgrade, Serbia*

Abstract

Aim of this paper is to present the possibility for application of Artificial Intelligence for determining fracture toughness and fatigue limit values of some grades of stainless steels. Experimental procedures for both, fracture toughness and fatigue limit determination are time consuming, thus application of artificial intelligence instead of long, time exhausting experiment could result in less time spent waiting on experimental results.
For this purpose, two Artificial Neural Networks (ANN) with same architecture were created and applied. Above mentioned properties are determined for the austenitic stainless steel X5CrNiMo17-12-2 and ferritic stainless steel X6Cr17. Complete work regarding ANN was conducted in Mathworks MATLAB 2017 software using nntool module. After completed training of ANN when adequate regression levels were reached, simulations were conducted using chemical composition of X5CrNiMo17-12-2 and X6Cr17 steels. Obtained results were compared with existing data. Conclusion that was drawn is that ANN that predicts K_{IC} values has greater precision than ANN for fatigue limit. Potential reason for that could be that input layer needs more input data to increase precision.

Keywords: Artificial Intelligence; fracture toughness; fatigue limit; stainless steels

* Corresponding author. Tel.: +381642769381
E-mail address: dusan.arsic@fink.rs

10.1016/j.prostr.2025.06.139

1. Introduction

In the field of materials engineering, having accurate data for some of key material properties is of great importance for achieving adequate reliability and longevity of structures. Engineers when design steel structures need to pay up special attention to some standards which refer to mechanical properties of materials, EN 1990:2002; EN 1993-1-1:2005; EN 1993-1-2:2005; EN 1993-1-3:2006; EN 1993-1-4:2006. When designing stainless steels structures, criterions are additionally set through following standards: EN 10088-1:2005, EN 10088-2:2005, EN 10088-3:2005, EN 10088-4:2009, EN 10088-5:2009. Tensile strength and yield stress are crucial properties for materials subjected to static working conditions, Jovanovic et al. (2017). If materials are exposed to dynamic loading conditions, impact toughness becomes the main material property to be assessed, as it represents material's ability to absorb energy during sudden impacts. When material is subjected to cycle loads, fatigue limit of material becomes key property as it tells number of cycles under certain load that material can withstand, Milovanovic et al. (2022). In the last few decades, fracture toughness, a new material property is introduced and it serves to assess material's resistance on crack propagation, thus assessing prevention of catastrophic failures, Sedmak (2003). All above mentioned properties are investigated experimentally and require great amount of resources and time to get spent. This specially refers to determining fatigue limit and fracture toughness, where testing a single sample can take hours. Application of artificial neural networks offers a new approach for faster gathering of information, through prediction of some material properties, thus less time and resources are spent, Ivković et al. (2024), Lisjak, D. (2004), Glavaš et al. (2007), Žmak, I. (2003). Property prediction is based on knowledge that is built in the network through network's training, Basheer et al. (2000). In this paper neural network approach was applied to predict fatigue limit and fracture toughness of some stainless steels.

2. Artificial neural networks, structures and training parameters

As it was mentioned before, the topic of this paper is the application of artificial neural networks (ANN) for predicting fatigue limit as well as fracture toughness of some stainless-steel grades. For the purposes of the paper, two feed forward back propagation artificial neural networks were created in the Mathworks Matlab's neural network module. Both neural networks were trained based on data that was available in the CES EDU PACK 2010. Input data was based on chemical composition of different stainless steel grades and output data consisted from fatigue limit and fracture toughness values of same steels used. Training was conducted with Bayesian regularization algorithm.

Both ANN have three layers, input layer with 18 neurons, hidden layer with 10 neurons and output layer with 1 neuron. Number of neurons in input layer is defined by the number of chemical elements that was inserted as input data. Number of neurons in hidden layer is default set as 10 and number of output layer is defined by the number of predicted values, in both cases. For both cases between layers tansigmoid transfer function was used.

For each ANN separate training parameters were applied, so that adequate regression could be achieved (Fig. 1). For the ANN that was used for fatigue limit, training parameters are shown in Table 1 and for fracture toughness ANN parameters are shown in Table 2.

Table 1. Training parameters for fatigue limit ANN.

Parameter	Value
Number of epochs	10000
Time	Infinite
Goal	0.1
Minimum gradient	0.00000001
Maximum fail	0
Momentum (mu)	0.5
Decline momentum	2
Incline momentum	10
Maximal momentum	10000000000

Table 2. Training parameters for fracture toughness ANN.

Parameter	Value
Number of epochs	10000000
Time	Infinite
Goal	0.00000001
Minimum gradient	0.0000001
Maximum fail	0
Momentum (mu)	0.005
Decline momentum	1
Incline momentum	10
Maximal momentum	10000000000000

a b

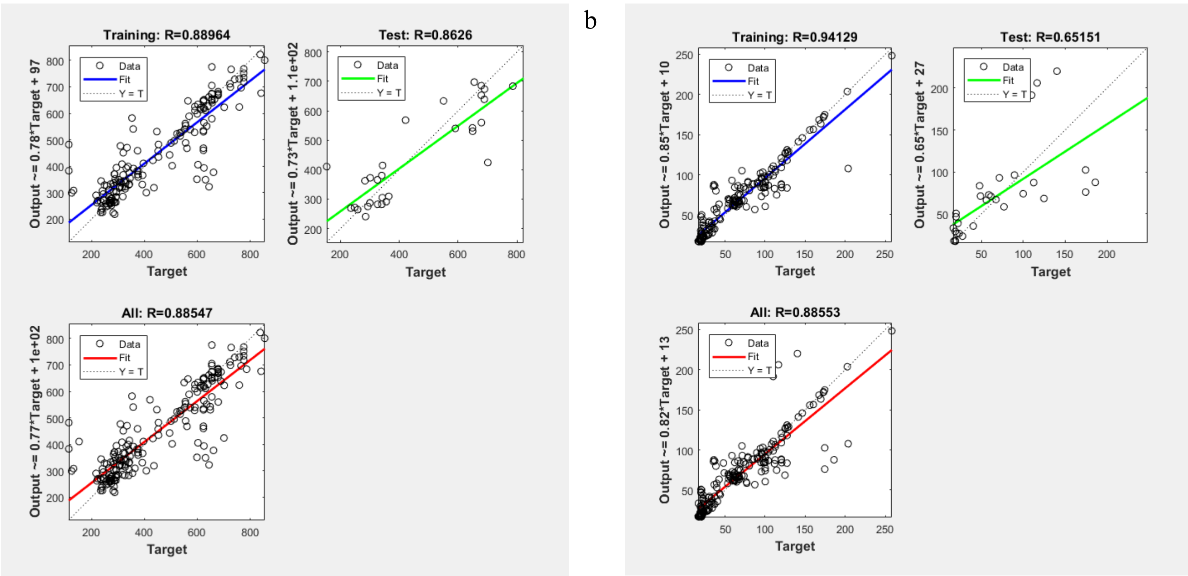

Fig. 1 Regression diagrams (a) for fatigue limit ANN (b) for fracture toughness.

With adequate regression values reached, ANN can be further used to predict fatigue limit and fracture toughness, applying chemical composition of two stainless steels. Chemical composition was inserted in the ANN and fatigue limit and fracture toughness are predicted and further compared with their real values, founded in the CES EDU PACK 2010. Values obtained from ANN are compared with values founded in the Cambridge Educational System EDU PACK 2010 and are given in Tables 3 and 4.

Table 3 Fatigue limit values from software and ANN.

	Fatigue limit, MPa	
CES EDU PACK 2010	266	263
ANN	240	237
Steels	X5CrNiMo 17-12-2	X6Cr17

Table 4 Fracture toughness K_{1C} values from software and ANN.

	Fracture toughness K_{1C}, MPa·m$^{1/2}$	
CES EDU PACK 2010	65	112
ANN	64	104
Steels	X5CrNiMo 17-12-2	X6Cr17

3. Discussion

Fatigue limit values of steels X5CrNiMo 17-12-2 and X6Cr17, founded in the CES EDU PACK 2010 software are 266 and 263 MPa, and values predicted by ANN are 240 and 237 MPa. Following results are displayed in Fig. 2. Comparing results from ANN with software values, it is noticeable that slight difference exists between the values. Calculated errors values in both cases are slightly less than 10%.

Fracture toughness (K_{1C}) values of stainless steels X5CrNiMo 17-12-2 and X6Cr17, founded in the CES EDU PACK 2010 software are 65 MPa·m$^{1/2}$ and 112 MPa·m$^{1/2}$. Values predicted by ANN are 64 and 104 MPa·m$^{1/2}$. Software and ANN values are displayed in Fig. 3. Comparing results from ANN with software values one can notice that correlation between obtained values is adequate. Calculated errors, for both steels are less than 10% and are lower than error values achieved in fatigue limit ANN.

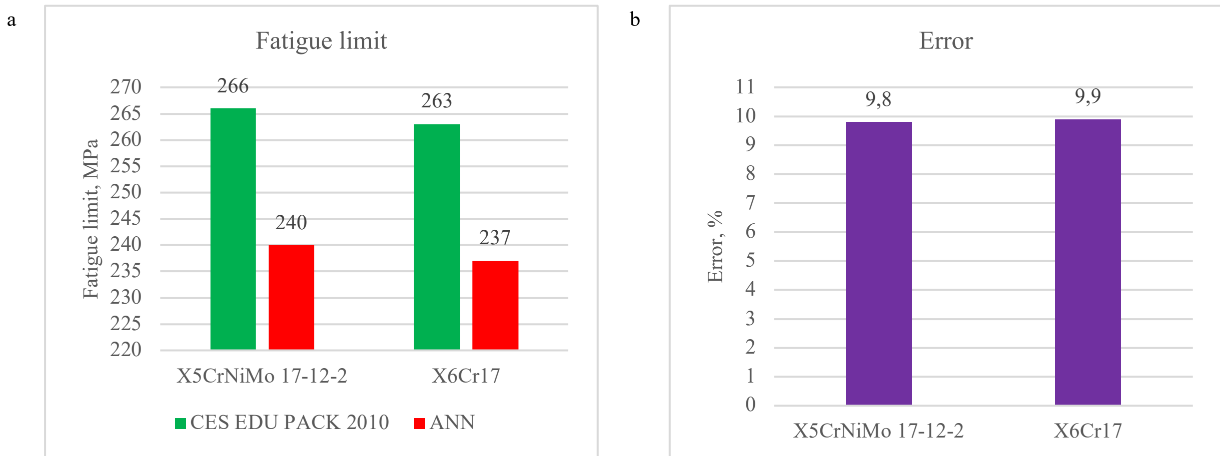

Fig. 2 Comparison of fatigue limit values founded in CES EDU PACK 2010 and values predicted by ANN (a) calculated error (b).

a b

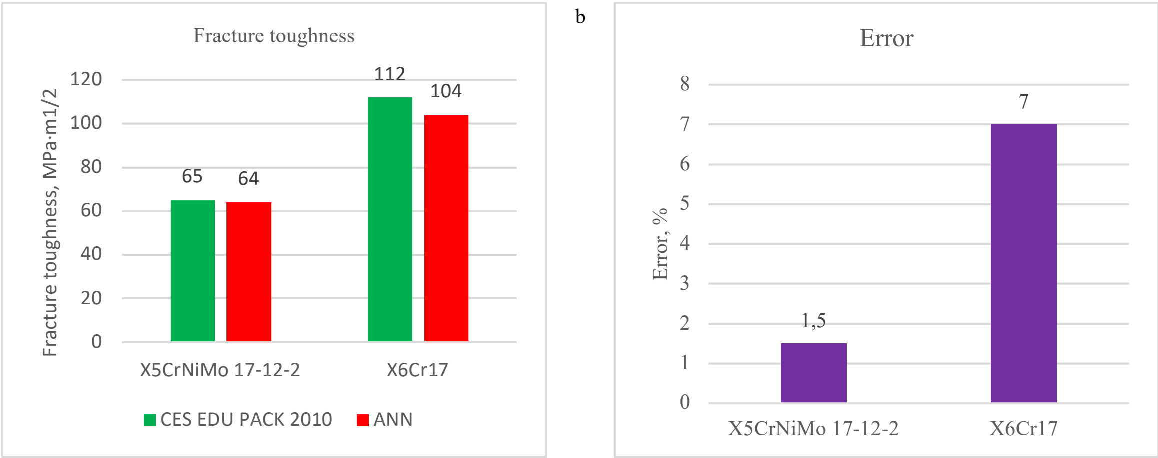

Fig. 3 Comparison of fracture toughness values founded in CES EDU PACK 2010 and values predicted by ANN (a) calculated error (b).

.

Conclusion

Materials engineering represents a key scientific field, as it provides wide specter of information about various materials and their properties. These properties are of great importance for constructors and it allows quality, reliability and longevity of products to be raised. Material testing requires a fair amount of resources as well as time. When fatigue limit and fracture mechanic tests are conducted, test time for a single sample can take hours. To be able to save some of the resources, artificial neural networks are used to predict values of material properties, based on selected input data. In this case, two ANN were created for fatigue limit and fracture toughness prediction. Property prediction was based on chemical composition of materials. After training of ANN, chemical composition of X5CrNiMo17-12-2 and X6Cr17 was inserted, and fatigue limit and fracture toughness values were predicted. Obtained values were compared with values from CES EDU PACK 2010.

The difference between predicted values and real values is less than 10%, so it could be concluded that following network model with described architecture and parameters can be used successfully for predicting mentioned properties of stainless-steel grades. The accuracy of network could be further improved through increasing number of input parameters and increasing number of data sets used for training.

Acknowledgements

Research presented in this paper was partially financially supported by the project TR35024 of the Ministry of Education, Science and Technological Development of Republic of Serbia.

References

Basheer, I., Hajmeer, M., 2000. Artificial neural networks: fundamentals, computing, design, and application, Journal of Microbiological Methods, 43, 3-31. https://doi.org/10.1016/S0167-7012(00)00201-3

EN 10088-1:2005. Stainless steels – Part 1: List of stainless steels https://standards.iteh.ai/catalog/standards/cen/952db42f-8160-4518-8932-c51bc76f8715/en-10088-1-2005

EN 10088-2:2005. Stainless steels – Part 2: Technical delivery conditions for sheet/plate and strip of corrosion resisting steels for general purposes https://standards.iteh.ai/catalog/standards/cen/5da77ead-c665-4c16-a063-1b086a1543c2/en-10088-2-2005

EN 10088-3:2005. Stainless steels – Part 3: Technical delivery conditions for semi-finished products, bars, rods, wire, sections and bright products of corrosion resisting steels for general purposes. https://standards.iteh.ai/catalog/standards/cen/4e6c80d2-c72d-42b3-aeae-2564ae23eb38/en-10088-3-2005

EN 10088-4:2009. Stainless steels – Part 4: Technical delivery conditions for sheet/plate and strip of corrosion resisting steels for construction purposes https://standards.iteh.ai/catalog/standards/cen/a9506eec-011c-47b3-9313-6ec0bb544a7b/en-10088-4-2009

EN 10088-5:2009. Stainless steels – Part 5: Technical delivery conditions for bars, rods, wire, sections and bright products of corrosion resisting steels for construction purposes https://standards.iteh.ai/catalog/standards/cen/affdda76-226f-42d3-b4c7-5d00eba17733/en-10088-5-2009

EN 1990:2002. Eurocode – Basis of structural design. https://www.phd.eng.br/wp-content/uploads/2015/12/en.1990.2002.pdf

EN 1993-1-1:2005. Eurocode 3 – Design of steel structures – Part 1-1: General rules and rules for buildings https://www.phd.eng.br/wp-content/uploads/2015/12/en.1993.1.1.2005.pdf

EN 1993-1-2:2005. Eurocode 3 – Design of steel structures – Part 1-2: General rules – structural fire design https://www.phd.eng.br/wp-content/uploads/2015/12/en.1993.1.2.2005.pdf

EN 1993-1-3:2006. Eurocode 3 – Design of steel structures – Part 1-3: General rules – Supplementary rules for cold-formed members and sheeting https://www.phd.eng.br/wp-content/uploads/2015/12/en.1993.1.3.2006.pdf

EN 1993-1-4:2006. Eurocode 3 – Design of steel structures – Part 1-4: General rules – Supplementary rules for stainless steels https://www.phd.eng.br/wp-content/uploads/2015/12/en.1993.1.4.2006.pdf

Glavaš, Z., Lisjak, D., Unkić, F., The application of artificial neural network in the prediction of the as-cast impact toughness of spheroidal graphite cast iron, Kovove Materialy, 2007, 45(1), pp. 41–49.

Ivković, Dj., Arsić, D., Adamović, D., Nikolić, R., Mitrović, A., Bokuvka, O., 2024. Predicting the mechanical properties of stainless steels using Artificial Neural Networks, Production Engineering Archives, 30(2), 225-232. https://doi.org/10.30657/pea.2024.30.21

Jovanović, M., Lazić, V., Arsić, D., Material Science 1, Faculty of Engineering, University of Kragujevac, Kragujevac, Serbia, 2017, ISBN: 978-86-6335-042-7 (in Serbian).

Lisjak, D. Application of artificial intelligence methods for material selection, PhD thesis, Faculty of Mechanical Engineering and Naval Architecture, University in Zagreb, Zagreb, 2004. (in Croatian)

Milovanović, V., Arsić, D., Milutinović, M., Živković, M., Topalović, M., A Comparison Study of Fatigue Behavior of S355J2+N, S690QL and X37CrMoV5-1 Steel, Metals, 12(7), 1199. 10.3390/met12071199

Sedmak, A. Application of fracture mechanics on structural integrity, Faculty of Mechanical Engineering, University of Belgrade, Belgrade, Serbia, 2003, ISBN:86-7083-473-1 (in Serbian).

Žmak, I. Prediction of material properties by artificial neural networks, master thesis, Faculty of Mechanical Engineering and Naval architecture, University of Zagreb, Zagreb, 2003. (in Croatian)