

DETERMINATION OF STRESS CONCENTRATION FACTOR FOR A RECTANGULAR BAR WITH FILLET UNDER AXIAL LOADING: AN ARTIFICIAL NEURAL NETWORKS APPROACH

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ABSTRACT

Using computer techniques, stress concentration factors from the graphs can be converted into numerical values. Stress concentration factor values were collected in a database and an Artificial Neural Network (ANN) model can be developed for improving and extending the database. ANN model provides accuracy in obtaining the stress concentration factor values.

KEYWORDS: Stress Concentration Factor (SCF), Artificial Neural Network (ANN), axial loading

1. Introduction

The main objective is to develop an ANN model to properly predict the static stress concentration factor for a rectangular bar with fillet under axial loading.

In practice, the data for determining the stress concentration factor can be found in graphs that are obtained experimentally.

The determination of the stress concentration factor can be obtained using finite element simulation with optimization modules. The numerical finite element simulation is often time-consuming even quite accurate if the aim is to evaluate the stress-strain behaviour at the notched area [11].

The development of a simplified numerical model would prove effective to reduce the time needed to reach a good approximation of the stress concentration factor (K_t) for a proposed design (Ihsan TOKTAS1 and others, 2020).

Toktas *et al.* [11], developed an ANN model that provided high accuracy for the prediction of stress concentration factor (K_t) for a Crankshaft under Bending Loading.

2. Experimental background

The data for determining the stress concentration factor can be found in graphs that represent a formulation of the results of the experimental studies.

These graphs are still used these days to define the stress concentration factors. It is necessary to read

carefully the data in these curves when defining the stress concentration factor for a particular problem. These curves can be converted into numerical values. An ANN database was created using these data. A new ANN model was developed using Matlab software [14].

The precision measurements for axially loaded variable cross-section bars showed that in the case of cross-section variations, the stresses are not uniformly distributed on the surface of the cross-section [7].

The elements that influence the stress concentration factor (K_t) for a bar with a rectangular cross-section and a fillet is represented in Fig. 1. The bar has an applied axial force (tensile or compressive).

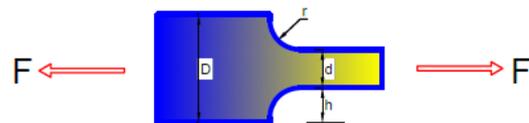


Fig. 1. Parameters involved in the calculation of the stress concentration factor. D = width of the larger section; d = width of smaller section; r = radius of fillet; t = bar thickness; F = applied force (tensile or compressive) [13]

The maximum stress σ_{max} is calculated as [13]:

$$\sigma_{max} = K_t \cdot \sigma_{nom} \quad (1)$$

Where K_t is the stress concentration factor that is determined from the Fig. 2, and σ_{nom} is calculated as [13]:

$$\sigma_{nom} = \frac{F}{d \cdot t} \quad (2)$$

The value of the stress concentration factor for rectangular bar fillet under axial loading is given by the formula [13]:

	$0.1 \leq h/r \leq 2$	$2 \leq h/r \leq 20$
C_1	$1.007 + 1.000\sqrt{h/r} - 0.031(h/r)$	$1.042 + 0.982\sqrt{h/r} - 0.036(h/r)$
C_2	$-0.114 - 0.585\sqrt{h/r} + 0.314(h/r)$	$-0.074 - 0.156\sqrt{h/r} - 0.010(h/r)$
C_3	$0.241 - 0.992\sqrt{h/r} - 0.271(h/r)$	$-3.418 + 1.220\sqrt{h/r} - 0.005(h/r)$
C_4	$-0.134 + 0.577\sqrt{h/r} - 0.012(h/r)$	$3.450 - 2.046\sqrt{h/r} + 0.051(h/r)$

$$K_t = C_1 + C_2 \left(\frac{2h}{D}\right) + C_3 \left(\frac{2h}{D}\right)^2 + C_4 \left(\frac{2h}{D}\right)^3 \quad (3)$$

Where the equation coefficients are calculated from Roark's formula for Stress and Strain, 8th Edition [12]:

The size of the coefficient K_t depends on the configuration and dimensions of the stress concentrators as well as the material of the piece. The stress concentration factors are the more dangerous

for the more fragile materials; if the material is tenacious, then the concentration effect is less important.

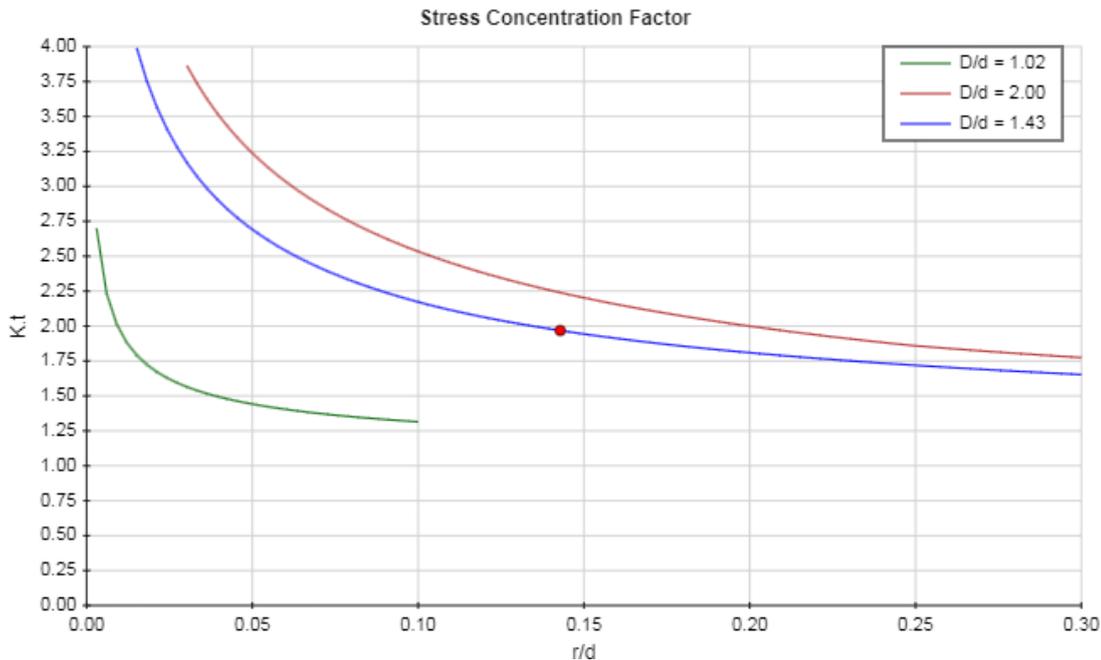


Fig. 2. Stress concentration factor [13]

The most important design variables are the ratio r/d , and ratio D/d as expressed in (Figure 1). These parameters are affected by the stress concentration factor.

The data used for training and testing ANN are given in Annex A and correspond to the following ranges of input variation:

- the $\frac{r}{d}$ varies in the range 0.01-0.09;

- for $\frac{D}{d}$ the following values were considered 1, 1.5 and 2.

3. Neural network modeling

An artificial neural network is a type of machine-learning process that uses interconnected

nodes or neurons in a layered structure that resembles the human brain (Fig. 3) [4].

This hierarchical network structure has an input layer receiving data from the outside and an output layer which sends final information to users. In the middle, hidden layers have no direct contact with the environment (Fig. 3).

As it has proved its efficiency for approaching non-linear functions [6], the Levenberg-Marquardt LM algorithm has been used for neural network training. Using notations in Figure 3, the output response is calculated using (eq. 4) [3]:

$$s = f(\sum w_i \cdot e_i + b) \quad (4)$$

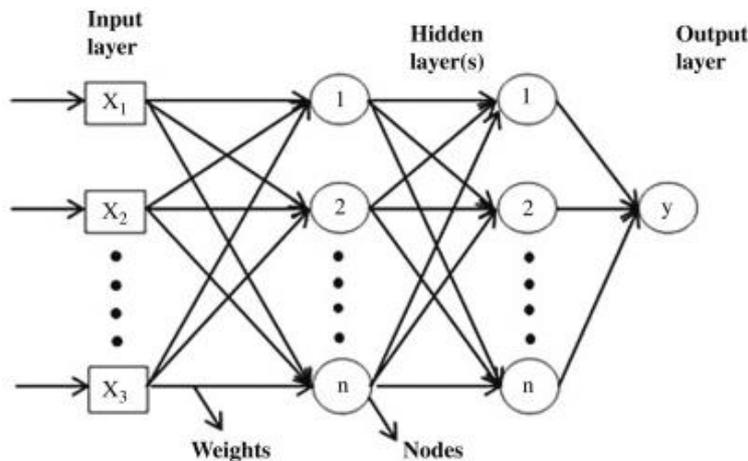


Fig. 3. An artificial neural network [4]

Two activation functions need first to be chosen: one applied in hidden layers and the second used in the output layer to determine the appropriate number of hidden neurons and output values. In practice it is used:

- Sigmoid function ($f(x) = 1/(1+e^{-x})$) in the hidden layer and;
- Linear function ($f(x) = x$) in the output layer (S.L.).

The Levenberg-Marquardt (LM) learning algorithm version was used at the training and testing stages of the Networks [14].

It is recommended that the number of hidden layers be 1-5, but many times good results can be obtained with a single hidden layer and in this sense, tests are made [11].

The hidden layers perform nonlinear transformations of the inputs entered into the network.

During training, weights “w” and biases “b” are initialized to small random values to avoid sharp saturation in activation functions “f”.

The main objective of this study is the development of an ANN numerical model to accurately predict the major element influence on the stress concentration factor for the rectangular bar with fillet axially loaded. Some major parameters used in the final ANN model have been optimized:

- the type of activation functions in hidden and output layers;
- the number of hidden layers;
- the number of neurons in the hidden layer.

One or two hidden layers are sufficient to solve any nonlinear complex problem.

In [1] two hidden layers are used to obtain the optimal Regression coefficient R for a nonlinear problem.

When any function contains a continuous mapping from one finite space to another, one has to make use of a single hidden layer [9].

The number of hidden layer neurons is 2/3 (or 70% to 90%) of the size of the input layer. If this is insufficient, then the number of hidden layer neurons can be added later on [1].

In specialized literature, calculation formulas for the number of neurons in a hidden layer are proposed; many of them use the number of tests as a variable in these formulas [9].

It is chosen a 2-4-1 ANN structure and the output response is calculated using the formula:

$$\text{output_response} = f\left(\sum w * \text{input_layer} + b\right) \quad (5)$$

Where “w” are the weights and “b” are biases and “f” are activation functions.

All numerical experiments were carried out using the MATLAB R2014b neural network toolbox [14].

Table 1. Tests in developing ANN structures and corresponding R-training values and Performance (Mean squared error)

ANN structure	R- training	Performance Mean squared error
2-2-1	0.98825 (Fig. 4a)	0.029472/118 epoch (Fig. 4b)
2-3-1	0.99704 (Fig. 5a)	0.007415/1000 epoch (Fig. 5b)
2-4-1	0.99945 (Fig. 6a)	0.0013558/ 1000 epoch (Fig. 6b)

The data for training and testing were determined using Roark’s formula [11].

The input and output variables are dimensionless quantities and therefore there is no need for their standardization to obtain a fast optimal Regression coefficient R.

The regression coefficients for training different ANN structures and performance from Table 1 are highlighted in Fig. 4-Fig. 6.

The data from Table 1 points out that the ANN selected model has a single hidden layer with 4 neurons.

Three coefficients are calculated to evaluate statistical network performance: RMSE, MAPE and linear regression coefficient R (Table 2).

The root means square error (RMSE) $RMSE = \sqrt{\frac{\sum_{i=1}^n \|y_i - \hat{y}_i\|^2}{n}}$

The mean absolute percentage error (MAPE)

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{y_i} \right| \times 100 \%$$

For linear regression coefficient R we used formula:

$$R = \frac{\sum_{i=1}^n (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2 \cdot (\hat{y}_i - \bar{\hat{y}})^2}}$$

Where n is the number of observations, y_i is the actual value, \hat{y}_i is the predicted value, \bar{y} and $\bar{\hat{y}}$ are mean target and predicted output values. The values of coefficients calculated to evaluate the statistical network performance of the ANN model (Table 2) show its accuracy.

Table 2. Statistical Performance of Training ANN model

Linear regression coefficient	Root Mean Square Error (RMSE)	Mean absolute percentage error (MAPE) %
0.99945	0.0368	1.04

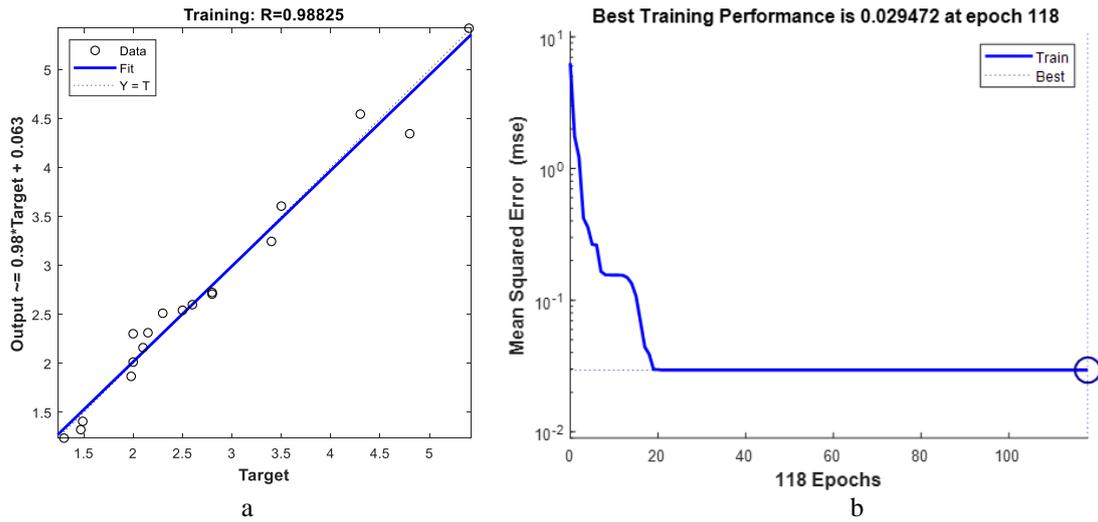


Fig. 4. a - ANN 2-2-1 Regression; b - ANN 2-2-1 Performance

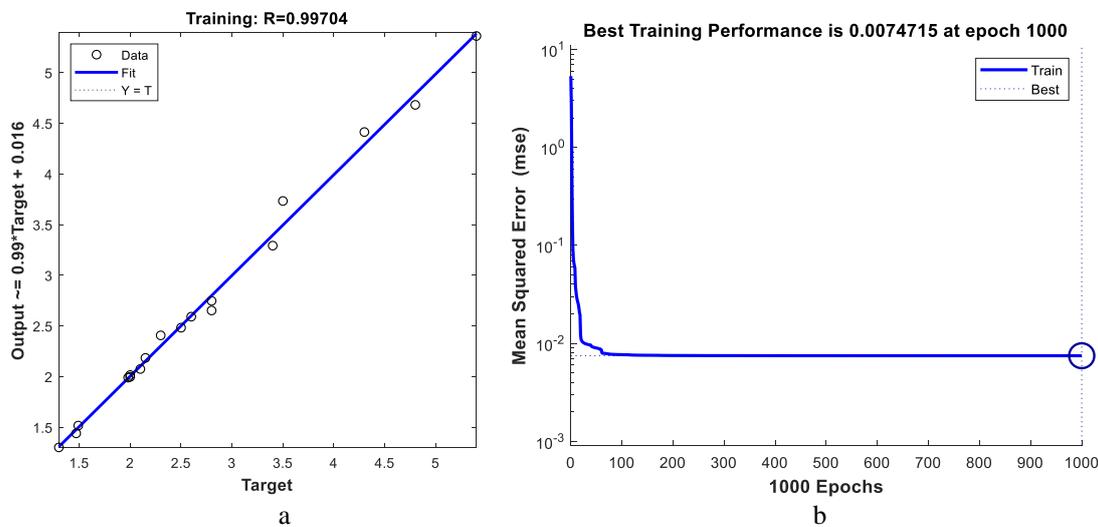


Fig. 5. a - ANN 2-3-1 Regression; b - ANN 2-3-1 Performance

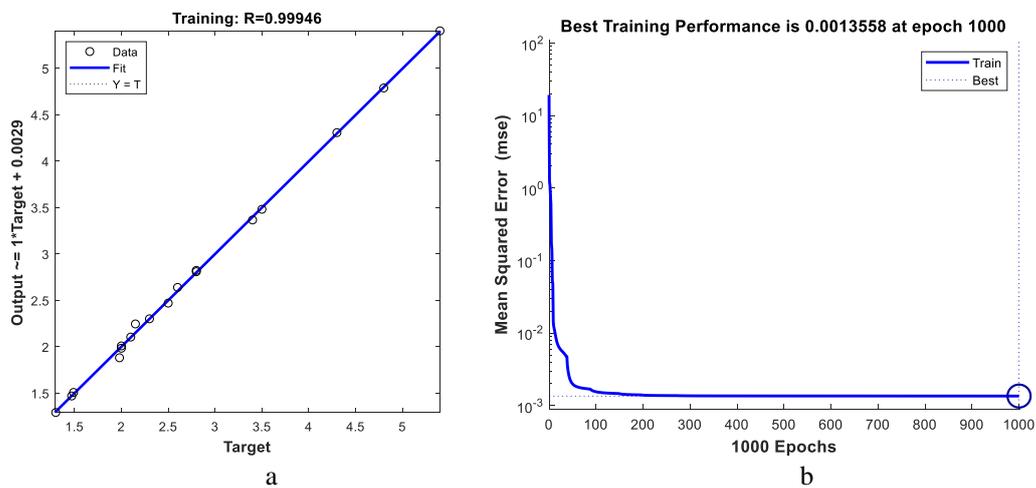


Fig. 6. a - ANN 2-4-1 Regression; b ANN 2-4-1 Performance

4. Prediction of static stress concentration factor

The Levenberg-Marquardt (LM) optimization algorithm has been used all along in this study to find out weights and biases.

The proposed ANN model has a single hidden layer with 4 neurons (Fig. 7).

Stress concentration factors K_t from experimental and predicted for training and testing data are given in Table 3 respectively in Table 4.

The graphic representation of the comparison between the experimental results and the predicted ones highlights the accuracy of the ANN model (Fig. 8 and Fig. 9).

The weights and biases values for the ANN model proposed are given in Table 5; with these values for weights and biases and taking into account the formula (5), values of the stress concentration factor K_t can be obtained for input data in the field in which the training was carried out.

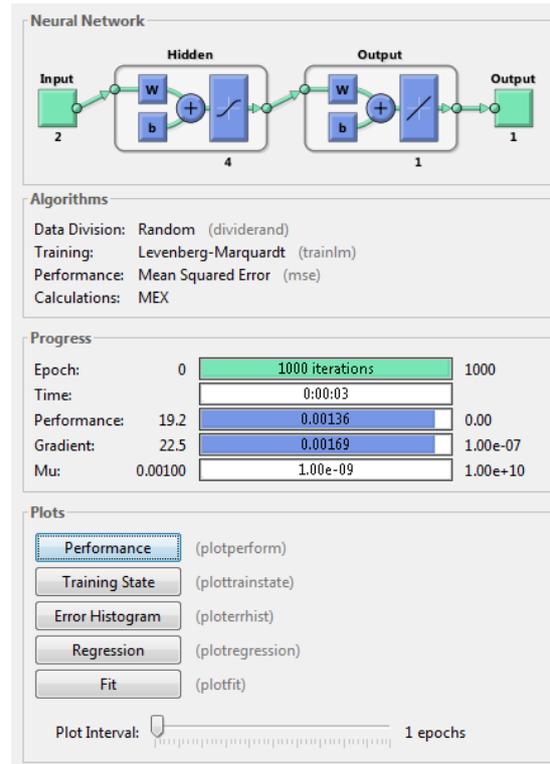


Fig. 7. ANN model using MATLAB

Table 3. Stress concentration factor K_t experimental and predicted for training data

Training data				
	$\frac{r}{d}$	$\frac{D}{d}$	K_t experimental	K_t predicted
1	0.01	1	2	2.0095
2	0.04	1	1.49	1.5082
3	0.05	1	1.47	1.47
4	0.09	1	1.3	1.2919
5	0.01	1.5	4.8	4.7887
6	0.02	1.5	3.5	3.4815
7	0.04	1.5	2.8	2.8234
8	0.06	1.5	2.15	2.2461
9	0.07	1.5	2.1	2.1047
10	0.08	1.5	2	1.9843
11	0.09	1.5	1.98	1.8817
12	0.01	2	5.4	5.4044
13	0.02	2	4.3	4.3075
14	0.04	2	3.4	3.3667
15	0.06	2	2.8	2.8093
16	0.07	2	2.6	2.6399
17	0.08	2	2.5	2.4706
18	0.09	2	2.3	2.3015

Table 4. Stress concentration factor K_t experimental and predicted for testing data

	Testing data			
	$\frac{r}{d}$	$\frac{D}{d}$	K_t experimental	K_t predicted
1	0.025	1	1.625	1.5154
2	0.075	1	1.375	1.2919
3	0.03	1.5	3	3.06
4	0.05	1.5	2.4	2.5381
5	0.07	1.5	2.1	2.1047
5	0.03	2	3.8	3.5779
7	0.05	2	3	3.0427

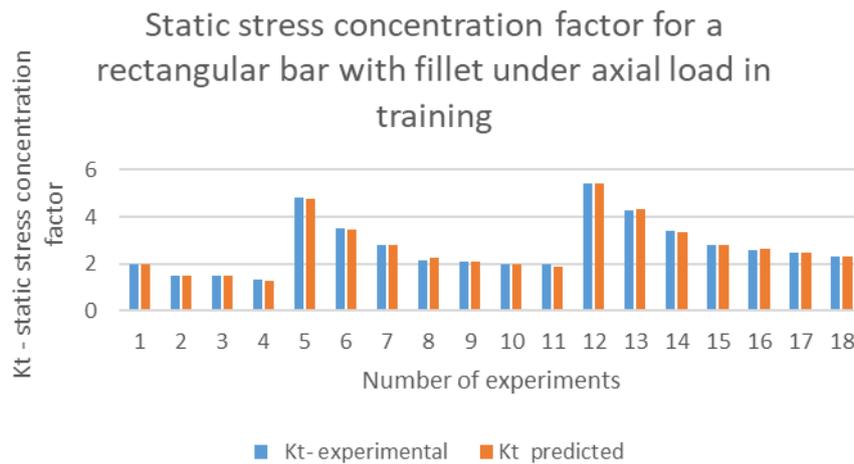


Fig 8. Stress concentration factor K_t for a rectangular bar with fillet Under Axial Loading, in training

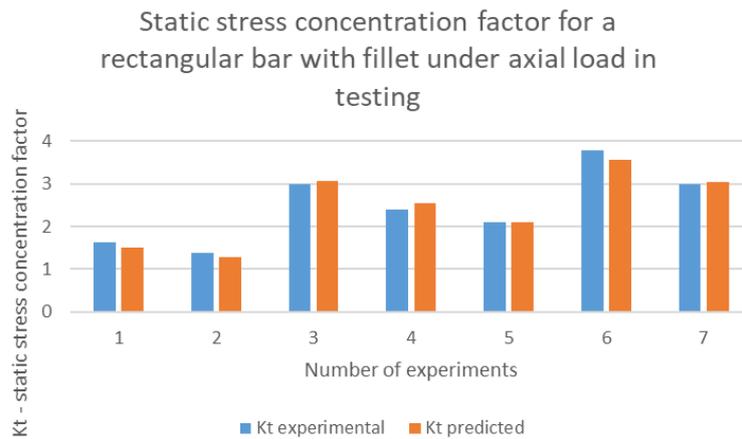


Fig. 9. Stress concentration factor K_t for a rectangular bar with fillet Under Axial Loading, in testing

Table 5. The weights and bias values for the ANN model proposed

The input-to-hidden layer weights	
W1	
0.0021	13.3296
0.321	-13.4838
-33.7648	-0.6031
6.1134	-0.8335

The hidden-to-output layer weights			
W2			
-291.208	-245.151	0.0527	-0.4038

The input-to-hidden layer bias
B1
-12.4989
3.3992
0.1677
5.6969

The hidden-to-output layer bias
B2
-46.6049

5. Conclusions

This study contains the determination of stress concentration factor using Peterson’s Stress Concentration Factor charts and formulas and ANN modelling. Peterson's graphs have been accepted as scientifically valid and so the Roark’s formula.

The values in these graphs can be defined only as a result of experimental studies. It is easier and more practical to determine these values using auxiliary software instead of using formulas.

A new ANN model was developed using Matlab software. Different ANN models were tried and the best model was determined.

The ANN model provided high accuracy for the prediction of stress concentration factor (K_t).

By using the ANN model, the user can avoid misreading the data in the charts.

The hierarchy of the two input variables assumes that the second variable D/d has a greater influence in determining the stress concentration factor than the r/d ratio.

Using weights and biases calculated, for r/d = 0.05 and D/d = 1.2 is obtained the stress concentration factor predicted $K_t = 2.0535$ (Table 6).

Table 6. Test for a pair of input variables that are not found in the training or testing data

r/d	D/d	K_t predicted
0.05	1.2	2.0535

References

[1]. **Boger Z., Guterman H.**, *Knowledge extraction from artificial neural network models*, IEEE Systems, Man, and Cybernetics Conference, Orlando, FL, USA, 1997.
 [2]. **Budynas-Nisbett**, *Shigley’s Mechanical Engineering Design*, 8th Edition.

[3]. **Haykin S.**, *Neural Network: A Comprehensive Foundation*, New York, Macmillan, 1994.
 [4]. **Abhishek K., Kishore D. J., Prakashkumar Kavalur, Akshay N. H.**, *ANN modeling for prediction of cutting force component during orthogonal turning*, International Research Journal of Engineering and Technology (IRJET), vol. 5, issue 6, June 2018.
 [5]. **Souâd Makhfi, Raphaël Velasco, Malek Habak, Kamel Haddouche, Pascal Vantomme.** *An Optimized ANN Approach for Cutting Forces Prediction in AISI 52100 Bearing Steel Hard Turning*, p-ISSN: 2163-2669, e-ISSN: 2163-2677, 3 (1), p. 24-32, doi: 10.5923/j.scit.20130301.03, 2013.
 [6]. **Maunayri H.**, *Novel Artificial Neural Networks Force Model for end Milling*, Springer, International Journal of Advanced Manufacturing Technology, 18, p. 693-700, 2001.
 [7]. **Krzysztof L. Molski**, *Stress concentration at load-carrying fillet welded cruciform joints subjected to tensile and bending loads*, Acta mechanica et automatica, vol. 13 no. 4, DOI 10.2478/ama-2019-0033, 2019.
 [8]. **Pilkey Walter D., Pilkey Deborah F.**, *Peterson’s stress Concentration Factors*, 3rd Edition.
 [9]. **Saurabh Karsoliya.** *Approximating Number of Hidden Layer neurons in Multiple Hidden Layer BPNN Architecture*, International Journal of Engineering Trends and Technology, vol. 3, issue 6, 2012.
 [10]. **Ihsan Toktas, Murat Tolga Ozkan, Fulya Erdemir, Nurullah Yuksel**, *Determination of Stress Concentration Factor (K_t) for a Crankshaft under Bending Loading: An Artificial Neural Networks Approach*, Politeknik Dergisi, Journal of Polytechnic, ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE), 2020.
 [11]. **Alan J. Thomas, Miltos Petridis, Simon D. Walters, Saeed Malekshahi Gheytsi, Robert E. Morgan.** *On Predicting the Optimal Number of Hidden Nodes*, International Conference on Computational Science and Computational Intelligence, 2015.
 [12]. **Warren C. Young, Richard G. Budynas**, *Roark’s Formulas for Stress and Strain*, 8th Edition.
 [13]. ***, <https://mechanicalc.com/calculators/stress-concentration/>.
 [14]. ***, *MATLAB 2018a*, The MathWorks, Inc., Natick, Massachusetts, United States.

ANNEX A

Training data			
	$\frac{r}{d}$	$\frac{D}{d}$	K_t experimental
1	0.01	1	2
2	0.04	1	1.49
3	0.05	1	1.47
4	0.09	1	1.3
5	0.01	1.5	4.8
6	0.02	1.5	3.5
7	0.04	1.5	2.8
8	0.06	1.5	2.15
9	0.07	1.5	2.1
10	0.08	1.5	2
11	0.09	1.5	1.98
12	0.01	2	5.4
13	0.02	2	4.3
14	0.04	2	3.4
15	0.06	2	2.8
16	0.07	2	2.6
17	0.08	2	2.5
18	0.09	2	2.3

Testing data			
	$\frac{r}{d}$	$\frac{D}{d}$	K_t experimental
1	0.025	1	1.625
2	0.075	1	1.375
3	0.03	1.5	3
4	0.05	1.5	2.4
5	0.07	1.5	2.1
5	0.03	2	3.8
7	0.05	2	3