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DETERMINATION OF THE NOTCH FACTOR FOR SHAFTS UNDER TORSIONAL STRESS WITH ARTIFICIAL NEURAL NETWORKS

UPORABA UMETNIH NEVRONSKIH MREŽ ZA DOLOČANJE FAKTORJA ZAREZNEGA UČINKA NA GREDEH, OBREMENJENIH S TORZIJSKIMI NAPETOSTMI

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When designing machine equipment, geometrical figures or discontinuities such as notches, holes, steps and curves can occur. Sudden cross-section changes, discontinuities and force flows cause concentrations, particularly in the stress area. Stress concentrations may be formed due to dimensional features of a material or directions of applied forces. Such stress concentrations are considered as they have a notch effect on the material. The notch effect may lead to a breaking and distortion of a material. In this study, a mathematical model estimating the notch-factor values for a grooved round bar in torsion, a round shaft with a transverse hole in torsion and a round shaft with a shoulder fillet in torsion, using artificial neural networks (ANN) is introduced. The model estimates the notch factor using shaft dimensions, torque and corner rounding values. The ANN model developed in the study quickly and accurately estimates the notch-factor values, otherwise obtained from the catalogues with complicated analytical calculations. In this model, the uncertainties occurring in analytical calculations and the calculation errors were eliminated, thus long calculation times were saved as well. The results reviewing the performance of the ANN model developed for a grooved round bar in torsion, a round shaft with a transverse hole in torsion and a round shaft with a shoulder fillet in torsion were quite good. In the study, a multiple regression analysis of the data was also performed, but no conclusion evaluating the data was obtained.

Keywords: shafts, notch-sensitivity factor, torsion, artificial neural network, statistical analysis

Pri konstruiranju strojnih delov se pojavljajo nezvezne geometrijske oblike, kot so zareze, luknje, stopnice in krivine. Nenadna sprememba prereza, nezveznosti in potek sil povzročajo koncentracijo napetosti v napetostnem območju. Koncentracije napetosti v materialu lahko nastanejo zaradi dimenzijskih sprememb ali sprememb smeri delovanja sil. Taka koncentracija napetosti se obravnava kot zarezni učinek v materialu. Zarezni učinek lahko povzroči porušitev ali izkrivljenje materiala. V tej študiji je predstavljen matematični model umetne nevronske mreže (ANN), ki lahko obravnava faktor zareznega učinka okrogle palice z utorom, okrogle gredi s prečno odprtino, obremenjeno s torzijo, in okrogle gredi z zaokroženim prehodom. Model določa faktor zareznega učinka z uporabo dimenzij, navora in radija zaokrožitev. Razvit ANN-model omogoča hitrejše in bolj zanesljivo določanje faktorja zareznega učinka, ki ga sicer dobimo iz katalogov z zapletenimi analitičnimi preračunavanji. V tem modelu so odpravljene nezanesljivosti, ki se pojavljajo pri analitskem preračunavanju, odpravljene so računske napake in prihranjeno nam je dolgotrajno preračunavanje. Pregledane so bile zmogljivosti ANN-modela, razvitega za torzijo okrogle palice z utorom, torzijo okrogle gredi s prečno odprtino in okrogle gredi z zaobljenim prehodom. V študiji je bila izvedena tudi multipla regresijska analiza podatkov, vendar ni bilo mogoče izluščiti ugotovitve, ki bi prispevala k oceni podatkov.

Ključne besede: gred, faktor zareznega učinka, torzija, umetna nevronska mreža, statistična analiza

1 INTRODUCTION

Breaks and deformations are observed on almost all machine parts used for a power and force transmission. In order not to have these undesired effects, the notch factor is considered in the calculations. Thus, a formation of such effects is minimized or eliminated. Theoretical notch factors used in the calculations according to the change in the calculations or type of strain affecting the shafts vary. For each different type of strain, there are many table values available, but it is an inconvenient procedure to obtain the values required for the design from such tables.

Mechanical damages formed as a result of fatigue have been a subject of engineering studies for many years. One of the first studies on this subject was made by W. A. J. Albert who tested metal chains lifted up under cyclic loadings in Germany in 1828. The term "fatigue" was first used in 1839 by J. V. Poncelet.[1]

During the studies he made in 1850s in Germany, August Wöhler started to develop design strategies in order to avoid fatigue damage, testing iron, steel and other metals under torsion, bending and axial loadings. With his studies, Wöhler proved that fatigue was affected by the average stress as well as by cyclic stresses.[2]

McClintock made the first theoretical research related to the ductile damage, taking place as void growth.[3] In this research, it was concluded that the rate of void growth definitely depends on three axial stress regions as well as on the rate of hydrostatic equivalent stress. As a result of his experiments, McClintock concluded that different samples do not always have the same unit deformation in crack formation.

The study made by Rice and Tracey took McClintock's study to a higher level. With this study, it was concluded that the rate of void growth definitely depends on three axial stress regions as well as on the rate of hydrostatic equivalent stress.[4]

With their experimental study, Hancock and Mackenzie supported the idea that the orientability of ductility for construction materials could be three-axial, and revealed that the material damage had been caused by high-degree hydrostatic pressure.[5]

By using the results of their experimental study, Bridgman, Hancock and Mackenzie revealed damage-unit-deformation and representation parameters of triaxiality in a closed damage curve.[6] Hancock and Brown examined stress-unit deformation spaces on a notched sample.[7] In the study, damage was reviewed at the centre point of the minimum cross-section where triaxiality is the highest on a cylindrical notched sample.

Ozkan made a study about the notch-sensitivity determination of shafts. He used an ANN model.[8] Ozkan et al. made a study about determining the notch factor on the shafts under tensile stress. They also used an ANN model.[9]

Recorded literature studies have revealed that notched tensile tests are commonly applied experiments. They show that notched tensile experiments include a large number of notch types. Therefore, it is obvious that modelling the data obtained from standard-experiment results and notched tensile experiments will provide an increase in the number of variables in experimental studies.

The notch-factor selection and the calculations made afterwards require long and inconvenient procedures and, consequently, a significant amount of time and labour. It is necessary to utilise computer programs to solve such problems.

The aim of this study was to develop a mathematical model that can provide for the best notch factors on a grooved round bar in torsion, a round shaft with a transverse hole in torsion and a round shaft with a shoulder fillet in torsion by considering the formal characteristics of the material affecting the notch factor and the torsional-stress effect influencing the shaft. The mathematical model was developed using a multilayer feedforward artificial neural network (MLP). In the study, a multiple regression analysis of the data was made. Multiple-regression and ANOVA analyses were also made, but since their results did not help us interpret the data, the study was focused on ANN. The artificial-neural-network model developed within the study consisted of three inputs for the round shaft with a shoulder fillet in torsion and the grooved round bar in torsion, two inputs for the round shaft with a transverse hole in torsion, one hidden layer and one output.

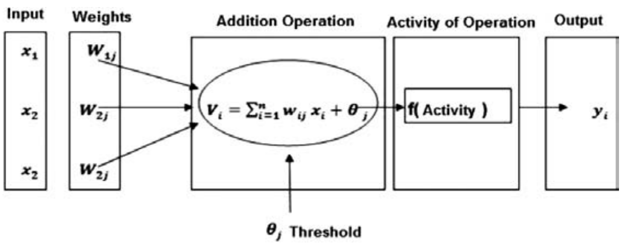


Figure 1: Artificial neural network
Slika 1: Umetna nevronska mreža

2 ARTIFICIAL NEURAL NETWORKS

The concept of artificial neural networks first appeared as the idea of simulating the principle operation of the brain on digital computers. An artificial neural network is a mathematical model inspired by the functional structure of a biological neural network.[10] Artificial neural networks consist of many operation elements connected to each other. Operation elements in artificial neural networks (nodes) function like simple nerves. An artificial neural network consists of many nodes connected to each other. The main unit of an artificial neural network is an artificial nerve. An artificial nerve is much simpler than a biological nerve. In **Figure 1**, an artificial neural element is shown. All the artificial neural networks are derived from this main structure. Differences in this structure allow different classifications of artificial neural networks.

An ANN model consists of two main steps: the training and the test. The meaning of learning in artificial neural networks is to allow a neural network to produce correct outputs by establishing the right connections between the input and the output data relating to the problem. This procedure continues until the difference between the estimated output and the desired output decreases to a certain value. Artificial neural networks learn with experience just like humans. For that purpose, an experimental group is divided into two parts: the training group and the test group. During the training period, the network uses an inductive training model to train the training group.[11] The training process continues in the network until the desired output value is obtained.[12] When certain amounts of the input are entered in the network during learning, the network makes changes to itself to be able to give similar responses. Here, the error in question is the difference between the estimated output and the generated output. After training, the network is tested to find whether ANN has actually learned, instead of just memorizing, the data. In the test section, the data not used during the training is used.

The performance of a developed ANN model is determined using different error-analysis methods. In general, such methods can be ranked as the absolute fraction of variance (R^2), the root-mean-square error (RMSE) and the mean absolute-percentage error

(MAPE). The best performance of an ANN model is at the highest value of R^2 and at the lowest values of RMSE and MAPE.[13] Such parameters are defined with the following equations:

$$R^2 = 1 - \left[\frac{\sum (MR_{exp,1} - MR_{ANN,i})^2}{\sum (MR_{ANN})^2} \right] \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (MR_{ANN,i} - MR_{exp,1})^2} \tag{2}$$

$$MAPE = \frac{MR_{ANN} - MR_{exp}}{MR_{ANN}} \cdot 100 \tag{3}$$

3 STRENGTH-REDUCTION FACTORS

Resistance diagrams are obtained using standard-experiment test-bar surfaces that have been polished. Dimensional and surface features of the actual machine elements are different from the test bars. Therefore, the values taken from a permanent-resistance diagram cannot be used without considering the resistance-reduction factors.[14] The resistance limits of materials are affected by the factors such as notch, surface roughness, dimension, manufacture method, heat treatment, environmental effect, etc.[15]

In some cases, the results obtained for machine elements with experiments show the existence of the stresses much bigger than the normal stresses. The reason for that is the geometrical difference between the parts. The notch is the generally defined dimensional difference.[16]

In design of machine elements, geometric figure differences or discontinuities such as notches, holes, steps or various groove roundings and keyways can occur for certain reasons. Sudden section changes and discontinuities cause concentrations in the force flow, particularly in the stress area. Such stress concentrations cause a notch effect on the material.[17]

3.1 Stress-concentration factor (K_t) and notch-sensitivity factor (q)

The stress-concentration factor (K_t) is defined as the ratio of the biggest stress generated at bottom of the notch to the nominal stress:[18,19]

$$K_t = \frac{\tau_{max}}{\tau_n} \tag{4}$$

In the calculation of torsional stress, the relations in equations 5 and 6 are used:

$$\tau_n = \frac{M}{W_p} \tag{5}$$

$$\tau_n = K_t \frac{M}{W_p} \tag{6}$$

In the machine elements, the stress that is times the calculated nominal stress is generated at the bottoms of geometric figures. If the material is brittle, the notched material is broken due to the static stress that is times lower than the nominal stress. For example, if there is a notch with a concentration factor K_t = 3 on a machine element made of hardened steel, such an element is three times more fragile than the unnotched one:[17–19]

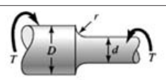
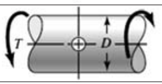
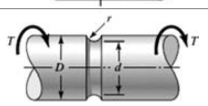
$$K_c = 1 + q(K_t - 1) \tag{7}$$

The stress-concentration factor (K_t) is a value depending on geometry. The fatigue-strength-reduction factor indicating an active reduction in the material strength is K_c. The notch factor depends on the geometrical shape of the notch and the sensitivity of the material to the notch. If the effect of the notch's geometrical shape is represented with the theoretical notch factor K_t, and the sensitivity of the material to the notch is represented with the notch-sensitivity factor q, the notch factor is calculated using the relation given in equation 7.

4 RESULTS AND DISCUSSION

The data in this study was obtained by examining the graphics relating to the notch factor from Peterson's book "Design Factors for Stress Concentration".[20,21] The

Table 1: Numbers of trainings and tests for the shafts under torsional stress
Tabela 1: Število usposabljanj in podatki za gred, izpostavljeni torzijski obremenitvi

Notch-factor values for the shafts under torsional stress					
			Training Data	Test Data	Total Data
Round shaft with a shoulder fillet in torsion		Torsion	590	100	690
Round shaft with a transverse hole in torsion		Torsion	130	30	160
Grooved round bar in torsion		Torsion	450	110	560

graphics were transformed to digital values, obtaining the data for the ANN learning and testing. In the notch charts, there are three basic figures for the shafts under the torsional-stress effect. These are a round shaft with a shoulder fillet in torsion, a round shaft with a transverse hole in torsion and a grooved round bar in torsion. In **Table 1**, there are the numbers of trainings and tests used for determining the notch factors for the three basic figures.

In **Table 1**, the classification and the numbers for the shafts under the torsional-stress effect are presented. The input data used in ANN includes the maximum shaft diameter (*D*), the minimum shaft diameter (*d*) and the chamfer radius (*r*), while the output data is the notch factor (**Table 2**).

Table 2: Input and output values for the notch factor of the shafts
Tabela 2: Vhodne in dobljene vrednosti za faktor zareze gredi

Determination input/output parameters for the shafts under torsional stress		
Symbol	Name	Input/output
D	Maximum diameter of the shaft	Input
d	Minimum diameter of the shaft	Input
r	Chamfer radius	Input
K_t	Stress-concentration factor	Output

As ANN has been generated, not all the experiment data is used in the training. After the ANN system has been established and the training procedure finished, 10 % of the experiment data is hidden from the system to check whether ANN has given correct results. In the scope of the study, 690 pieces of data for the round shaft with a shoulder fillet in torsion, 160 for the round shaft with a transverse hole in torsion and 560 for the grooved round bar in torsion have been obtained with theoretical calculations (**Table 3**). Out of such data, 590 pieces for the round shaft with a shoulder fillet in torsion, 130 for the round shaft with a transverse hole in torsion and 450 pieces for the grooved round bar in torsion were used for the training purposes. The other data was saved for the test purposes. The test data is used to find the error rate of the ANN system estimations.

In the study, a feedforward, multiple-layer neural-learning mechanism was used as the learning mechanism. For the learning model, the Levenberg-Marquardt algorithm (LMA) was used. During the determination of the learning criteria in ANN, different network structures were tried and the network structure with the minimum error and maximum learning rate was selected. According to that, the best learning for the round shaft with a shoulder fillet in torsion took place within a 3-4-1 network structure, for the grooved round bar in torsion within a 3-3-1 structure and for the round shaft with a transverse hole in torsion it took place within a 2-3-1 network structure (**Figure 2**). In this study, a single output layer and a single hidden layer were selected for

Table 3: Input and output samples used in the ANN model
Tabela 3: Vhodni in izhodni vzorci, uporabljeni v ANN-modelu

Round shaft with a shoulder fillet in torsion				Grooved round bar in torsion				Round shaft with a transverse hole in torsion		
D	d	r	K_t	D	d	r	K_t	D	d	K_t
2	2.04	0.024	2.29	1	1.02	0.025	2.082	2	153.846	3.643
3	3.06	0.051	2.12	2	2.04	0.068	1.928	3	120.000	3.430
4	4.08	0.084	2	3	3.06	0.12	1.835	4	117.647	3.300
5	5.1	0.125	1.926	4	4.08	0.2	1.767	5	100.000	3.160
13	13.26	1.95	1.33	11	11.22	1.375	1.464	6	96.774	3.080
14	14.28	2.45	1.297	12	12.24	1.644	1.44	7	93.333	3.000
15	15.3	3	1.264	13	13.26	1.95	1.414	8	80.000	2.910
16	16.32	3.6	1.242	14	14.28	2.45	1.386	9	72.000	2.840
35	36.75	8.75	1.286	15	15.3	3	1.36	12	60.000	2.708
36	37.8	9.9	1.264	16	16.32	3.6	1.325	13	57.778	2.680
37	38.85	11.1	1.242	17	17.34	4.25	1.3	14	56.000	2.650
38	41.8	0.456	2.7	18	18.36	4.95	1.276	15	54.545	2.640
39	42.9	0.663	2.5	35	36.75	7.875	1.425	16	53.333	2.630
62	93	3.844	1.925	36	37.8	9	1.4			
63	94.5	4.725	1.8	37	38.85	10.175	1.364			
64	96	5.568	1.728	38	39.9	11.4	1.338			
65	97.5	6.5	1.66	45	67.5	3.375	2.144			
66	99	8.25	1.584	46	69	3.956	2.04			
67	100.5	10.05	1.51	47	70.5	4.7	1.94			
87	261	17.4	1.457	48	72	5.376	1.872			
88	264	19.8	1.41	53	79.5	10.6	1.574			
89	267	22.25	1.374	54	81	12.15	1.53			
90	270	24.75	1.34	55	82.5	13.75	1.486			
91	273	27.3	1.32	56	84	15.4	1.44			

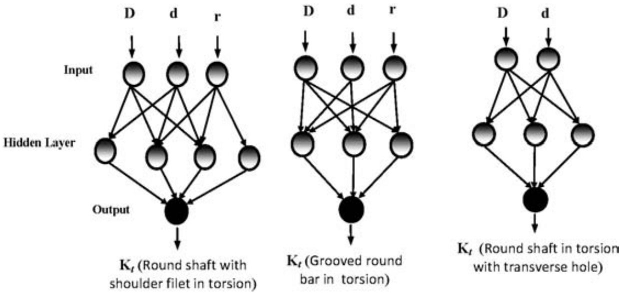


Figure 2: Suitable network structures for the notch factors of the shafts for: a) round shaft with a shoulder fillet in torsion, b) grooved round bar in torsion, c) round shaft with a transverse hole in torsion
Slika 2: Primerne strukture mreže za faktor zareznega učinka na gredi pri torziji: a) okrogla gred z zaokroženim prehodom, b) okrogla palica z utorom, c) okrogla gred s prečno odprtino

each type of the shafts. As a result of the experimental-data training, it was observed that optimum outputs were the models having eight neurons for the round shaft with a shoulder fillet in torsion, seven neurons for the grooved round bar in torsion and six for the round shaft with a transverse hole in torsion. For all of these experimental-data trainings, determination of the network structure and its optimization, the Pythia software was used.

In the software, for each different notch situation (the grooved round bar in torsion, the round shaft with a transverse hole in torsion and the round shaft with a shoulder fillet), the ANN model with the highest performance was determined. For this purpose, different variations were tried to determine the notch factor of the shafts under the torsional effect, and the model with the highest performance was selected as the ANN model (**Table 4**).

In order to test the network structure of ANN, a normalization of the inputs was implemented at first. The normalization of the inputs and outputs was made within the ranges of (–1, +1) or (0, –1). The normalization of the input (x_{nor}) is made with equation 8:

$$x_{nor}=\frac{(x_r-x_{min})}{(x_{max}-x_{min})} \tag{8}$$

Table 4: Determination of the appropriate network design
Tabela 4: Določanje oblikovanja primerne mreže

Round shaft with a shoulder fillet in torsion	Grooved round bar in torsion	Round shaft with a transverse hole in torsion
MLP 3-15-1	MLP 3-22-1	MLP 2-3-1
MLP 3-13-1	MLP 3-19-1	MLP 2-11-1
MLP 3-23-1	MLP 3-30-1	RBF 2-9-1
MLP 3-13-1	MLP 3-5-1	MLP 2-7-1
MLP 3-20-1	MLP 3-8-1	MLP 2-7-1
RBF 3-24-1	MLP 3-32-1	RBF 2-2-1
MLP 3-30-1	RBF 3-7-1	MLP 2-5-1
MLP 3-30-1	RBF 3-18-1	MLP 2-8-1
MLP 3-20-1	RBF 3-15-1	MLP 2-4-1
MLP 3-21-1	RBF 3-22-1	RBF 2-10-1
MLP 3-47-1	RBF 3-30-1	RBF 2-5-1

Here, x_r represents the actual input value, x_{min} is the minimum input value and x_{max} is the maximum input value. The values used for the normalization are given in **Table 5**.

Table 5: Values used for normalization
Tabela 5: Vrednosti, uporabljene za normalizacijo

Shafts under torsion	Parameters	x_{max}	x_{min}
Round shaft with a shoulder fillet in torsion	*D* (maximum diameter of shaft)	91	2
	d (minimum diameter of shaft)	273	2.04
	r (chamfer radius)	27.3	0.024
Grooved round bar in torsion	*D* (maximum diameter of shaft)	57	1
	d (minimum diameter of shaft)	85.5	1.02
	r (chamfer radius)	17.1	0.025
Round shaft with a transverse hole in torsion	*D* (maximum diameter of shaft)	16	2
	d (minimum diameter of shaft)	153.846	53.333

Formulization of neurons was made with the Fermi-transfer function that is widely used in the ANN training (equation 9). The Fermi-transfer function is a commonly preferred function in the studies conducted in different areas:

$$F_i=\frac{1}{1+e^{-4(\sum x_{nor}\cdot w_1-0.5)}} \tag{9}$$

Here, x_{nor} represents the normalized value of the input as (I = 1, 2, 3, ..., n) and represents its weight value. The weights obtained in the ANN model are given in **Table 6**. The Fermi functions created for each shaft type considered in the study are given in equations 10, 11 and 12:

$$F_{i_{\text{Shoulder filet}}(1-4)}=\frac{1}{1+e^{-4(\sum D_{nor}\cdot w_{21}+d_{nor}\cdot w_{21}+r_{nor}\cdot w_{21}-0.5)}} \tag{10}$$

$$F_{i_{\text{Grooved}}(1-3)}=\frac{1}{1+e^{-4(\sum D_{nor}\cdot w_{21}+d_{nor}\cdot w_{21}+r_{nor}\cdot w_{21}-0.5)}} \tag{11}$$

$$F_{i_{\text{Transverse hole}}(1-3)}=\frac{1}{1+e^{-4(\sum D_{nor}\cdot w_{21}+d_{nor}\cdot w_{21}-0.5)}} \tag{12}$$

At the end of all these calculations, the output value of the network is calculated with equation 13:

$$S_{ann}=f_i(S_{max}-S_{min})+S_{min} \tag{13}$$

Here, S_{max} represents the maximum output value as fi (I = 1, 2... n) and S_{min} represents the minimum output value.

After the training and test procedures, the results obtained from the ANN model were compared to the theoretical (actual) calculation results considering the statistical error. In the error analysis, the performance of both the training and test data is evaluated. In the study,

Table 6: Weights calculated for the shafts under the torsional-stress effect
Tabela 6: Izračunane uteži gredi pri torzijskih napetostih

Round shaft with a shoulder fillet in torsion				Grooved round bar in torsion				Round shaft with a transverse hole in torsion		
i	W_{1i}	W_{2i}	W_{3i}	i	W_{1i}	W_{2i}	W_{3i}	i	W_{1i}	W_{2i}
1	1.034673	–0.994349	1.193954	1	–1.383967	1.996118	–11.65191	1	0.576589	–1.068331
2	2.166340	–1.506025	5.954506	2	–0.228184	–1.205579	1.134065	2	0.062530	–0.394452
3	–5.204485	–3.426240	–2.290548	3	–0.626798	0.816721	–1.226995	3	–1.182488	0.407942
4	0.550379	0.391485	–1.669116							

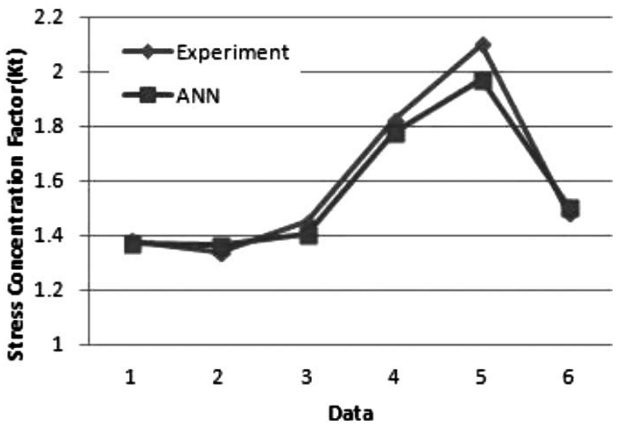


Figure 3: Comparison of the notch-sensitivity factors for a grooved round bar in torsion (ANN – the actual data)
Slika 3: Primerjava faktorja občutljivosti na zarezo pri okrogli palici z utorom (ANN – dejanski podatki)

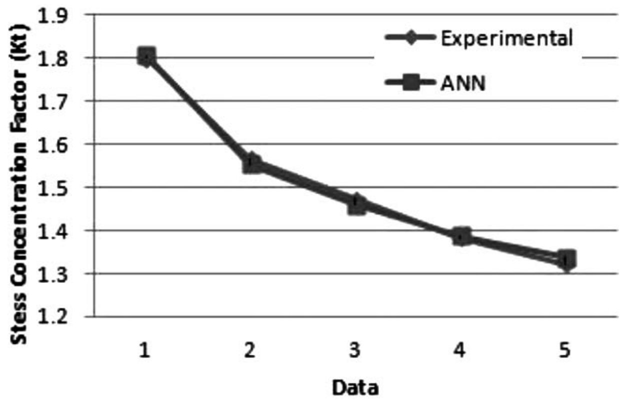


Figure 4: Comparison of the notch-sensitivity factors for a round shaft with a shoulder fillet in torsion (ANN – the actual data)
Slika 4: Primerjava faktorja občutljivosti na zarezo pri okrogli gredi z zaokroženim prehodom pri torziji (ANN – dejanski podatki)

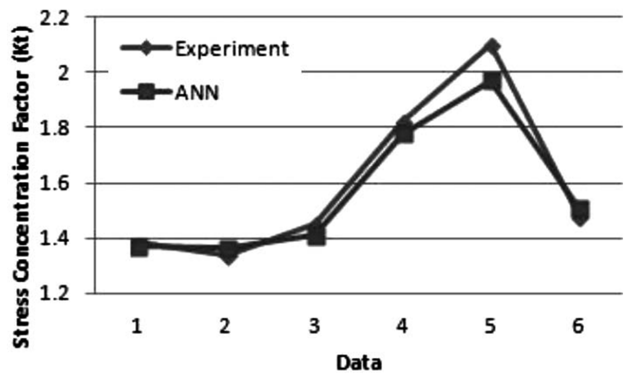


Figure 5: Comparison of the notch-sensitivity factors for a round shaft with a transverse hole in torsion (ANN – the actual data)
Slika 5: Primerjava faktorja občutljivosti na zarezo pri okrogli gredi s prečno odprtino pri torziji (ANN – dejanski podatki)

while statistical analyses were made with the Statistica software, the graphics were created with the MATLAB software. When **Figures 3**, **4** and **5** are reviewed, it can be seen that theoretical-calculation results and ANN results are very close. With the developed ANN model, the results determining the notch factors are very close to the actual values.

The performance of the ANN model depends on the deviation amount (the error) between the actual output values and the output values obtained with the ANN model. For the analysis of such error amounts, three statistical values were used. These are the statistical error amount (the root-mean-square error – RMSE), the absolute rate of change (and the average error rate (MAPE). If, in a model, the RMSE value is low, the value is close to one and the MAPE value is close to zero, it is concluded that the data sample was solved with the ANN model with a very low deviation. When **Figures 6**, **7**, **8** and **Table 7** are reviewed, it can be observed that the test performance of the ANN model developed to estimate the notch factors is very good.

Table 7: Statistical values of the notch factors for a round shaft with a shoulder fillet in torsion, grooved round bar in torsion and round shaft with a transverse hole in torsion
Tabela 7: Statistične vrednosti faktorja zareze pri okrogli gredi z zaokroženim prehodom pri torziji, okrogli palici z utorom in okrogli gredi s prečno odprtino

	R^2	RMSE	MAPE
Round shaft with a shoulder fillet in torsion	0.998496193	0.00045234	0.00133894419
Grooved round bar in torsion	0.999026056	0.000929826	0.00092129141
Round shaft with a transverse hole in torsion	0.999852111	0.00048452	0.00013216197

Table 8: Statistical error amounts obtained with the regression analysis and ANN
Tabela 8: Statistična napaka, dobljena z regresijsko analizo ANN

	Multiple regression analysis		Artificial neural network (ANN)
	R^2	Adjusted R	R^2 (ANN)
Round shaft with a transverse hole in torsion	0.98972458	0.98766949	0.998496193
Round shaft with a shoulder fillet in torsion	0.65122920	0.63513208	0.999026056
Grooved round bar in torsion	0.72001774	0.69953123	0.999852111

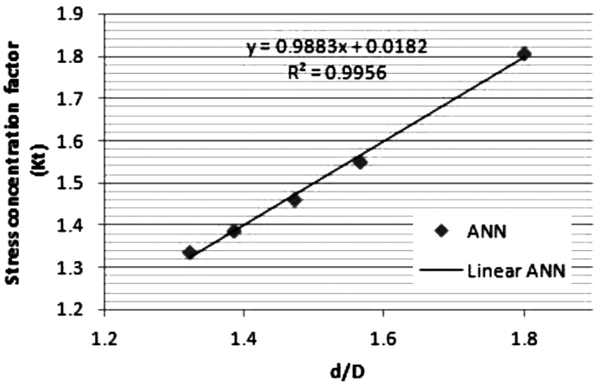


Figure 6: Notch factor for a round shaft with a shoulder fillet in torsion
Slika 6: Faktor zareze pri okrogli gredi z zaokroženim prehodom pri torziji

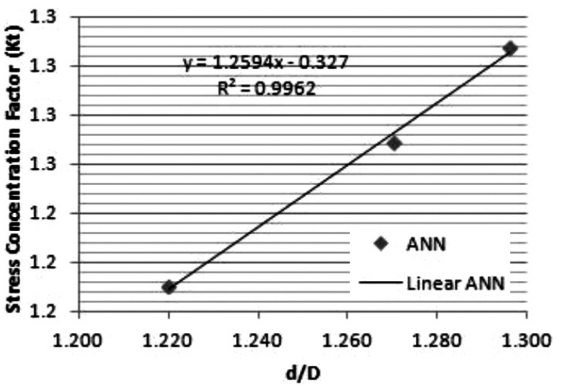


Figure 7: Notch factor for a grooved round bar under the torsional effect
Slika 7: Faktor zareze pri okrogli palici z utorom pri torziji

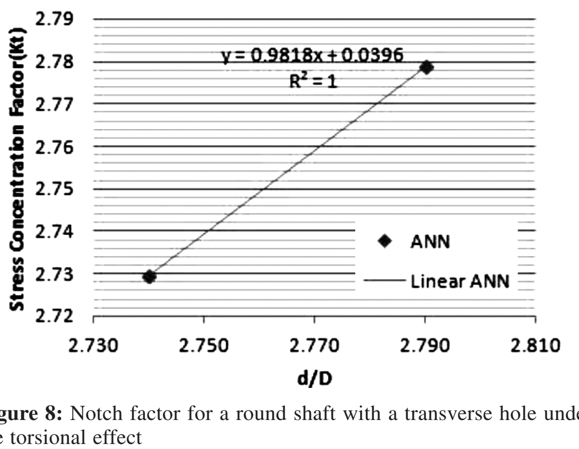


Figure 8: Notch factor for a round shaft with a transverse hole under the torsional effect
Slika 8: Faktor zareze pri okrogli gredi s prečno odprtino pri torziji

In **Figures 5**, **6** and **7**, the performance of a YSA model is available for the notch-factor estimation. Here, the closeness value between the actual values and the estimated values is graphically shown. As seen in the figures, the estimations made by the ANN model were rather close to the actual values.

In the study, a multiple regression analysis (RA) of the data was made as well and specifically adjusted R^2 values were observed. In the analysis, a suitable R^2 could

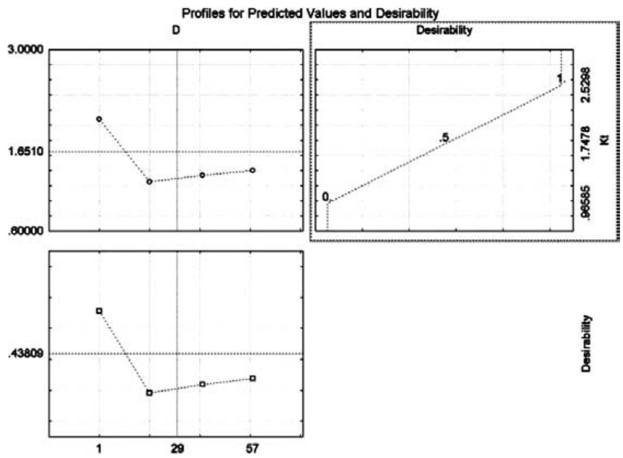


Figure 9: ANOVA analysis; notch-sensitivity factor for a grooved round bar in torsion
Slika 9: ANOVA analiza; faktor zareznega učinka pri okrogli palici z utorom pri torziji

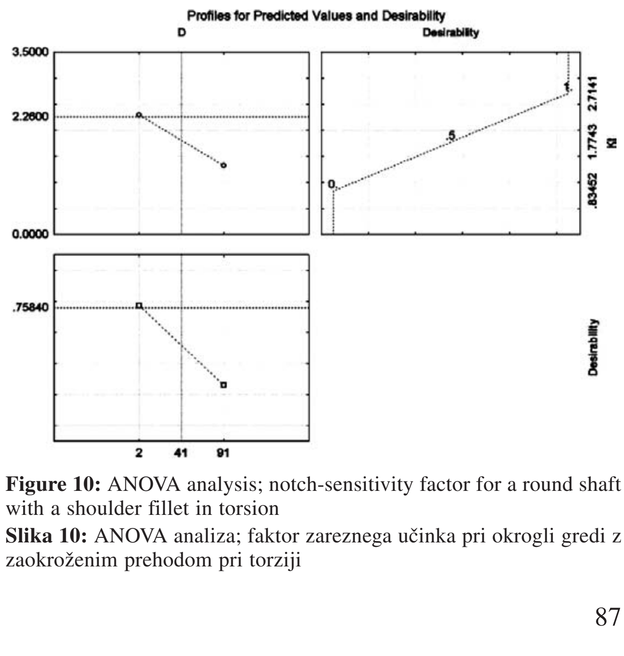


Figure 10: ANOVA analysis; notch-sensitivity factor for a round shaft with a shoulder fillet in torsion
Slika 10: ANOVA analiza; faktor zareznega učinka pri okrogli gredi z zaokroženim prehodom pri torziji

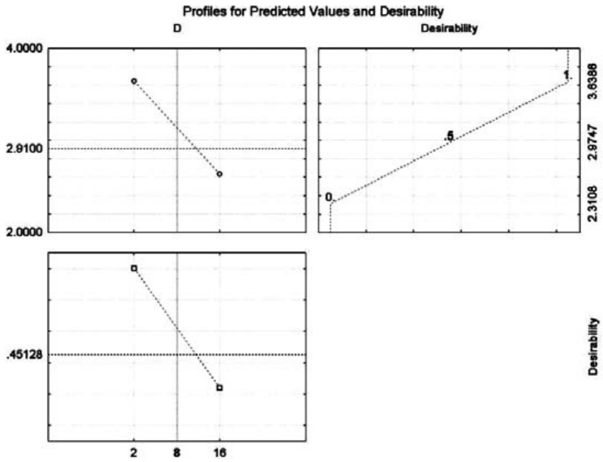


Figure 11: ANOVA analysis; notch-sensitivity factor for a round shaft with a transverse hole in torsion

Slika 11: ANOVA analiza; faktor zareznega učinka pri okrogli gredi s prečno odprtino

only be obtained for the round shaft with a transverse hole in torsion. In **Table 8**, the statistical error amounts (R^2) obtained with the regression analysis and the statistical error amounts (R^2) of the ANN test data were compared. An ANOVA analysis of the data was made as well, but no results interpreting the data were obtained (**Figures 9**, **10** and **11**). Statistically, only the parameter of the maximum diameter of the shaft affected the notch sensitivity.

5 CONCLUSIONS

In this study, an ANN model developed for estimating the notch factors of the shafts under the torsional effect has been introduced. The values trained and tested with ANN were obtained by reviewing the charts in the literature.[19,20] When comparing the notch-factor values calculated with the equations obtained from the ANN model with the experimental values, very good results were obtained. With this study, it was clearly found that the notch factors of the shafts can be estimated using ANN without the need for theoretical number crunching. With ANN, complicated and long calculations, individual chart readings and interpolation errors have been eliminated. Thus, this enabled us to obtain more correct results in a faster way. Also, in the study, the data was subject to a multiple regression analysis. At the end of this analysis, since no results interpreting the data could be obtained, the study was focused on ANN.

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Appendix A: Notch-determining examples for the shafts under the torsional stress using ANN mathematical formulae

Example 1: Round shaft with a transverse hole in torsion
Primer 1: Okrogla gred s prečno odprtino pri torziji

N/*W*	INPUT NEURONS			OUTPUT NEURON	
	N1	N2	N3	N1	2.919787
WEIGHTS (*W*)	–1.175518	0.574674	0.061991	N2	–2.252147
	0.405123	–1.101991	–0.384738	N3	4.610924
$Q = 1/(1+\mathrm{Exp}(-4 \cdot (i1 \cdot w1 + i2 \cdot w2 + i3 \cdot w4 - 0.5)))$					

WEIGHTS					
N1	0.007621	*N*4	0.09827	*Q*	2.7295444
N2	0.280911				
N3	0.120636				

Example 2: Round shaft with a shoulder fillet in torsion
Primer 2: Okrogla gred z zaokroženim prehodom pri torziji

N/*W*	INPUT NEURONS					OUTPUT NEURON	
	N1	N2	N3	N4	N5	N1	–1.192632
WEIGHTS (*W*)	–0.527014	0.436152	–7.038280	0.600414	–4.732217	N2	3.673670
	–0.866854	0.590241	–2.128378	0.041027	–3.205369	N3	7.462569
	1.456036	–11.101250	–4.762488	–1.340877	5.252158	N4	1.609339
						N5	–6.440091
$Q = 1/(1+\mathrm{Exp}(-4 \cdot (i1 \cdot w1 + i2 \cdot w2 + i3 \cdot w4 - 0.5)))$							

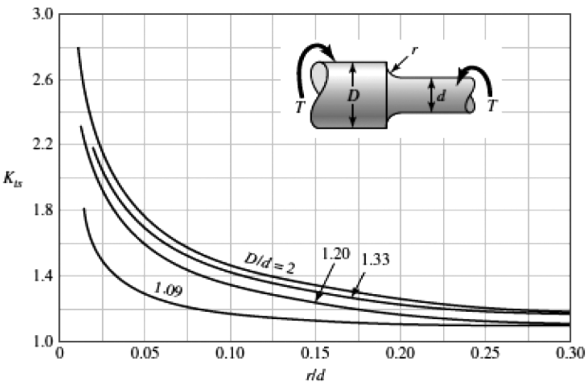
WEIGHTS					
N1	0.079370	*N*4	0.20223	*Q*	1.564021224
N2	0.005604				
N3	0.000003				
N4	0.147278				
N5	0.000942				

Example 3: Grooved round bar in torsion
Primer 3: Okrogla palica z utorom pri torziji

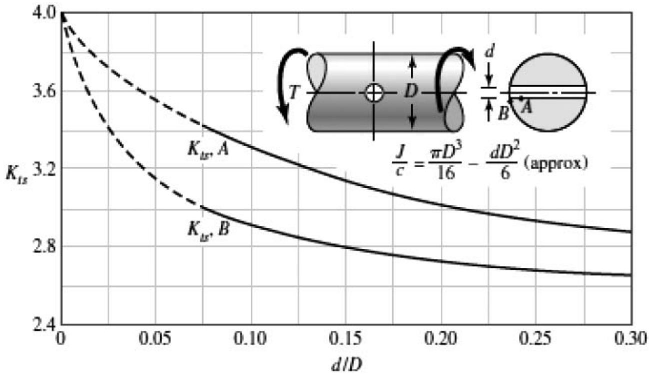
N/*W*	INPUT NEURONS			OUTPUT NEURON	
	N1	N2	N3	N4	
WEIGHTS (*W*)	3.759538	–1.522419	3.805108	N1	1.946942
	–1.108545	–1.898673	–3.206606	N2	3.777504
				N3	–1.771848
$Q = 1/(1+\mathrm{Exp}(-4 \cdot (i1 \cdot w1 + i2 \cdot w2 + i3 \cdot w4 - 0.5)))$					
WEIGHTS					
N1	0.935048	*N*4	0.19874	*Q*	1.600998225
N2	0.280911				
N3	0.120636				

Appendix B: Stress-concentration-factor charts

Round shaft with a shoulder fillet in torsion[20,21]
$\tau_0 = Tc/J$, where
$c = d/2$ and $J = \pi d^4/32$



Round shaft with a transverse hole in torsion[20,21]



Grooved round bar in torsion[20,21]
$\tau_0 = Tc/J$
where $c = d/2$
and $J = \tau d^4/32$