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Spremljanje obrabe vijačnega svedra (S390) z uporabo nevronskih mrež

Using Neural Networks to Follow the Wear of a S390 Twist Drill

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Prispevek opisuje uporabo nevronskih mrež za zbiranje informacij ter postopkovnih parametrov odrezovalnega procesa (hitrost, podajanje in premer). Opazovan je vpliv dveh načinov ostrenja pri različnih časih obdelave na parametre obrabe. Material vijačnih svedrov (S390) je pridobljen s tehnologijo sintranja. Postopek za modeliranje pojava je učenje nevronske mreže z uporabo eksperimentalno pridobljenih podatkov. Nevronske mreže delujejo na načelu algoritma vzvratnega razširjanja napake. Nevronske mreže so učene s testnimi oblikami (posredno). Prikazani so dobljeni rezultati.

(Ključne besede: mreže nevronalne, vrtanje, svedri vijačni, procesi obrabe)

This paper deals with the use of neural networks for the integration of information as well as the parameters of the cutting process (speed, feed and diameter). Two sharpening methods and different working times related to the wear parameters are studied. The material used for the twist drill (S390) is obtained with power technology. Experimental results are used to train the neural networks, as one approach to the modeling of this process. The back-propagation algorithm is used as a model for neural networks. The neural networks with test shapes are trained (offline). The obtained results are presented.

(Keywords: neural networks, drilling, twist drill, wear processes)

0 INTRODUCTION

A great deal of attention has recently been paid by researchers to the application of neural networks in following the wear process of drilling ([1] to [5]).

The application of neural networks for the information integration of the cutting-process parameters, the drill-sharpening method and the operation time in relation to the tool-wear parameters is treated in this paper. The experimental results obtained in the laboratory of the School of Mechanical Engineering were used for the neural-network training. The following train of effects was studied in particular: knowledge degree, the number of layers and the number of neurons in a discrete layer. The transformation function in f-number in the function of the neurons in a layer was analyzed as well.

1 NEURAL NETWORKS

There are quite a number of neural network architectures. The back-propagation neural network model is among the most widely used in the state-following process. In this model, data are processed from the input to the output layer, whereas knowledge is performed by the algorithm of minimizing the square error by backward movement. The knowledge is controlled. It is the simplicity of the algorithm for this model that makes this architecture an attractive one, and the reason why it is analyzed in this paper.

Fig. 1 shows the architecture of neural networks specific to the back-propagation model. The basic structure of this network is made up of three layers: input, secret and output. The data from the external environment are taken over by the input layer, whereas the output to the environment is generated by the output layer. It is the secret layer, one or more of them, that makes the transformation by extracting the input data, by means of the chosen transformed function (f).

A procedure for determining the output values resulting from the observed neurons is shown in Fig. 2.

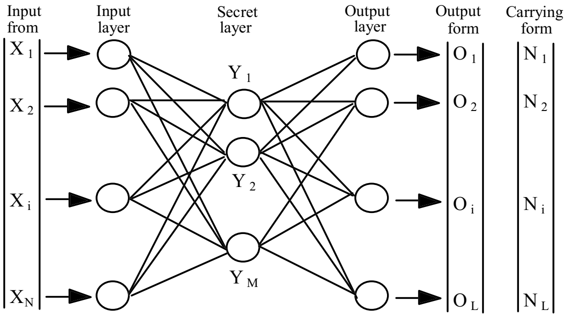

Fig. 1. *Neural network architecture*

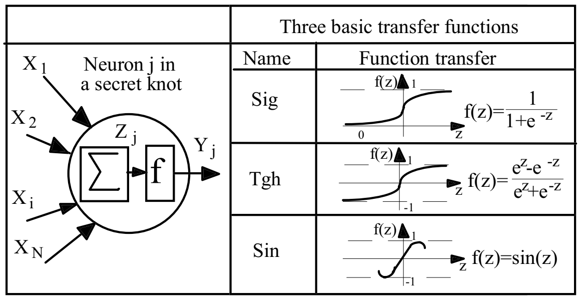

Fig. 2. *Neural network functioning algorithm*

2 EXPERIMENT PROJECTION

The experiment was carried out according to the Box–Wilson method of complex processes modeling using a complete multifactorial first-order plan with repeating in the central point of the multifactorial orthogonal plan. The characteristics employed in the experiment are listed in Table 1**.**

The scheme for carrying out the experiment is illustrated in Figure 3.

On the basis of the relation between the flank wear and the drilling duration (working time - stability) of the twist drill, for different cutting regimes, as illustrated in Figure 4 and Figure 5, it can be seen that it is very difficult to establish a relationship between the wearing belt and the drilling duration, so this paper presents an approach based on the employment of neural networks, as one of the possible approaches for establishing this relationship.

3 ANALYSIS OF THE RESULTS

Five parameters were used to train the neural network, as follows: three parameters for the cutting process (nominal diameter, r. p. m., and feedrate), the sharpening method, and the drilling length, while the value of the flank wear (h_a) served as an output value, as illustrated in Figure 6.

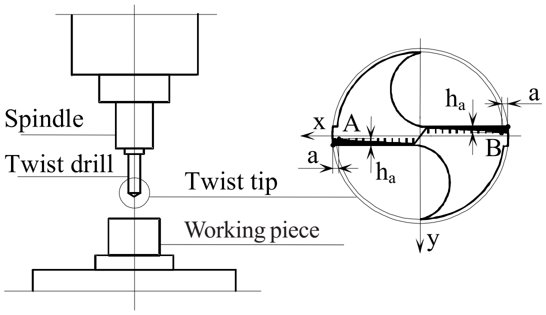

Fig. 3. *The scheme for carrying out the experiment*

Table 1.

Characteristic		Value/type
Twist drill	Standard	DIN 338
	Dimension	Ø6; Ø7,75; Ø10
	Material	S –390 MICROCLEAN
	Point angle	135°
	Spiral grad. angle	15°
	Way of sharpening	KRI / KO
Material for examination	Standard	Č.4237
	Thermal treatment	Hardening/loosening
	Hardness HB/HRc	410 to 425 / 43 to 45
	Tension hardness [dN/mm^2]	1400-1450
Cutting regimes	Drilling depth [mm]	l = 3xd
	Number of revolutions [r.p.m.]	250; 355; 500
	Feedrate [mm/r]	0.027, 0.053, 0.107
Cooling medium		Yes
Machine for examination		FGU-32
Measuring device of flank wearing		DORMER

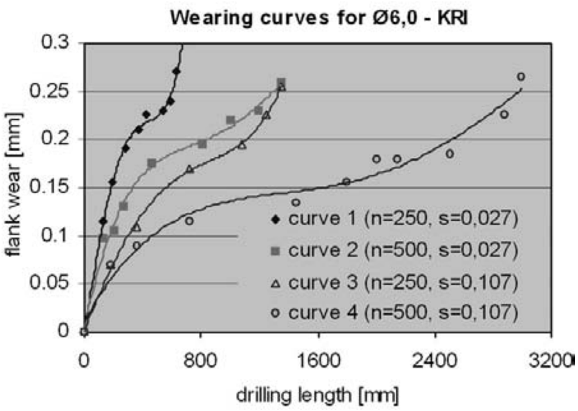

Fig. 4. *Wearing curves during drilling with the Ø6 twist drill, sharpened with a corrected cutting edge (KRI)*

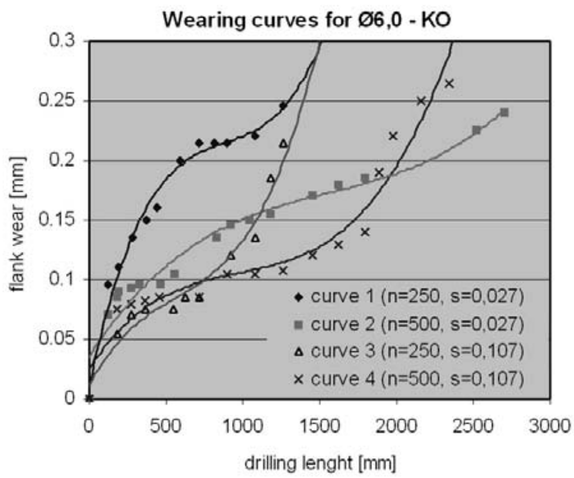

Fig. 5 *Wearing curves during drilling with Ø6 crossly sharpened twist drill (KO)*

In order to perform the training of a neural network, 90 data were chosen from the set of experimental results, as follows: 40 Ø6 data, 40 Ø10 data, and 10 Ø7.75 data, as presented in Table 2.

Table 2. *Data for training the neural network*

	INPUT					OUTPUT
	d [mm]	N	n [r.p.m.]	s [mm/r]	l [mm]	ha [mm]
1	6.00	1	500	0.027	1350	0.260
2	10.00	1	250	0.027	375	0.245
3	10.00	1	500	0.027	2400	0.230
4	6.00	2	500	0.107	0	0.000
5	10.00	1	250	0.107	0	0.000
. .						
42	6.00	2	250	0.027	540	0.190
43	6.00	1	500	0.027	460	0.175
44	7.75	1	355	0.053	580	0.160
45	6.00	2	500	0.027	1000	0.150
46	10.00	1	500	0.107	60	0.095
47	10.00	2	500	0.027	750	0.130
48	6.00	1	500	0.107	720	0.115
. .						
85	7.75	1	355	0.053	230	0.086
86	10.00	2	250	0.107	1350	0.230
87	7.75	2	355	0.053	1860	0.220
88	10.00	1	250	0.107	1350	0.270
89	10.00	1	500	0.027	1230	0.195
90	10.00	1	500	0.027	3000	0.295
Sharpening method:	1- corrected cutting edge (KRI) 2 - crossly sharpening (KO)					

Neural network of the feed-forward back-propagation type was used during training, where the following parameters were changed within the available software:

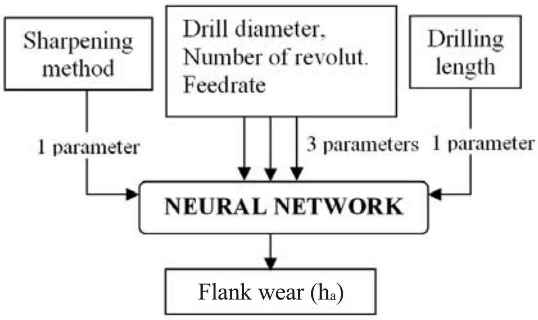

Fig. 6. *Access scheme of neural-network training*

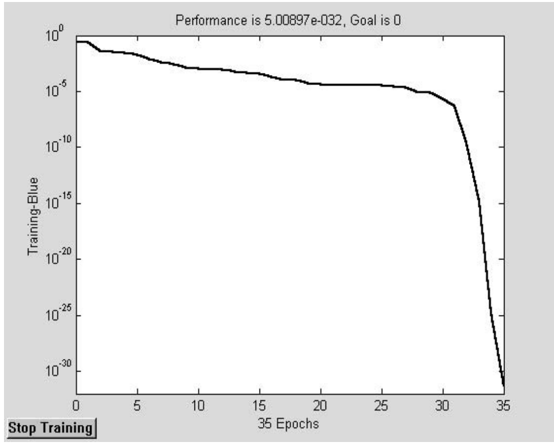

Fig. 7.

Table 3. *Parameters of neural-network training*

Trained function		TRAINLM
Adaptation of function learning		LEARNGDM
Function performance		MSE
Number of layers		3
Number of neurons	I layer	18
	II layer	15
	III layer	1
Transfer function	I layer	TANSIG
	II layer	
	III layer	

- Transformation function (trained function),
- Adjustment of function learning,
- Function performance,
- Number of layers,
- Number of neurons and the transmission function for all layers.

The neural network converged with a performance of 5.00897×10^{-032} with 35 epochs (Fig. 7), wherein the parameters specified in Table 3 were employed.

Table 4 presents the output values of flank wear (h_a), column A targeted values, column B values gained through training of the neural network, as well as the appropriate errors.

The testing of the trained network was performed for Ø6 – KO with the drilling parameters, n=500 r.p.m., s=0.027 mm/r, and the drilling lengths that were not trained. The results of the work (simulation) are represented by a wearing curve in relation to the wearing curve derived based on the experimental data (Figure 8).

Figure 9 presents a wearing curve for BV Ø6.00 – KO, which was obtained by the simulation of a trained network for the cutting parameters, n=500r.p.m. and s=0.053mm/r, in relation to the wearing curve for cutting parameters, n=500r.p.m. and s=0.027mm/r, as well as n=500r.p.m. and s=0.107mm/r, obtained on the basis of experimental data.

4 CONCLUSION

The modern conditions of processing by cutting and the growing requirements concerning the quality of cutting materials make the study of cutting regimes very important. The incorrect choice of cutting-regime values – in addition to the fact that a tool has all the other qualities – brings about rapid wear and a decrease of durability, and even the breakage of certain parts.

Traditional methods of experimental work demand a significant waste of time and resources, because of the subject of reference, i.e., the influence of every factor is being examined separately, with a fixation on other factors' meaning.

In modern conditions of production, where there are no algorithmic solutions and there are no completely defined theoretical solutions, or where

Table 4.

Record number	A	B	Error
1	0.260	0.26	2.2204e-016
2	0.245	0.245	-6.3838e-016
3	0.230	0.23	-2.2204e-016
4	0.000	2.2204e-016	4.4409e-016
5	0.000	-4.4409e-016	1.6653e-016
. . .			
42	0.190	0.19	2.7756e-016
43	0.175	0.175	-5.5511e-017
44	0.160	0.16	3.0531e-016
45	0.150	0.15	-1.3878e-016
46	0.095	0.095	-4.1633e-016
47	0.130	0.13	1.1102e-016
48	0.115	0.115	1.3878e-017
. . .			
85	0.086	0.086	1.3878e-016
86	0.230	0.23	4.7184e-016
87	0.220	0.22	2.7756e-017
88	0.270	0.27	0
89	0.195	0.195	1.6653e-016
90	0.295	0.295	5.5511e-017

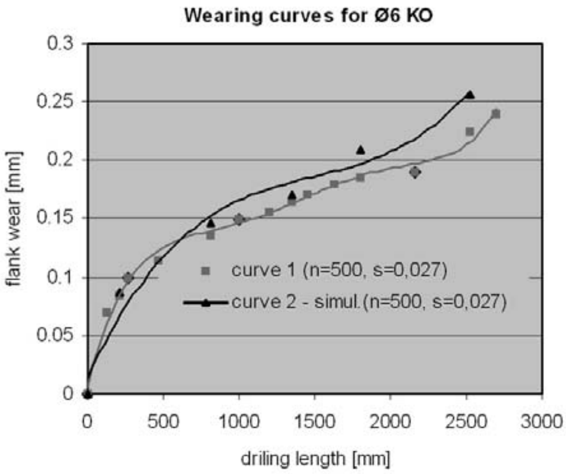

Fig. 8.

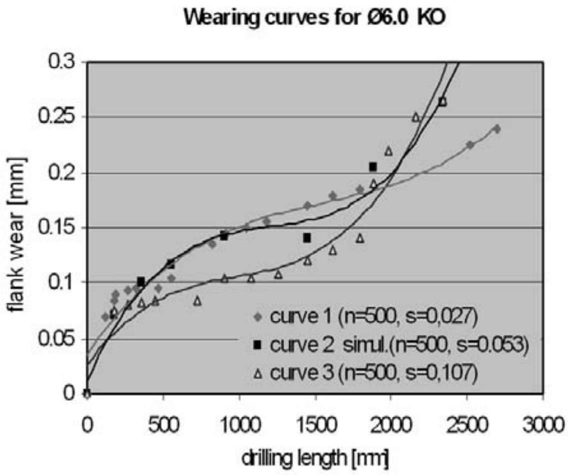

Fig. 9.

there is a theory but it is not possible in practice to process all theoretical cases using an algorithm in a satisfactorily time interval, expert systems are used.

This paper presents a performed training of a neural network based on experimental data with five input parameters and one output parameter. The inputs were the cutting process parameters, the method of sharpening and the drilling length, and the output (targeted) dimension was the value of the wearing parameter.

The trained network was tested on experimental data, and then employed in the determination of a wearing belt under regimes that were not used in the experiment.

These initialized studies should serve as the initial starting point for the tracking of tool conditions using artificial intelligence, i.e., the intelligent tracking of tool conditions.

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