Cutting Capability Assessment of Highly Porous CBN Wheels by Microrelief of Plane Parts from 06Cr14Ni6Cu2MoWTi-Sh Steel Using Artificial Intelligence System

Soler Yakov Iosifovich*, Nguyen Manh Tiem & Nguyen Van Le

Technology and Equipment of Mechanical Manufacture Department,
Irkutsk National Research Technical University, 664074,
Irkutsk, Lermontov St., Bldg. 83., Russian Federation
*E-mail: solera@istu.irk.ru

Abstract. The abrasive tools are the weakest element in the grinding process system, to which great attention is being paid by scientific and industrial collectives. Eleven highly porous wheels (HPWs) were tested: CBN30 (B76, B107, B126, B151) 100 OVK27-KF40; CBN30 B107 100 OVKC10-KF40; CBN30 B126 100(M, L) VK27- (KF25, KF40); LKV50 (B107, B126) 100 (M, O) VK27-KF40. Assessment of the surface topography was carried out by roughness parameters R_a, R_{max}, and S_m (GOST 25472-82), which were considered random variables with their position and dispersion measures. Two artificial intelligence systems – fuzzy logic (FL) and neural networks (NN) – were used to analyze the HPW's cutting capability (CC). In both cases, the best CC was predicted for grinding with CBN30 (B76 and B151) 100 OVK27-KF40 and LKV50 (B107) 100 OVK27-KF40. In the absence of a training process in FL modeling, the assessments for the wheels with a low CC were less reliable.

Keywords: *activation function; fuzzy logic; grinding; neural network; roughness.*

1 Introduction

Finish machining has a great influence on the quality of the surface layer and service properties of machine parts. The most widely used method is grinding, which provides high productivity and part quality. Roughness is the most important indicator for the assessment of part surface integrity, to which high demands are made in the manufacture of responsible highly loaded aggregates in aircraft and energy equipment operated under different climatic conditions and in contact with fuel [1]. Surface roughness can be represented by a number of parameters that are correlated to each other: R_a, R_q, R_z, R_{max}, S, S_m, t_p, p = 5-95% [1,2]. Quantitative evaluation with high accuracy of surface roughness is complicated. In view of the above, it is difficult to get physical models while their experimental analogs have a private character and thus a limited field of application. For this reason, artificial intelligence systems are employed for

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making simulation models. These include fuzzy logic (FL) and neural networks (NN), which are a new form of computer engineering used in different technological fields (finance, medicine, engineering, etc.) to solve complex problems, data analysis, management, clusterization, simulation of the production process parameters and in the case of the present study grinding. In the grinding field, this makes available new possibilities for analysis of multiple grinding variables and problem solving.

FL is a perspective trend in cybernetics first suggested and elaborated by L.A. Zadeh [3]. He suggested using words and phrases as linguistic variables for approximate reasoning. As a result, the content meaning of the information and processing logic are passed in the form of probability for problem solving that cannot be described exactly, in engineering for applications such as automatic control, diagnostics, artificial intelligence etc. In this regard FL is equivalent to fuzzy-set theory A_l, i.e. classes with fuzzy boundaries presented with an ordered couple package consisting of the elements y_l of the universal sets $\{y_{lv}\}$ with corresponding grade of membership $\mu_A(y_l)$:

$$A_l = \{(y_l, \mu_A(y_l)) \mid y_l \hat{I} \{y_{lv}\}\}, \quad v=\overline{1,n}.$$

NN is another perspective direction in cybernetics. NN and FL are most often used for solving complex classifications. In the theory of artificial intelligence, FL and NN are considered to be equivalent, supplementing each other to solve complicated problems [4,5]. We consider it appropriate to analyze their capability, in particular, for selecting abrasive wheels.

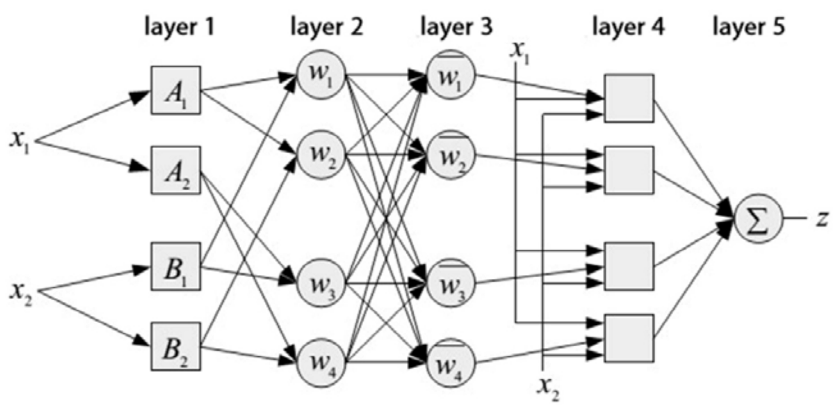


Figure 1 Model of a simple neuro-fuzzy network.

A simple model of a neuro-fuzzy network is shown in Figure 1. This system has two inputs (x_1, x_2) and one output (z) [6]. It is designed as a network of five layers. The nodes of the first layer are the terms of the input variables. The output of each l^{th} node has the form $\mu_{A_i}(x_1)$ and $\mu_{B_j}(x_2)$, where i = 1, 2; j = 1, 2; x_1, x_2 – input signals of the l^{th} node; A_i, B_j – linguistic variables; μ_{A_i}, μ_{B_j} – membership functions. Each node of the second layer, w_l, $l = \overline{1;4}$, corresponds to one fuzzy rule: the output signal of the l^{th} node is the rule conclusion and is calculated by the following expression:

$$w_l = \mu_{A_i}(x_1) \times \mu_{B_j}(x_2).$$

The output signal of l^{th} node of the third layer is the rate of the conclusion of the l^{th} rule, determined by the following formula:

$$\overline{w}_l = \frac{w_l}{w_1+w_2+w_3+w_4}.$$

In the fourth layer, the function of the output node is represented in the form $\overline{w}_l f_l$, where $f_i = p_l x_1 + q_l x_2 + r_l$ – the membership function of the output variable, corresponding to l^{th} fuzzy rule; p_l, q_l, r_l – the parameters of the membership function.

The single-node output signal of the fifth layer is calculated from the expression:

$$z = \sum_l \overline{w}_l f_l = \frac{\sum_l w_l f_l}{\sum_l w_l}.$$

This model is used for realization with ANFIS editor in MATLAB.

The purpose of the present work was to study the surface roughness of parts made of corrosion-resistant 06Cr14Ni6Cu2MoWTi-Sh (EP-817) steel used in aircraft and to select a highly porous wheel (HPW) in order to improve the quality of the microrelief and the precision of the ground parts. At the same time, a comparison of the effectiveness of the artificial intelligence systems that were applied was carried out.

2 Experimental Procedure

The experimental procedure consisted of three sequentially executed steps: 1) conducting the experiment; 2) interpreting the experimental data using statistical methods; and 3) FL and NN modeling.

The verification nature tests were carried out under the following constant conditions: flat-surface grinding machine 3E711V; HPW made from CBN with 1A1 form and dimensions of 200 × 20 × 76 × 5 mm [7]. The process-dependent parameters were: cutting speed $v_w = 28$ m/s, longitudinal feed $s_l = 6$ m/min, cross-feed $s_c = 4$ mm/double stroke, cutting depth t = 0.01 mm, and operational allowance z = 0.1 mm. Lubricoolant 5% Akvol-6 emulsion (TU 0258-024-0014842-98) was supplied flowing on the workpiece in the amount of 7-10 l/min; the number of duplicate tests in Eq. (1) – n = 30. Subject of the tests were forms made of 06Cr14Ni6Cu2MoWTi-Sh steel with the following mechanical properties: σ_{UST} = 1310-1400 MPa, $\sigma_{0.2}$ = 1210-1240 MPa, δ = 12-14%, ψ = 57-60% [8] and dimensions of $B \times L \times H = 60 \times 60 \times 60$ mm, ground butt end $B \times L$. The index $l = \overline{1;11}$ reflects the characteristics of HPW: 1-CBN30 B76 100 OVK27-KF40; 2-CBN30 B107 100 OVK27-KF40; 3-CBN30 B107 100 OVKC10-KF40; 4-CBN30 B126 100 OVK27-KF40; 5-CBN30 B126 100 MVK27-KF40; 6-CBN30 B126 100 LVK27-KF40; 7-CBN30 B126 100 LVK27-KF25; 8-CBN30 B151 100 OVK27-KF40; 9-LKV50 B107 100 OVK27-KF40; 10-LKV50 B126 100 O K27-KF40; and 11-LKV50 B126 100 MVK27-KF40 [7,9]. The surface roughness parameters [2] (R_a, R_z, R_{max}, S and S_m) were measured with a Caliber profilograph-profilometer (type 252) in two mutually orthogonal directions $i = \overline{1;2}$ and correspondingly according to the vectors s_l (R_{a1}, R_{z1}, R_{max1} and etc.) and s_c (R_{a2}, R_{z2}, R_{max2} and *etc*.). For FL and NN modeling the three parameters that have the greatest influence on the part operating properties [1] were selected, i.e. R_{a1}, R_{max1}, S_{m2}.

The specificity of grinding is that the cutting capability (CC) of an HPW cannot be imagined as a determined value during edge cutting machining. This is conditioned by the fact that the abrasive grain of the tool has an arbitrary shape, a chaotic arrangement of the bonded abrasive particles, a different height in the radial axis, and a different number of operating grain particles and cutting edges per area unit of its contact area upon entry into the workpiece. This allows examination by observation of random variables (RV) and estimate their behavior on the basis of probability-theoretic approaches. In this case the experimental data presentation is supposed to be given in the form of independent sets $l = \overline{1;11}$:

$$\{y_{lv}\}, v = \overline{1;30}, \tag{1}$$

where v is the number of replicate tests.

The statistical methods used can be divided into two groups: parametric and nonparametric, specifically rank ones. Each of them has its own requirements [10] for effective use. In the first case, it is necessary to ensure the fulfillment of the two constraints imposed on RV: homogeneity of variance of deviation and normalcy of distribution. The discussed grinding requirements are often violated to any extent, which can be accompanied by a considerable bias of estimator, confidence bounds and factors [10]. In such a situation it is reasonable to use a nonparametric method that is not connected with a certain family of distributions and does not use its properties. RVs can be estimated by the following univariate frequency allocation [10-14]:

1. position measures (reference values)

average $\overline{y_l} = y_{l\bullet}$, (2)

medians $\widetilde{y_l}$; (3)

2. scattering measures (precision)

deviation standards SD_l, (4)

swing $R_l = (y_{max} - y_{min})_l$, (5)

quartile latitudes $QL_l = (y_{0.75} - y_{0.25})_l$. (6)

From theoretical statistics it is known that parametric methods are based on univariate frequency allocation Eqs. (2),(4),(5) and that rank statistics are related to Eqs. (3),(6). The acceptance of the null-hypothesis (H_0) by the homogeneity of variance of deviation and the normalcy of distribution is discussed in [11-14]. To decrease the labor content of the statistical calculations, in this research the Statistica 10.0.1011.0 software application was used.

The technique of FL simulation is described in detail in [15,16]. In this paper, a multiple statement is presented to better understand the gist of the work. For the assessment of the part surface topography quality, Harrington's desirability function $d_l \in [0;1]$ is used [17,18]. The increase of d_l characterizes raising the CC of the HPW. In addition, NN is used to control the grinding process. Its model is presented simultaneously here using two programs: MATLAB and STATISTICA.

The main advantage of NNs over FL is their training ability. The preparation of the solution in the NN task always starts with the amendment of demands: how many and what kind of data should be submitted on its input in training. If they are absent, the network cannot be trained for solving the assigned task [19,20]. In a NN model, the synapses implement a communication between the neurons and multiply the input signals by a number, which characterizes the communication strength (synapse weight). The accumulator ($\sum$, Figure 2) performs addition of the signals entering via the synaptic connections from the other neurons and external input signals. The converter realizes the function of an argument and an output of the accumulator to a certain output value of the neurons. This function is the neuron activation function F (Figure 2). A neuron generally implements a scalar function of a vector argument. In general, the input signal and weight coefficients may recognize the real values. The output is determined by an activation function and can be both valid and intact. Synaptic connections with positive weight are called excitatory and those with negative weight are called inhibitory. Thus, the neuron is completely described by its weight and activation function *F*. After receiving a set of numbers (vectors) as input, the neuron produces some numbers on the output (Figure 2).

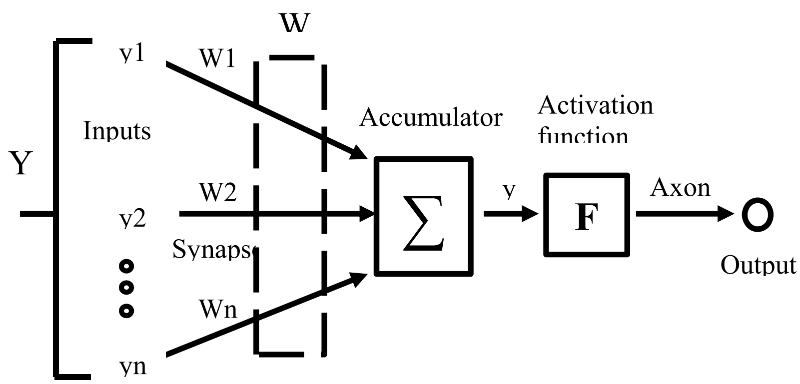


Figure 2 Structural scheme of NN.

The activation function (excitation function) is a function that computes the output signal of the artificial neuron. The *Y* signal is accepted as an argument obtained on the output of the input adder $\sum$. There are different types of activation functions [21]. The most widely used functions are shown in Table 1.

Table 1 Activation functions of neurons.

Type of functions	Formula	Field of application
Linear	$Y = y_j$	$(-\infty, \infty)$
Sigmoid	$Y = \frac{1}{1+e^{-y_j}}$ (7)	(0, 1)
Hyperbolic tangent	$Y = \frac{e^{y_j}-e^{-y_j}}{e^{y_j}+e^{-y_j}}$	(-1, 1)
Softmax	$Y = \frac{e^{y_j}}{\sum_{j=1}^{n} e^{y_j}}\cdots$ (8)	(0, 1)

Notes. $y_i, j = \overline{1;n}$ – input variables, Y – output variable

Function Eqs. (7) and (8) are differentiated through abscissa. This procedure is widely used in training algorithms. In addition, they have the best feature to amplify weak signals and prevent saturation from strong signals, as they correspond to the argument fields, where the sigmoid has a gentle slope [22]. In this study, Eqs. (7) and (8) were used as the functions.

3 Research Results and Discussion

The null-hypothesis (H_0) by the homogeneity of variance of deviation is the strictest requirement for RV in the context of the parametric method. Taking into account the probabilistic nature of statistical decisions, we cannot exclude the risk of the second kind of acceptance of an incorrect hypothesis. In view of the above, testing Eq. (1) on the homogeneity of variance of deviation was conducted according to three groups of criteria: $m = \overline{1;3}$: 1 – Hartley, Cochren, Barlett (in the software these are united into one package); 2 – Levene; 3 – Brown-Forsythe. The distribution of Eq. (1) is characterized by homogeneous dispersion if the number of decisions f_0 for H_0 satisfies the condition $f_0 \in [2; 3]$. Table 2 shows the test results of Eq. (1) on the homoscedasticity of distribution of sets $l = \overline{1;11}$ by all investigated parameters of the surface topography.

Table 2 Testing of dispersion homogeneity.

Parameter	**Calculated significance level α_m for the sets of Eq. (1) by criterion $m=\overline{1;3}$ in the condition $\alpha<0.05$**			**Acceptance H_0**
	1	**2**	**3**	
R_{a1}	0.001	0.001	0.011	+
R_{max1}	0.048	0.039	0.096	+ (*)
S_{m2}	0.000	0.000	0.000	+

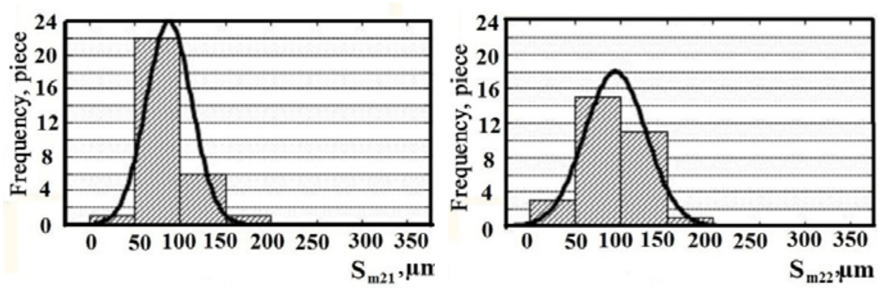
As can be seen from Table 2, the null-hypothesis H_0 about the homogeneity of variance of deviance was accepted by two roughness parameters: $R_{a1}; S_{m2}$, confirmed in the condition f_0 = 3. The exception was composed for the observation Eq. (1) by the parameter R_{max1}. According to the Brown-Forsythe criterion (m = 3), the H_0 hypothesis was rejected. This shows that the homoscedasticity of distribution for R_{max1} was accepted in the condition f_0 = 2 (marked with (*)).

Testing Eq. (1) on the normalcy of distribution was carried out by the Shapiro-Wilk criterion (Table 1), for which H_0 was accepted for the grinding variables $l = \overline{1; 11}$ in the condition of fulfilment of the inequality $\alpha_l > 0.5$.

Table 3 Normalcy of distribution testing according to Shapiro-Wilk criterion.

Param-eter	**Calculated significance level α_l with variables $l = \overline{1; 11}$**										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
R_{a1l}	$\underline{0.837}$	0.005	0.080	$\underline{0.861}$	$\underline{0.663}$	0.070	0.398	0.000	0.477	0.075	0.038
R_{max1l}	$\underline{0.793}$	0.034	0.297	$\underline{0.794}$	$\underline{0.812}$	0.179	0.205	0.000	0.029	0.261	0.276
S_{m2l}	$\underline{0.524}$	0.268	0.083	0.055	0.013	0.034	0.000	0.020	0.014	0.011	0.240

As can be seen from Table 3, normal distributions were found only in the 7 underlined cases out of 33 analyzed. As an example, Figure 3 shows the histograms with normal distribution curves by the longitudinal mean spacing received from grinding with two CBN wheels. In Figure 3(a) the H_0 hypothesis was confirmed with reliability $\alpha_1 = 0.524$. In Figure 3(b) it was rejected with $\alpha_2 = 0.268$ (Table 3).



(a) (b)

Figure 3 Quality histograms with normal distribution curves for parameter Sm2 while grinding EP-817 steel with the wheels CBN30 B76 100 OVK27-KF40 (a) and CBN30 B107 100 OVK27-KF40 (b).

Under the condition of the normalcy of distribution violation of Eq. (1), it is reasonable to use the rank statistics method with its one-dimensional distribution of frequencies Eq. (3) and Eq. (6). Modeling in MATLAB, the input data were assumed to be the parameters $\tilde{y}_l, QL_l, l = \overline{1;11}$, as given in Table 4.

Table 4 Input variables of modeling influence of HPW characteristics on topography of ground parts.

Wheel $l = \overline{1;11}$	Quality parameters of the surface					
	R_{a1l}, μm		R_{max1l}, μm		S_{m2l}, μm	
	$\tilde{y}$	QL	$\tilde{y}$	QL	$\tilde{y}$	QL
1	0.61	0.07	3.72	0.54	83.36	28.39
2	0.66	0.15	3.82	0.92	87.46	47.91
3	0.65	0.20	3.81	0.71	77.11	45.76
4	0.60	0.27	3.58	1.27	84.91	48.24
5	0.84	0.21	4.57	1.18	86.92	28.88
6	0.63	0.15	3.72	0.86	91.62	51.61
7	0.66	0.11	3.66	0.71	86.64	30.81
8	0.56	0.11	3.37	0.79	80.52	36.88
9	0.59	0.10	3.51	0.52	99.45	38.53
10	0.80	0.20	4.70	0.58	129.63	62.75
11	0.71	0.12	4.37	1.06	100.50	45.15

Note: HPW *l* – see Experimental method

The assessment of the CCs of the wheels, presented in Table 4, will look more convincing when the roughness is evaluated by regulated quantities. As can be seen from Table 4, the quality parameters were modified at the following intervals: $R_{a1l} \in [0.56\ (0.63); 0.84(1.00)]$, $R_{max1l} \in [3.37\ (4.0); 4.70(5.0)]$, $S_{m2l} \in [77.11\ (80); 129.63(160)]$. Here, the categorical values (CV) are shown in brackets [23]. Thus, the optimal selection of HPWs allows to reduce the roughness from one to four CVs or the grinding laboriousness of parts from one to two technological crossings.

The statistical methods do not allow to lead the analysis of the topography of the ground surface in the situation where each parameter of roughness is represented by two univariate frequency distributions of Eq. (1), in this case for example Eqs. (3) and (6). This is their significant disadvantage in classification of large databases. In a situation like this, in practice, the question always arises which HPW is advisable to be selected in order to improve the quality of ground parts of EP-817 steel. This situation is mostly solved using reference values, which is closer and more understandable for factory workers. The discussed problem is exacerbated when the grinding process optimization is carried out by several variables, as in our case by three.

Table 5 Integral assessment of the influence of HPW on the surface roughness of FL model.

Wheel l	**Desirability function and linguistic valuation**							
	R_{a1l}		R_{max1l}		S_{m2l}		**Integral assessment**	
	d_{l1}	**valuation**	d_{l2}	**valuation**	d_{l3}	**valuation**	$d_{l\bullet}$	**valuation**
1	0.814	VG	0.824	VG	0.839	VG	0.825	VG
2	0.512	S	0.526	S	0.697	G	0.503	S
3	0.536	S	0.596	S	0.842	VG	0.535	S
4	0.474	S	0.452	S	0.764	G	0.477	S
5	0.132	VB	0.235	B	0.830	VG	0.158	VB
6	0.589	S	0.581	S	0.541	S	0.560	S
7	0.625	S	0.634	G	0.822	VG	0.611	S
8	0.820	VG	0.837	VG	0.814	VG	0.841	VG
9	0.764	G	0.837	VG	0.557	S	0.819	VG
10	0.237	B	0.495	S	0.158	VB	0.372	S
11	0.571	S	0.430	S	0.500	S	0.472	S

Note: 1-CBN30 B76 100 OVK27-KF40; 2-CBN30 B107 100 OVK27-KF40; 3-CBN30 B107 100 OVKC10-KF40; 4-CBN30 B126 100 OVK27-KF40; 5-CBN30 B126 100 MVK27-KF40; 6-CBN30 B126 100 LVK27-KF40; 7-CBN30 B126 100 LVK27-KF25; 8-CBN30 B151 100 OVK27-KF40; 9-LKV50 B107 100 OVK27-KF40; 10- LKV50 B126 100 OVK27-KF40; 11- LKV50 B126 100 MVK27-KF40. VG – very good; G – good; S – satisfactory; B – bad; VB – very bad.

Summing up, in this study FL and NN methods were used. They allow to create an expert system of classification by a whole complex of the studied parameters. The construction method of fuzzy logic modeling is disclosed in detail in the studies [15] and [16]. Their results are illustrated in Table 5. The fuzzy logic modeling in the condition of an integral estimate of CC of HPWs discovered the following three most effective HPWs with linguistic valuation "VG": CBN30 B76 100 OVK27-KF40 ($d_{1\bullet} = 0.8246$), CBN30 B151 100 OVK27-KF40 ($d_{8\bullet} = 0.8409$) and LKV50 B107 100 OVK27-KF40 ($d_{9\bullet} = 0.8189$). These HPW provided the lowest roughness and the highest precision when grinding the flat parts from EP-817 steel.

The data shown in Table 4 were used for NN modeling. The NN models consisted of six input variables and one output. Each input variable was divided into three classes, corresponding to the linguistic valuations "good", "normal" and "bad" (Table 6).

Table 6 Assessment ranges of input variables of NN modeling.

Input variable		Linguistic valuation		
		good	**normal**	**bad**
R_{a1}, μm	$\widetilde{y}$	0.55	0.7	0.85
	QL	0.05	0.175	0.3
R_{max1}, μm	$\widetilde{y}$	3.30	4.05	4.8
	QL	0.50	0.9	1.3
S_{m2}, μm	$\widetilde{y}$	77.00	103.5	130
	QL	25.00	44	63

The output variable was represented by five classes of quality of ground parts: VG – very good, G – good, S – satisfactory, B – bad, VB – very bad. Their numerical characteristics are shown in Table 7. A set of training rules of NN was organized on the basis of the results shown in Tables 6 and 7. It contains N = 3^6 = 729 possible combinations of output parameters.

Table 7 Assessment ranges of output variables of NN modeling.

Assessment	Output variables				
Linguistic	VB	B	S	G	VG
Numerical	1	2	3	4	5

Table 8 shows a truncated version of the set according to the number of rules. 75% of the presented rules were used for NN training and 15% for control and testing. NN training is one of the significant advantages over FL modeling.

Table 9 shows the results of the influence of HPW ($l = \overline{1;11}$) on the complex assessment of the surface roughness of flat parts made from corrosion-resistant 06Cr14Ni6Cu2MoWTi-Sh steel using the software applications MATLAB and

STATISTICA. It was found that the NN simulation results coincided completely in both programs.

Table 8 Training rules of the neural network.

Rule	R_{a1},µm		R_{max1}, µm		S_{m2}, µm		Linguistic valuation	Numeric valuation
	$\tilde{y}$	QL	$\tilde{y}$	QL	$\tilde{y}$	QL		
1	0.55	0.05	3.3	0.5	77	25	VG	5
2	0.55	0.05	3.3	0.5	77	44	VG	5
3	0.55	0.05	3.3	0.5	77	63	G	4
4	0.55	0.05	3.3	0.5	103.5	25	VG	5
5	0.55	0.05	3.3	0.5	103.5	44	G	4
6	0.55	0.05	3.3	0.5	103.5	63	G	4
7	0.55	0.05	3.3	0.5	130	25	G	4
…	…	…	…	…	…	…	…	…
727	0.85	0.3	4.8	1.3	130	25	B	2
728	0.85	0.3	4.8	1.3	130	44	VB	1
729	0.85	0.3	4.8	1.3	130	63	VB	1

Table 9 Simulation results of neural network.

Wheel ($l = \overline{1;11}$)	STATISTICA	MATLAB	
		Numeric valuation	Linguistic valuation
CBN30 B76 100 OVK27-KF40 (1)	VG	4.866745958	VG
CBN30 B107 100 OVK27-KF40 (2)	S	3.254134441	S
CBN30 B107 100 OVKC10-KF40 (3)	S	3.250570267	S
CBN30 B126 100 OVK27-KF40 (4)	S	3.258041314	S
CBN30 B126 100 MVK27-KF40 (5)	S	2.979018187	S
CBN30 B126 100 LVK27-KF40 (6)	S	3.236583301	S
CBN30 B126 100 LVK27-KF25 (7)	G	3.985202781	G
CBN30 B151 100 OVK27-KF40 (8)	VG	4.812614048	VG
LKV50 B107 100 OVK27-KF40 (9)	VG	4.666104257	VG
LKV50 B126 100 OVK27-KF40 (10)	B	2.024600805	B
LKV50 B126 100 MVK27-KF40 (11)	S	3.266963219	S

Note: VG – very good; G – good; S – satisfactory; B – bad; VB – very bad

The results of the NN simulation showed that the wheels CBN30 B76 100 OVK27-KF40, CBN30 B151 100 OVK27-KF40 and LKV50 B107 100 OVK27-KF40 were the most effective HPWs, i.e. with integral linguistic valuation "VG". They provided the lowest roughness and the highest precision while grinding flat parts from the EP-817 steel. It was established that the results of the FL model for the HPWs with the highest CC coincided completely with the NN models. However, it was found that there were completed cases of CC of the FL model in comparison with the NN model for the HPW: i = 7 (G –

by FL model and S – by NN model); i =10 (S – by FL model, and B – by NN model). The above is due to the fact that the FL model does not have a training process, so the assessment levels of its models differ from those of NN.

Possibilities of increasing the CC of the studied wheels (Table 9) were considered. The LKV50 grains with increased strength showed their advantages over the CBN30 grains only in B107 graininess, the CC of which increased by one or two classes of linguistic assessment. The wheels with K27, KC10 bonds and O, C, M hardness were predicted equivalent according to their cutting capability. For the CBN30 HPW, the dependency CC = f(B76, B107, B126, B151) had a parabolic relationship with a local minimum in the area B107, B126. The reduction of pore-forming sizes from KF40 to KF25 (for the wheels i = 6; 7 respectively) was turned to expediently. The results allowed to predict two HPWs, i.e. CBN30 (B76 or B151) 100 OVK27-KF25 and LKV50 B107 100 OVK27-KF25, to be the best for grinding parts made of EP-817 steel.

The STATISTICA program has the possibility to predict the sensitivity of the neural network to input variables that are independent. This sensitivity analysis defines the influence degree of the individual input parameter on its decision-making. The more sensitive the network is to a particular input, the greater the deterioration we can expect and therefore the greater the ratio.

Table 10 Sensitivity analysis of input parameters to decision-making.

Parameter	R_{a1}	**QL(**R_{a1}**)**	R_{max1}	**QL(**R_{max1}**)**	S_{m2}	**QL(**S_{m2}**)**
Attitude	142.6281	158.4617	148.9865	136.8633	133.7157	123.9719
Rank	3	1	2	4	5	6

The results presented in Table 10 indicate that the parameter with the highest influence on the surface quality is the quartile latitude of parameter R_{a1}. Second place was for $m\hat{R}_{max1i}$. The third and fourth place were taken by parameters $m\hat{R}_{a1i}$ and QL(R_{max1i}). In the last two positions were $m\hat{S}_{2i}$ and QL(S_{m2i}). The network sensitivity of each input value is an advantage of NN modeling over FL, to which attributes are analyzed including Eq. (3) and Eq. (6) together.

4 Conclusion

In conditions where homoscedasticity and normalcy of distribution of experimental data are violated, to realize artificial intelligence it is reasonable to consider nonparametric assessment of the position and scattering measures to which medians $\tilde{y}_l$ and quartile latitude QL_l relate.

In this paper, a fuzzy logic model was constructed in MATLAB only using the Fuzzy Logic Toolbox package, while the neural network model was not only constructed in MATLAB but also in STATISTICA. In both cases, the results of FL and NN coincided.

In the absence of a training process in FL modeling, its output parameters were proved to be less reliable than those of the NN model only for the HPWs (i = 5; 7; 10) of which the cutting capabilities were the lowest.

The HPWs CBN30 B76 100 OVK27-KF40, CBN30 B151 100 OVK27-KF40 and LKV50 B107 100 OVK27-KF40 with the valuation “VG” were the best wheels by their cutting capability and by the surface roughness. These HPWs were recommended by both methods for grinding parts made of high-strength corrosion-resistant steel 06Cr14Ni6Cu2MoWTi-Sh used in aircraft.

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