Technological capabilities of increasing surface quality of workpieces made of titanium alloy VT22 and stability of surface grinding

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Abstract. Surface grinding of flat workpieces made of alloy VT22 was conducted by the periphery of a highly porous wheel (HPW) from cubic boron nitride CBN30 B107 100 OV K27 KF40 with three processing techniques (ij). They are 10 - cross-feed per stroke, HPW cutting into a workpiece changes alternately from up to down; 12 – cross-feed per double stroke during the up HPW cutting-in at the working stroke; 22 – cross-feed per double stroke during the down HPW cutting-in at the working stroke. With the involvement of artificial neural network models, it was revealed that to improve the quality of surfaces and stability of its formation, grinding should be conducted if $ij = 12$.

1. Introduction

It is known that one of the final methods of mechanical processing is grinding, ensuring high precision (6-10 tolerance degrees) and a small surface roughness ($R_a = 0.32 \div 2.5$ µm) at a sufficiently high performance and low cost of commercial products. This allows the grinding operation to be widely used for the manufacture of high quality critical parts of aircrafts, including titanium alloy parts [1].

Titanium alloys belong to hard-to-machine materials. But all brands of titanium alloys, especially high strength ($\sigma_{\text{strength limit}} > 1000$ MPa), have low workability by traditional abrasive tools (electrocorundum, silicon carbide) of standard porosity: (6-7)th structures. The reasons for their low grinding ability are adhesion and diffusion interaction between the abrasive and the material being treated, as well as the intense loading of the working surface of an abrasive tool [2, 3]. Highly porous wheels (HPW) made of cubic boron nitride were developed for their grinding; sizes of pores in these wheels are much larger than in the standard ones. That promotes better chip disposal, reduces wheels loading rate and improves the conditions of grinding zone cooling [4].

Another way to improve the grinding process of titanium alloy is the choice of specifying methods of cross-feed and wheel cutting-in into a workpiece. Nevertheless, there is a problem with the integrated assessment of a large number of parameters of workpieces' surface quality, which must be simultaneously provided to ensure each of the required operational properties. The surface topography is estimated by measures of position and dispersion [5, 6]. The last one plays an important role, especially in a flexible automated production, as it holds the process output parameters at a constant level during the entire operation time. A large number of the studied variables lead to difficulty in complex evaluation of conventional statistical methods. Models of artificial neural networks (ANN) have a number of

valuable properties that make them suitable for modeling complex, non-stationary processes that depend on many input variables [7, 8]. First, to build a model of the ANN process does not require analytical expressions that reflect the physical phenomena of the process. The ANN model is built automatically through a teaching procedure, based on information about the process. Second, ANN models are able to process information simultaneously from different sensors and physical quantities, which must not necessarily be correlated. Thirdly, the ANN models can be effectively combined with physical models to further improve simulation performance. Because of these properties, ANN models are considered as an effective tool for modeling of grinding processes. Using the ANN models, multiple tasks of classification and regression analysis are mainly solved.

    The aim of this study is to evaluate specifying methods of cross-feed and cutting-in of HPW CBN30 B107 100 OV K27 KF40 into a workpiece made of titanium alloy VT22 by quality of its surface and process stability using ANN.

2.. Methodology of the experiment

The subject of the research is workpieces of titanium alloy VT22 with dimensions $L \times B \times H = 40 \times 40 \times 40$ mm, processed by machine model 3E711B along plane $L \times B$ without sparking-out at the end of the cycle; the flooded coolant is the 5% emulsion "Akwol–6" (TU 0258-024-00148845-98) with a 7-10 l/min flow. The number of parallel observations is $n = 30$. The form and dimensions of the HPW and grinding modes are given in table 1.

Table 1. Abrasive tool and grinding modes of workpieces made of BT22

Form and dimensions of HPW, mm	Technological parameters					
	v_w, m/s	s_l, m/min	t, mm	z, mm	$s_{c(ij)}$	
					ij	Quantity
1A1 200×20×76×5 (GOST 53923–2010)	28	6	0.01	0.10	10	2 mm/stroke
					21	4 mm/double-stroke
					22	4 mm/double-stroke

Note: v_w – cutting speed, s_l – longitude feed, t – cutting depth, z – operating allowance, $s_{c(ij)}$ – cross-feed

    Variable grinding conditions (ij) in table 1 provide the following information. Index $i = 1; 2$ characterizes representation $s_{c(ij)}$. Both schemes have equal performance of metal removal. Second grinding variable $j = \overline{0;2}$ describes the verities of HPW cutting-in and descending of the grinding wheelhead to cutting depth t: 1 – up, 2 – down, 0 – up and down cutting-in change at each stroke.

    In order to evaluate the quality of machine parts, the following parameters are used: surface roughness (R_{a1}, R_{max1} – in the direction of vector s_c; S_{m2} – in the direction of s_l); flatness deviations EFE_{max}, EFE_a, EFE_q, which are named as the greatest, the arithmetical mean and quadratic mean; microhardness HV taking into account the stability of their formation.

    Considering the volatility and the stochastic nature of the grinding process, interpretation of the observations is made with help of statistical approaches, considering them as random qualities (RQ). In the experiment, they are generally represented by the sets:

$$\left\{ y_{ijv} \right\}, i = 1; 2, j = \overline{0; 2}, v = \overline{1; 30}. \tag{1}$$

Methods of interpretation of experimental data using statistical methods are given in the works [9, 10]. These methods are divided into two groups: parametric and non-parametric (in particular the rank one). Involving the parametric method is possible if (1) satisfies two conditions: homoscedasticity (uniformity or homogeneity of dispersions) and normality of distributions. Under grinding conditions, these restrictions of RQ (1) are often violated in one way or another. In such situation, it is better to make use of nonparametric statistics, which does not depend on families of distributions and does not use their properties. The following one-dimensional distributions of frequencies are used for the eval-

uation of RQ: for parametric method – average $\bar{y}_{ij} = y_{ij \bullet}$, standards of deviations $(SD)_{ij}$, ranges $R_{ij} = |y_{max} - y_{min}|_{ij}$; for rank statistics - medians $\tilde{y}_{ij}$, quartile latitude $QL_{ij} = |y_{0.75} - y_{0.25}|_{ij}$, covering 50% of observations (1).

Methods of ANN implementation are presented in work [8]. However, in this case, the type of analysis is regression, which allows obtaining a numeric estimate that is convenient in the analysis.

3.. Results and discussion

To choose the method of statistical analysis of (1), methods were tested to ensure the homogeneity of dispersions and normality of distributions. Positive test results are reflected as the acceptance of the null hypotheses (H_o) and their reject - as alternative hypothesis (H_1). Theoretical statistics imposes the most strict requirements for dispersion homogeneity at the assumed level of significance $\alpha = 0.05$. Taking into account the statistical nature of the decisions, three groups of criteria are involved in the program *Statistica* $\omega = \overline{1;3}$: 1 – Hartley's, Cochran's, Bartlett's (they are represented in the program by a single set); 2 – Levene's; 3 – Brown-Forsythe's. Acceptance conditions of their homogeneous and the test results are presented in table 2.

Table 2. Test of dispersion homogeneity for the studied parameters of the workpieces' surface quality

Parameter	Expected confidence level $\alpha_\omega < 0,05$ for criteria $\omega = \overline{1;3}$			Acceptation of H_o
	1	2	3	
R_{a1}	0.42	0.48	0.49	-
R_{max1}	0.53	0.23	0.29	-
S_{m2}	**0.00**	**0.01**	0.08	+
EFE_{max}	**0.00**	**0.00**	**0.00**	+
EFE_a	**0.00**	**0.00**	**0.00**	+
EFE_q	**0.00**	**0.00**	**0.00**	+
HV	**0.047**	**0.049**	0.053	+

Note: $\omega = \overline{1;3}$: 1 – Hartley's, Cochran's and Bartlett's; 2 – Levene's; 3 – Brown–Forsythe's, sign «+» – H_o is accepted, sign «-» – H_o is rejected

H_o indicators were taken for 5 of the 7 parameters concerning dispersion homogeneity of observations (table 2) and it was rejected - for R_{a1} and R_{max1}.

Table 3. Distribution normality testing (1)

ij	Expected confidence level α_{ij}						
	R_{a1ij}	R_{max1ij}	S_{m2ij}	EFE_{maxij}	EFE_{aij}	EFE_{qij}	HV_{ij}
10	**0.66**	0.005	0.005	0.02	0.11	0.06	0.49
21	**0.84**	0.41	0.03	0.01	**0.58**	0.49	**0.62**
22	**0.59**	**0.51**	0.001	0.15	0.14	0.22	**0.98**

Normality of distributions (1) was verified by the Shapiro-Wilk's criterion in table 3, provided that $\alpha_{ij} \geq 0,5$. It was revealed that indicators H_o have been rejected in most cases, which confirms the incomplete provision of requirements from parametric statistics. This forced us to turn to a nonparametric method using medians $\tilde{y}_{ij}$ (measures of position) and quartile latitude QL_{ij} (measures of dispersion), the values of which are presented in table 4.

Table 4. Effect of cross-feed specifying scheme and method of wheel cutting-in on quality of grinding workpieces

ij	R_{a1ij}, μm		R_{max1ij}, μm		S_{m2ij}, μm		EFE_{maxij}, μm		EFE_{aij}, μm		EFE_{qij}, μm		HV_{ij}, MPa	
	$\tilde{y}_{ij}$	КШ$_{ij}$	$\tilde{y}_{ij}$	КШ$_{ij}$	$\tilde{y}_{ij}$	КШ$_{ij}$	$\tilde{y}_{ij}$	КШ$_{ij}$	$\tilde{y}_{ij}$	КШ$_{ij}$	$\tilde{y}_{ij}$	КШ$_{ij}$	$\tilde{y}_{ij}$	КШ$_{ij}$
10	0.31 (0.32)	0.06	1.8	0.3	94.34 (100)	33.26	6.0 (TFE5)	3.0	3.54	1.33	3.84	1.59	2887.6	278.5
21	0.47 (0.50)	0.08	2.68	0.58	87.68 (100)	26.08	4.0 (TFE4)	1.0	2.67	0.67	2.8	0.42	3518.7	264.6
22	0.47 (0.50)	0.09	2.81	0.62	99.98 (100)	36.13	8.0 (TFE6)	3.0	5.38	2.67	5.65	2.36	3598.7	368.9

Note: there are QL in the brackets (GOST 2789–73), for roughness parameters, for flatness deviations - *TFE* (GOST 24643-81); *ij* – see the experimental method

According to the table, mode $ij = 10$ provides a reduction of high-rise parameters of a roughness not only for experienced medians, but also for the stability of their formation compared to modes $ij = 21$; 22: median $\widetilde{R}_{a111} = 0.31$ μm was predicted less than its analogues ($\widetilde{R}_{a121} = \widetilde{R}_{a122} = 0.47$ μm) 1.52 times, $QL_{Ra111} = 0.3$ μm – up to 2.07 times ($QL_{Ra121} = 0.58$ μm, $QL_{Ra122} = 0.62$ μm). For S_{m2ij}, EFE_{maxij}, EFE_{aij}, EFE_{qij}, the best result was predicted for the second scheme - $ij = 21$, and mixed results were predicted for $HV_{ij} - \widetilde{HV}_{ij}$ and QL_{HVij}. This fact excludes the possibility to give an overall assessment of all the parameters of the surface quality of polished workpieces by conventional statistical analysis methods. The ANN model was used in the package «*STATISTICA Neural Network*» to select the optimal method of cross-feed and wheel cutting-in under surface grinding of titanium workpieces.
Initially the Ann model search was carried out separately for surface roughness, for accuracy and for micro-hardness, by which differential estimation was predicted numerically. Then the overall estimate is the sum of the differential estimates.

For input variables, there are three levels of estimates during searching: low, average and high (table 5), and for output – 5 levels: 5 - is very good, 4 – good, 3 – average, 2 – poor and 1 – very poor.

Table 5. Linguistic input variables and their ranges for roughness parameters

Parameter		Input parameters Linguistic variables	Level of factors, μm
R_{a1ij}	$\tilde{y}_{ij}$	low (H), average (C), high (B)	0.31; 0.39; 0.47
	QL$_{ij}$	low (H), average (C), high (B)	0.06; 0.075; 0.09
R_{max1ij}	$\tilde{y}_{ij}$	low (H), average (C), high (B)	1.80; 2.305; 2.81
	QL$_{ij}$	low (H), average (C), high (B)	0.30; 0.46; 0.62
S_{m2ij}	$\tilde{y}_{ij}$	low (H), average (C), high (B)	87.68; 93.83; 99.98
	QL$_{ij}$	low (H), average (C), high (B)	26.08; 31.105; 36.13

The total number of rules used to build the neural networks is equal to $3^6 = 729$ possible combinations of input parameters and linguistic estimates of grinded part qualities (table 6). Different ANN models with varied architectures were obtained as a result of the prediction, among which the model of multilayer perceptron MLP 6-9-1 type was selected. It had a three-layer structure: an input layer (of 6 neurons), one hidden layer (of 9 neurons) and an output layer (of 1 neuron). This model provides the fastest performance and the smallest error for all three subsets: teaching, checking and testing.

Table 6. The structure of linguistic simulation rules

№	Structure of rules						Estimation
	R_{a1ij}		R_{max1ij}		S_{m2ij}		
	$\tilde{y}_{ij}$	QL_{ij}	$\tilde{y}_{ij}$	QL_{ij}	$\tilde{y}_{ij}$	QL_{ij}	
1	L	L	L	L	L	L	5
2	L	L	L	L	L	A	5
3	L	L	L	L	L	H	4
…	…	…	…	…	…	…	…
727	H	H	H	H	H	L	2
728	H	H	H	H	H	A	1
729	H	H	H	H	H	H	1

Search of the ANN model for form accuracy parameters, taking into account the stability of their formation carried out similarly, and as a result the MLP 6-5-1 model was obtained.

Table 7. Structure of rules for ANN training in microhardness

№	HV_{ij}, MPa		Numerical estimation
	$\tilde{y}_{ij}$	QL_{ij}	
1	3598.74	264.60	5
2	3598.74	316.75	4
3	3598.74	368.90	3
4	3243.19	264.60	4
5	3243.19	316.75	3
6	3243.19	368.90	2
7	2887.63	264.60	3
8	2887.63	316.75	2
9	2887.63	368.90	1

The structure combinations for microhardness estimations are shown in table 7. In this case, the 2-5-1 MLP model is selected.

Table 8. Estimation of technological grinding methods by quality parameter parts of workpieces

ij	Differential estimate on			Integral estimation
	Roughness	Form accuracy	Microhardness	
10	3.95	3.06	2.41	9.42
21	**3.2**	**5.0**	**3.96**	**12.16**
22	1.0	1.0	3.24	5.24

Differential estimates (table 8) were obtained as a result of predictions based on ANN models. It has been established that for surface roughness of grinded parts, first technological method $ij = 10$ (cross feed per stroke and HPW cutting-in change alternately from up to down) with a numeric estima-

tion of 3.95 (good) has proven to be the most effective. The second place was taken by second grinding option ij = 21 (cross feed per double stroke with upward HPW cutting-in at the working stroke). However, the second variant with the appropriate estimates of 5.00 (very good) and 3.96 (good) was the best for form accuracy and microhardness of the surface layer.

In case of integral estimation of all studied parameters of surface qualities (roughness, form accuracy, micro-hardness) with allowance for stability of the formation, the following results were obtained. The second grinding variant had the best estimate (12.16) and the worst was given to the third one with a numeric estimate of 5.24 and with a very bad estimate for roughness and form accuracy.

Hereby, in the case of surface grinding of titanium workpieces of alloy VT22, the cross-feed specifying s_c at a double stroke during the upward grinding wheel, cutting-in at the working stroke, turned out the most effective technique.

4. Conclusions
The test results of the experimental data for homogeneity of dispersions and normality of distributions have shown the expediency of application of the nonparametric method for their interpretation. The neural network models have demonstrated effectiveness in solving the problem of complex evaluation of experimental data.

It was established that in order to improve the quality of the titanium workpieces surface, surface grinding should be conducted when specifying cross-feed s_c at a double-stroke during the upward grinding wheel cutting-in at the working stroke.

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