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Study on optimization of grinding parameters under different diameters

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Abstract

In order to study the influence of ultra-precision grinding parameters on the accuracy between the same clamping method and different workpiece sizes. In this paper, the same clamping method is used to grind two kinds of parts with equal length and different diameter, and the parametric precision model is carried out. Combined with neural network algorithm, the precision model is optimized and ground. It shown that the coaxiality of end face A is the maximum, reaching 2.6 µm. At the same time, it can be seen from the data at both ends of A (left end of workpiece) and B (right end of workpiece) measurements that the precision gradually increases with the measurement depth, with the highest accuracy reaching 5.5 µm. The reason is that the parts in the processing of the use of two—top processing, and the use of both ends is the way of positioning. Therefore, fixture errors will occur, which will eventually affect the overall part errors.

Keywords：ultra-precision grinding；neural network algorithm；measurement；optimized

1. Introduction

In the global machinery manufacturing industry, grinding is one of the most important links in the processing steps. Grinding is usually one of the final manufacturing processes [1]. The accuracy of the final part and the stability of the precision depend on the grinding process. Therefore, the grinding process is particularly important. Ultra-precision and ultra-high speed grinding is one of the difficult problems in the machining industry. This difficulty mainly lies in the guarantee and stability of grinding precision. Many authors have also studied some contributions. For example, in the aspect of grinding precision control; Tawakoli T et al. [2] studied the influence of workpiece, and grinding parameters on minimum lubrication MQL grinding. The relationship between grinding parameters, grinding accuracy, and performance is analyzed from the perspective of abrasive microscopy. It is also concluded that the metal removal rate in MQL grinding is mainly affected by shear and fracture. Unlike conventional fluid grinding and dry grinding, plastic deformation, abrasive particle pullout and ploughing are not easy to occur.

Padda A S et al. [3] studied the influence of different surface grinding parameters on the surface roughness of stainless steel. The author analyzed the influence of cutting depth, grinding wheel speed and particle size on roughness when inputting grinding parameters and using white alumina grinding wheel. The au-thor thinks that the most influential factor in surface grinding is grinding wheel speed, followed by crystal particle size and cutting depth. Research on grinding parameters, Vishal Francis et. al. [4] stated that if feed and depth of cut were varied and spindle speed was kept constant to observe their effect on surface roughness. Then feed rate was found to be the most significant factor in case of cast iron and none of the factor was found be significant for mild steel and stainless steel. In this paper, the same clamping method is used to grind two kinds of parts with equal length and different diameter, and the parametric precision model is carried out. Combined with neural network algorithm, the precision model is optimized and ground.

2. Optimization model

2.1 Optimization variables

Before analyzing the parametric precision model, it is necessary to determine the most important parameters that affect the grinding precision. In addition to considering the most commonly used parameters, such as grinding wheel speed S_n, cutting speed S_v, cutting depth S_p, feed S_f. There are more parameters to consider, such as light grinding times H, cutting power P, spindle acceleration power P_{SA}, and workpiece shaft speed Z_n. Meanwhile, these parameters are taken as optimized variables.

$$\begin{aligned} X &= \left[X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8\right] \\ &= \left[S_n, S_v, S_p, S_f, H, P, P_{SA}, Z_n\right] \end{aligned}$$

(1)

2.2 Constraint condition

Ultra-precision grinding belongs to fine micro-surface processing. So grinding wheels with different particle densities and types are selected according to different materials [5]. This paper mainly focuses on the ultra-precision grinding of 45 steel after turning, boring, rough grinding, grinding and surface hardening. According to the optimized variables in Equation (1), the restriction conditions and value range of each variable are analyzed.

（1）Grinding wheel speed S_n.

According to the two parts processed, the grinding wheel speed model is set as:

$$S_{n_{\min}} \le S_n \le S_{n_{\max}}$$

(2)

(2) Grinding speed S_v.

For different grinding materials and parts sizes, the grinding speed selected is also different. Its main mathematical model is set as:

$$S_{v_{\min}} \le S_v \le S_{v_{\max}}$$

(3)

(3) Grinding depth S_p.

The grinding depth also has a great influence on the grinding precision, and its mathematical model is set as: $S_{p_{\min}} \le S_p \le S_{p_{\max}}$

(4)

(4) Feed S_f.

In the same way, the mathematical model of feed is set:

$$S_{f_{\min}} \le S_f \le S_{f_{\max}} .$$

(5)

(5) Light grinding times H.

The number of light grinding mainly refers to the last processing of fine grinding, according to the final size of fine grinding without feed processing. Therefore, its mathematical model is set as: $1 \le H \le 3$

(6)

(6) Grinding power P.

In the process of processing and production of ultra-precision grinding machine according to actual requirements, it is necessary to ensure that the grinding precision parameters of the grinding machine is within the range that the spindle motor can provide, i.e. Always ensure that the grinding power cannot exceed the maximum power that the spindle motor of the machine tool can provide [6].

$$\frac{C_{F_C} a_p{}^{x_{F_C}} f^{y_{F_C}} K_{F_C}}{\eta} \left(\frac{\pi dN}{1000 \times i} \right)^{n_{F_C}+1} \le P_{\max} \tag{7}$$

Where; η is the total transmission efficiency of the machine tool; $P_{\max}$ is the peak power of the spindle motor; N is the speed of the spindle motor; i is the transmission ratio of the mechanical transmission system; F_c is that main cutting force; d is the workpiece diameter; x_{F_c} is the exponential coefficient of cutting depth S_p; y_{F_c} is the exponential coefficient of feed S_f; K_{F_c} is the product of the correction coefficients of each factor to F_c when the grinding conditions do not meet the empirical equation.

(7) Spindle acceleration power P_{SA}.

During the acceleration period of the spindle, the maximum rotational acceleration power of the spindle shall not exceed the rated power of the spindle motor [7]. The rotational acceleration power of the spindle consists of two aspects: the power used to maintain the rotation of the spindle, and the power used to accelerate the spindle by overcoming the inertia of the mechanical drive system.

$$P_{SA} = P_{SR} + J_s \alpha_m \omega_m \le P_N \tag{8}$$

Where; P_{SA} is the spindle acceleration power; P_{SR} is the spindle rotation power; $P_{SR} = f(n)$ is the spindle rotation speed with a linear relationship. J_s is the moment of inertia of the spindle system equivalent to the spindle motor shaft; α_m is that angular acceleration of the spindle motor; ω_m is the angular velocity of the spindle motor.

$$\alpha_m = \frac{2\pi f_{BA}}{pt_A} \tag{9}$$

$$\omega_m = \frac{2\pi n_1}{60u} + \frac{2\pi f_{BA} T}{pt_A} \tag{10}$$

Where; f_{BA} is the basic frequency of the spindle inverter; p is that number of magnetic poles of the spindle motor; t_A is the acceleration time of the spindle inverter; n_1 is the initial spindle speed; u is the transmission ratio from the main shaft to the output shaft of the motor; T is the spindle rotation acceleration duration. According to the grinder design data, the above design parameters can be obtained.

Therefore, the power used to overcome the inertia of the mechanical transmission system, and accelerate the spindle can be obtained by bringing in the calculation of design parameters. The spindle acceleration power is mainly related to the spindle speed.

$a S_n / i + b \le P_{S_n}$

(11)

(8) Workpiece spindle speed Z_n.

The matching of workpiece spindle and grinding wheel speed directly affect the roughness of workpiece grinding surface. Meanwhile, it is set to: $Z_{n_{\min}} \le Z_n \le Z_{n_{\max}}$. (12)

2.3 Objective function

In this study, the energy consumption of the grinding machine is the lowest on the premise of ensuring the accuracy. Therefore, high precision and low energy consumption are optimized for multi-objective functions. High precision is expressed by A_{CC}. Energy consumption is represented by E. Among them, the grinding machine energy consumption is mainly related to the above 8 optimized variables. Meanwhile, according to the manual query and establish the energy consumption objective function:

$$E = \int_0^{t+H} P_{in} dt = \int_0^{t+H} \frac{P_{im}}{\eta(t)} =$$

$$\int_0^{t+H} \frac{2\pi M_0 N + 4\pi^2 B S_n{}^2 + \alpha C_{F_c} S_p{}^{x_{F_c}} S_f{}^{y_{F_c}} (\pi dN) S_v{}^{Z_{F_c}+1} K_{F_c}}{(1000 \times i)^{S_v{}^{Z_{F_c}}} \eta(t)} dt \tag{13}$$

Where; t is the number of grinding times; H is that number of light grin; M_0 is the non-load Coulomb friction resistance moment equivalent to the spindle motor shaft of the grinder main transmission system; B is the viscous friction damping coefficient of the grinding machine main transmission system equivalent to the motor spindle; ω is the angular velocity of the motor spindle; α is the load factor of the mechanical transmission system ; N is that rotate speed of the spindle motor, $S_v = N/i$; S_v is the cutting speed, $S_v = \pi d Z_n / 1000$; Z_n is the spindle speed; C_{F_c} is the influence coefficient of cutting force, which is related to the material and processing conditions of the workpiece to be processed; Z_{F_c} is the exponential coefficient of cutting speed S_v.

2.4 Optimize parameters

According to the analysis in this paper, neural network is used to optimize this. BP (Back Propagation Network) neural network is a multi-layer feedforward neural network, which consists of input layer, hidden layer and output layer [8-9]. Before optimization, it is necessary to design an optimization model for the whole grinding parameters. The model is shown in Equation (14). Initially, the energy consumption model (Equation 13) is imported into the MATLAB neural network optimization interface. Constraints are applied (Equation 14). Set the initial value of the outer circle [30, 30, 30, 1.5, 1, 15, 18, 80], the minimum value of the outer circle parameter [25, 25, 20, 1, 1, 11, 15, 70], and the maximum value of the outer circle parameter [40, 40, 40, 3, 3, 20, 25, 120]. At the same time, the initial value of the inner circle [30, 30, 30, 1.5, 1, 15, 18, 80], the minimum value of the inner circle parameter [25, 15, 20, 1, 1, 11, 15, 70] and the maximum value of the inner circle parameter [40, 30, 40, 3, 3, 20, 25, 130] are also set. Finally, the optimal grinding rounding parameters are shown in Table 1.

$$\min F(S_{n_{\max}}, S_{v_{\min}}, S_p, S_f, P_{\max}, P_{S_n}, Z_n) = \{\max A_{CC}; \min E\}$$

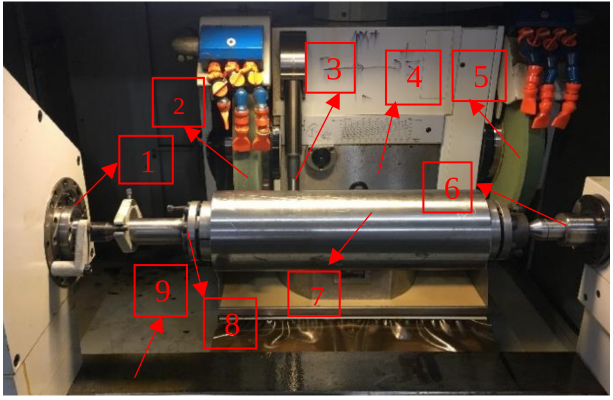
$$\begin{cases} S_{n_{\min}} \le S_n \le S_{n_{\max}} \\ S_{v_{\min}} \le S_v \le S_{v_{\max}} \\ S_{p_{\min}} \le S_p \le S_{p_{\max}} \\ S_{f_{\min}} \le S_f \le S_{f_{\max}} \\ 1 \le H \le 3 \\ \dfrac{C_{F_C} a_p^{x_{F_C}} f^{y_{F_C}} K_{F_C}}{\eta} \left(\dfrac{\pi d N}{1000 \times i} \right)^{n_{F_C}+1} \le P_{\max} \\ a S_n / i + b \le P_{S_n} \\ Z_{n_{\min}} \le Z_n \le Z_{n_{\max}} \end{cases} \tag{14}$$

Table 1. Optimal parameters of outer circle and inner hole.

Outer circle				Inner bore			
Variable	Initial value	Scope	Results	Variable	Initial value	Scope	Results
S_n (m/s)	30	25-40	30	S_n (m/s)	30	25-40	35
S_v (mm/min)	30	25-40	25	S_v (mm/min)	20	15-30	18
S_P (um)	30	20-40	25	S_P (um)	30	20-40	35
S_f (um)	1.5	1-3	1.6	S_f (um)	1.5	1-3	1
H	1	1-3	3	H	1	1-3	3
P (KW)	15	11-20	16	P (KW)	15	11-20	15
P_{SA} (KW)	18	15-25	23	P_{SA} (KW)	18	15-25	22
Z_n (r/min)	80	70-120	90	Z_n (r/min)	80	70-130	120

3. Test analysis

The optimized results of grinding parameters are set so that the parts with the same length and different diameters can be processed, respectively. Because this study mainly studies the parameters of high-precision grinder. The machine is Kellenbergaer universal grinder from Switzerland, and the machining precision is 0.2 µm. The processing site is shown in Fig. 1.



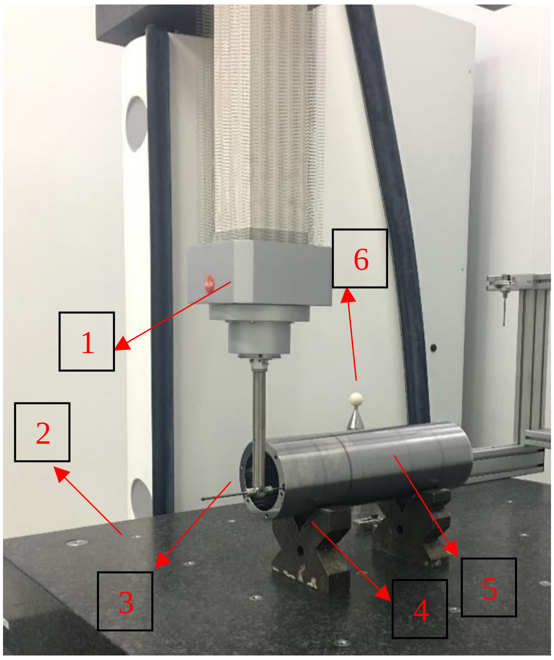
1—workpiece C axis; 2—cylindrical grinding wheel; 3—ruby probe; 4—Axis B; 5—30 ° end face grinding wheel; 6 tailstock; 7—motorized spindle part; 8—tooling fixture; 9—guide Rail

Fig. 1 Actual machining site of motorized spindle.

As shown in Fig. 1,the part has no positioning stepped shoulder. So it is clamped and processed in a two-top way. Parts with small diameter and the same length are processed by the same clamping method. The finished parts are shown in Fig. 2.

Fig. 2. Machined parts.

Firstly, a large diameter part is randomly taken and measured by Leitz precision three coordinates. The uncertainty of the measuring instrument is 0.01 µm. The measurement site is shown in Fig. 3. The measurement results are shown in Table 2.



1—telescopic probe; 2—workbench; 3—probe; 4—V block; 5—motorized spindle part; 6—school team coordinate system

Fig. 3. Inspection site of motorized spindle.

Table 2 Detection accuracy error table.

Test items	Error/um	Test items	Error/um
End face 3 jumping	7.2	Internal bore surface 1 for the first time	20.1
End face 4 runout	8.4	Inner bore surface 1 second time	19.5
A verticality of end face	3	Inner bore surface 1 third time	5.6
B verticality of end face	4.5	Internal bore surface 2 for the first time	15.8
A end coaxiality	2.6	Inner bore surface 2 second time	11.6
B end coaxiality	1.2	Inner bore surface 2 third time	5.5

4. Conclusion

Referring to the test results in Fig. 3 and Table 2, it can be clearly seen that the coaxiality of end face A is the maximum, reaching 2.6 µm. At the same time, it can be seen from the data at both ends of A and B measurements that the precision gradually increases with the measurement depth, with the highest accuracy reaching 5.5 µm. The reason is that in the grinding of parts, the error accuracy and operation debugging accuracy of fixtures will affect the coaxiality of the left and right ends of parts.

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