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Research of EDG honeycomb based on GM(1,N) model and BP neural network

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Abstract In order to predict the influences of electrical discharge grinding(EDG) honeycomb ring process and enhance material removal rate(MRR). A model is presented for predictions of MRR in EDG honeycomb ring process for nickle-based superalloys GH3536 based on the construction method of gray GM(1,N) model and BP neural network model (GNNM).The prediction model was verified with MATLAB simulation.The results show that the GNNM is credible with the maximum absolute error 3.58％, the minimum absolute error 0.01％ and the mean error 0.53％were obtained .The results indicate that the model can reflect the technological law of EDG honeycomb and successfully predict its processing speed .The paper provides references and basis for selecting processing parameters of EDG honeycomb and has practical significance.

Keywords EDG;MRR;GNNM;GH3536;BP neural network;honeycomb ring

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1. Introduction

Honeycomb structure has been widely used in various jet or vortex engines at home and abroad. Engine performance and service are affected by honeycomb quality.Honeycomb ring is typical thin-walled part with thickness of 0.03mm .Meanwhile,surface roughness ($R_a \leqslant$ 0.8μm~1.6μm) and deterioration layer thickness (t $\leqslant$ 0.02mm)without crack were required. Honeycomb ring is made of nickle-based superalloys (GH3536) characterized by excellent resistance to oxidation , corrosiveness resistance,high thermal stability and fatigue , however,it is regarded as one of the most difficult-to-machine materials because of hard particle,work hardening and low thermal conductivity,the properties of GH3536 were shown in Table.1 [1-4].

EDM has gained importance due to its capability to remove material with good accuracy and precision.EDM accomplishes shapes that could hardly been achieved with any other conventional method,regardless the hardness of material and the complex of the part to be machined. Therefore ,EDG was suitable for machining honeycomb with special shape and material.The physical mechanism of EDM is complex and volatile,randomness and uncertainty.While artificial neural network is an effectual method to solve nonlinear problem .The gray theory, first initiated by Dr. Deng in 1982, can provide a solution to a system in which the model is unsure or the information is incomplete[5].It avoids the inherent shortcomings of conventional statistical methods and requires limited data to estimate the behavior of an uncertain system. It also provides an efficient solution to the uncertain, multi-input, and discrete data problem.The gray relational analysis based on this theory is applied in different manufacturing processes to effectively solve the complicated interrelationships among multiple quality characteristics and to determine the optimal parameter setting[6].The gray dynamic model GM(1,N),which stands for the first order,N variable prediction model based on gray system theory.GNNM combines with the advantages of GM(1,N) model and BP neural network model and improve the prediction accuracy.

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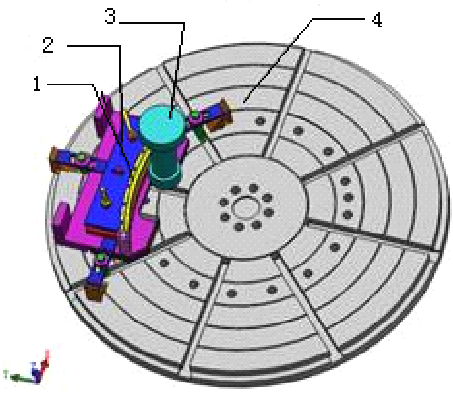
Table.1 physical and mechanical properties of GH3536

Physical property	Density g/cm^3	Melting point ℃	Thermal conductivity λ/(W/m℃)	Specific heat capacity J/kg℃	Modulus of elasticity GPa	Resistivity $\mu\Omega m$	Coefficient of linear expansion $a/10^{6*}C^{-1}$
	8.28	1259~1381	13.38（100℃）	372.6	199	1.18	12.1（20~100℃）
Mechanical property	Heat treatment	σ_b MPa	σ_s MPa	δ %	HBS	Working temperature $^{\circ}C$	
	Solution treatment	580~690	275~286	30	≥241	800~1200	

2. Description of the experiments

2.1 Principal and conditions

EDG is a process whereby unnecessary material is removed by the action of electrical discharges between the workpiece and the tool electrode. In EDG process,the honeycomb ring was fixed on the rotating table,and tool electrode was moved to machine the inner cambered surface .A relatively stable discharge gap (0.01~0.07mm)was maintained between tool electrode and workpiece rotating in opposite direction to complete radial compensation processing. The concept of EDG honeycomb ring was illustrated in Fig.1,and the structure of honeycomb ring was shown in Fig 2.



1—honeycomb 2— fixture 3—tool electrode 4— rotating table

Fig.1 The concept of EDG honeycomb ring

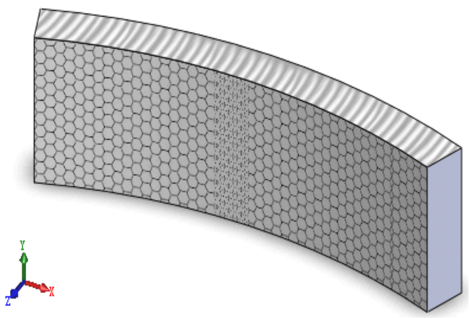


Fig.2 The structure of honeycomb ring

A series of experiments were performed on a CNC electrical discharge grinding machine "ZT-034 ",detailed processing parameters are shown in Table.2. Clavate tool electrode was designed to not only facilitate chip removal and deionization but also enhance the machining precision of honeycomb ring [7].Graphite with good electrical conductivity and low price was chosen as tool electrode material with linear velocity (0.25 ms^{-1} ~1.25 ms^{-1})[8].The working liquid feed system was employed to ensure that the workpiece and tool electrode was completely immersed with kerosene of low viscosity and good deionization property.Positive polarity machining was applied to obtain high processing quality [9] .

Table.2 The detailed parameters of ZT-034

Process stage	Equipment model	Pulse-on time	Pulse-off time	Envelope width	Envelope interval	Low voltage current	High voltage current	Servo given
Finishing machining	ZT-034	50	100	1000	1000	8	1	70%
Unit		μs	μs	μs	μs	A	A	

Name	Machine input power	Max work current	Input power	Surface roughness	Electrode loss
Value	100	480	380	1.25	≤6%
Unit	KVA	A	VAC	μ m	

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2.2 Material removal rate

MRR is calculated by using the volume loss from the work piece divided by the time of machining.The calculated weight loss is converted to volumetric loss in cubic millimeter per minute as Eq(1).

$$MRR = \frac{\Delta V_w}{T} = \frac{\Delta W_w}{\rho_w T} \qquad (1)$$

Where ΔV_w is the volume loss from the work piece, ΔW_w is the weight loss from the work piece,T is the duration of the machining process,and ρ_w=8.28 g/cm^3 is the density of the work piece.

2.3 Machining parameter selection and orthogonal array table

MRR is affected by numerous certain or uncertain factors,based on experience and literatures on EDM research and the working characteristics of the EDM machine . The four main electric parameters:pulse-on time(t_{on}),pulse-off time(t_{off}),peak current(I_p) and peak voltage(U_e) were chosen.Preferred levels for each machining parameter were shown in Table3.Four levels were selected for each machining parameter.An $L_{16}(4^4)$ orthogonal array table was employed to produce the experimental layout.The experimental results were summarized in Table4.

Table .3 Machining parameters and their levels

Factors	Unit	Factor levels			
		1	2	3	4
Pulse-on time(t_{on})	μs	10	25	35	45
Pulse-off time(t_{off})	μs	50	80	160	230
Peak current(I_p)	A	3	8	12	15
Peak voltage(U_e)	V	3	5	7	9

Table.4 Experimental layout using an $L_{16}(4^4)$ orthogonal array

Experimental number	Pulse-on time t_{on} (μs)	Pulse-off time t_{off} (μs)	Peak voltage $U_e(V)$	Peak current I_p (A)	Process speed $V(mm^3/\min)$
1	10	50	3	3	0.38
2	10	80	5	8	1.25
3	10	160	7	12	1.76
4	10	230	9	15	2.43
5	25	50	5	12	2.05
6	25	80	3	15	2.50
7	25	160	9	3	0.49
8	25	230	7	8	1.29
9	35	50	7	15	2.66
10	35	80	9	12	2.12
11	35	160	3	8	1.44
12	35	230	5	3	0.64
13	45	50	9	8	1.55
14	45	80	7	3	0.76
15	45	160	5	15	3.25
16	45	230	3	12	2.39

2.4 Result and discussion based on GRA

GRA is an improved method for identifying and prioritizing key system factors, provides a straightforward mechanism for proposal evaluation, and is useful for variable independence analysis.Therefore it has been widely used in engineering analysis, and it reveals the potential to solve the setting of optimal machining parameters associated with a process with multiple performance characteristics[10].But in this study,the weights of four factors are different and weight differences could not be neglected.

One sequence of data was defined as the original series,where X_i is the original pattern with

n entries $X_0=[x_0(1),x_0(2),.....,x_0(n)]$. The comparative series are X_1, $X_2,...,X_n$, where $X_1=[x_1(1),x_2(1),...,x_n(1)]$, $X_2=[x_2(1),x_2(2),...,x_2(n)]$..... $X_m=[x_m(1),x_m(2),...x_m(n)]$.

The basic procedures of GRA calculation were as follows:

Step 1: The raw experimental data are normalized by

$$x(k)=\frac{x_i(k)}{x_i(1)}=\{\frac{x_i(1)}{x_i(1)},\frac{x_i(2)}{x_i(1)},...,\frac{x_i(3)}{x_i(1)}\} \qquad (k=1,2,...,n;i=1,2,...,m) \tag{2}$$

Step 2: Calculating the GRC(gray relational coefficient).

The GRC $\gamma_{0i}(k)$ can be defined as

$$\gamma_{0i}(k)=\frac{\min\limits_i\min\limits_k|x_0(k)-x_i(k)|+\xi\max\limits_i\max\limits_k|x_0(k)-x_i(k)|}{|x_0(k)-x_i(k)|+\xi\max\limits_i\max\limits_k|x_0(k)-x_i(k)|} \tag{3}$$

Where $\xi\in[0,1]$ was a distinguishing coefficient for controlling the resolution scale, usually being assigned the value of 0.5, $i=1,2,...,m;k=1,2,...,n$.

Step3: Calculating the weight factor β_k

This paper adopted the means of definite weighted function to calculate β_k. The sum of attribute factors D_k could be obtained by $D_k=\sum_{i=1}^{m}x_k(i)$ .The entropy

$$e_k=\frac{1}{n}\sum_{i=1}^{m}f[\frac{x_i(k)}{D_K}] \tag{4}$$

where $f(x)=xe^{1-x}+(1-x)e^x-1$ .Each factor of relative weight can be calculated by $r_k=\frac{1}{m-E}(1-e_k)$,

where $E=\sum_{k=1}^{n}e_k$ .Therefore,the weight factor is expressed as $\beta_k=\frac{r_k}{\sum_{k=1}^{n}r_k}$ (5)

Step4: Calculating GRG(gray relational grade).

GRG was given by the average of the GRC as

$\gamma_{0i}=\frac{1}{n}\sum_{k=1}^{n}\beta_k\gamma_{0i}(k)$, where β_k is the weighting factor for the kth quality characteristic and n is the number of quality characteristics.

After the sequences data pre-processing,the weighted values of four factors were calculated ,shown in Table5.The GRC between four factors with MRR based on weighted gray correlation analyzing were listed in Table6.

Table.5 The results of weighted values

Factors	t_{on}	t_{off}	U_c	I_p
Attribute factors	46.0	41.6	32.0	50.7
Entropy value	0.15515	0.15405	0.155925	0.154875
Relative weight	0.24996	0.25028	0.24973	0.25004
Weighted value	0.25769	0.25802	0.25745	0.25777

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Table.6 The GRC between four factors with MRR

Experiment number	t_{on}/μs	t_{off}/μs	U_e/V	I_p/A	Actual Values V(mm³/min)	Predicted Values V(mm³/min)
1	10	50	3	3	0.38	0.38
2	10	80	5	8	1.25	1.16
3	10	160	7	12	1.76	1.86
4	10	230	9	15	2.43	2.18
5	25	50	5	12	2.05	2.10
6	25	80	3	15	2.50	2.71
7	25	160	9	3	0.49	0.46
8	25	230	7	8	1.29	1.31
9	35	50	7	15	2.66	2.63
10	35	80	9	12	2.12	2.02
11	35	160	3	8	1.44	1.58
12	35	230	5	3	0.64	0.73
13	45	50	9	8	1.55	1.50
14	45	80	7	3	0.76	0.77
15	45	160	5	15	3.25	3.07
16	45	230	3	12	2.39	2.58

The results of GRG $\gamma_{I_p}=0.8588,\gamma_{t_{on}}=0.6473,\gamma_{U_e}=0.6849,\gamma_{t_{off}}=0.6287$ clearly presented the importance degree of determinants ranked by $\gamma_{I_p}>\gamma_{U_e}>\gamma_{t_{on}}>\gamma_{t_{off}}$.

3. **Material removal rate model**

GM(1， N) has been widely used for small sample forecasting because of the advantages of weakening sequence randomness and exploring the system evolution regular ,which makes GM(1,N) have strong integration and penetration.Therefore,GM(1,N) can be incorporated into modeling process to achieve complementary functions and greatly develop prediction accuracy [11]. EDG was influenced by various factors ,including electrical parameters and non-electrical parameters,Therefore,it was difficult to conduct quantitative analysis for the non-linear relationship between these parameters and the material removal rate.This study proposed GM(1,N) approach to solve the material removal rate prediction model of EDG honeycomb ring.

3.1 The basic ideas of GNNM

The combination of gray system theory and ANN in series wae chosen ,namely,the output of gray system theory was regarded as the next level of the next neural network input,finally using neural network simulation,in this paper.The flow chart of GNNM was shown in Fig3.First,the series of MMR,pulse-on time(t_{on}),pulse-off time(t_{off}),peak current(I_p) and peak voltage(U_e) were set to $x_1^{(0)}$, $x_2^{(0)},x_3^{(0)},x_4^{(0)},x_5^{(0)}$ .While $x_1^{(0)}$ was signature sequence and $x_2^{(0)},x_3^{(0)},x_4^{(0)},x_5^{(0)}$ were relative factor sequences.Next,the GM(1,N) was established based on the data of $x_1^{(0)}$ $x_2^{(0)},x_3^{(0)},x_4^{(0)},x_5^{(0)}$ .The prediction sequences $\hat{x}_1^{(0)}$ was generated after gray prediction on GM(1,N).Finally,the neural network model was built based on the input vector $\hat{x}_1^{(0)}$ and the target vector $x_1^{(0)}$.

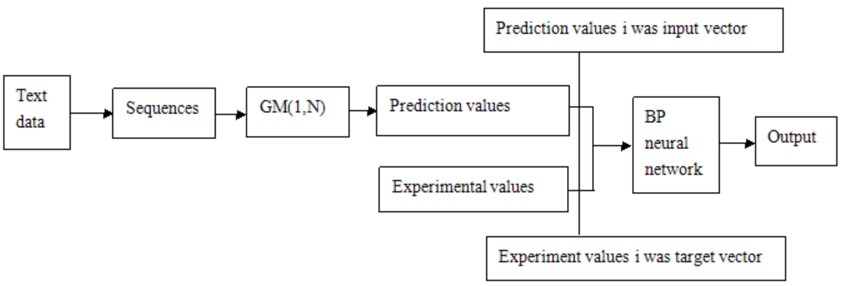

Fig.3 Flow chart of GNNM

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3.2 The establishment and simulation of GNNM

GM(1，N) was usually represented as differential equation with N variables,the forecasting equation of GM(1,N) is denoted as follows:

$$\frac{dx_1^{(1)}}{dt}+ax_1^{(1)}=b_1x_2^{(1)}+b_2x_3^{(1)}+b_3x_4^{(1)}+b_4x_5^{(1)}.....+b_Nx_N^{(1)} \qquad (6)$$

Where $x_i^{(0)}$ is an initial series, $x_i^{(1)}$ is the AGO(Accumulated generating operation) series. In the formula above, $[a,b_1,b_2,...,b_N]^T$ is a parameter sequence which could be calculated by least-square method ,the developing coefficients a and control variable b can be obtained as follows:

$$[a,b_1,b_2,...,b_N]^T=(B^TB)^{-1}B^TY \ ,$$

$$\vec{Y}=[x_1^{(0)}(2),x_1^{(0)}(3),...,x_1^{(0)}(n)]^T ,$$

$$\vec{B}=\begin{pmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & \cdots x_N^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & \cdots x_N^{(1)}(3) \\ \vdots & \vdots & \vdots \\ -z_1(n) & x_2^{(1)}(n) & \cdots x_N^{(1)}(n) \end{pmatrix}$$

where, z_1 was background value, $z_1^{(1)}=0.5x_1^{(1)}(k)+0.5x_1^{(1)}(k-1)$ (7)

According to the GRA,pulse-on time,pulse-off time,peak current and peak voltage were chosen as variables to construct the gray forecasting model GM(1,4).The data of Table.3 was conducted respectively and generated series $x_1^{(0)},x_2^{(0)},x_3^{(0)},x_4^{(0)},x_5^{(0)}$, z_1 was calculated by Eq(7) based on $x_1^{(0)}$ series.After constructing $\vec{Y}$ and $\vec{B}$ and programming by Matlab ,the equation of GM(1,4) was obtained as follows:

$$\frac{dx_1^{(1)}}{dt}+2.1983x_1^{(1)}=0.0324x_2^{(1)}-0.0001x_3^{(1)}\ -0.1216x_4^{(1)}+0.3678x_5^{(1)} \qquad (8)$$

where, $x_2^{(1)},x_3^{(1)},x_4^{(1)},x_5^{(1)}$ were taken as the AGO input values of pulse-on time,pulse-off time,peak electric current and peak voltage.

The equation of response function and IAGO(inverse accumulated generated operation) were defined as: $x_1^{(1)}(k+1)=(x_1^{(0)}(1)-\frac{1}{a}\sum_{i=1}^{5}b_ix_i^{(1)}(k+1))e^{-ak}+\frac{1}{a}\sum_{i=1}^{5}b_ix_i^{(1)}(k+1)$ (9)

$$x_1^{(0)}(k+1)=x_1^{(1)}(k+1)-x_1^{(1)}(k) \qquad (10)$$

The following formula can be chosen as reference formula: $m=\sqrt{n+l}+\alpha$ [12]，Where n is the number of neuron in input layer, m is that of neuron in hidden layer, l is the number of neuron in output layer, α is the regulating constant ($1\leqslant\alpha\leqslant10$).In considering the convergence speed and generalization accuracy ,the optimum value foy the number of hidden layer nodes was determined by trial and error to be 11. So the topologic structure was [4-11-1],shown in Fig 4.the basic parameters of BP network algorithm were set as: shown frequency was1,learning efficiency was 0.07,the training time was 1000(s) and goal mean error was 0.001.

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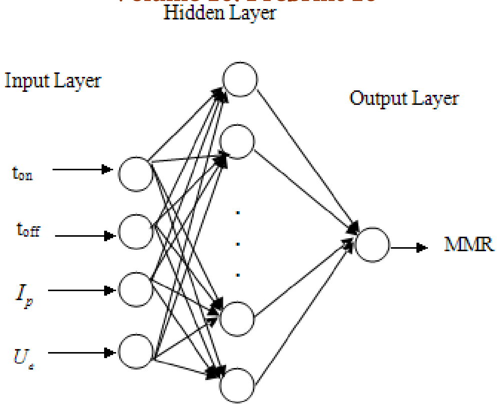

Fig.4 Neural network topology of prediction model

The prediction data of GM(1,4) were obtained ,as shown in Table 7.Data 1 to 14 was chosen as training samples, and data of 14 to 16 belonged to prediction samples .

Table.7 forecast data

Experiment number	Input Values t_{on}/μs	t_{off}/μs	U_e/V	I_p/A	Actual Values $V(mm^3/min)$	Predicted Values $V(mm^3/min)$
1	10	50	3	3	0.38	0.38
2	10	80	5	8	1.25	1.16
3	10	160	7	12	1.76	1.88
4	10	230	9	15	2.43	2.18
5	25	50	5	12	2.05	3.10
6	25	80	3	15	2.50	2.41
7	25	160	9	3	0.49	0.46
8	25	230	7	8	1.29	1.31
9	35	50	7	15	2.66	2.63
10	35	80	9	12	2.12	1.22
11	35	160	3	8	1.44	1.38
12	35	230	5	3	0.64	0.73
13	45	50	9	8	1.55	1.50
14	45	80	7	3	0.76	0.77
15	45	160	5	15	3.25	3.07
16	45	230	3	12	2.39	2.58

The results simulated by Matlab were shown in Fig 5,with 45 training epochs,neural training error was very close to goal accuracy 0.001.The neural training network curve was proved to be stable convergence smoothly without significant fluctuations.

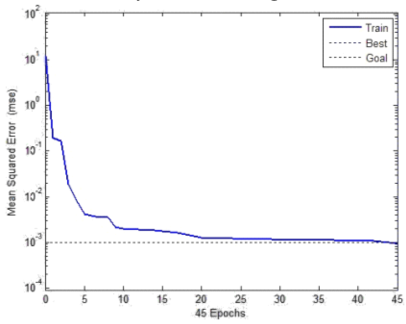

Fig.5 mean squared error curve

The actual data and fitting data were almost overlap,as shown in Fig 6.The superiority and accuracy of GNNM on EDG honeycomb ring (GH3536) was completely proved by the error curve,shown in Fig .7. It could be found from Fig.7 that the maximum absolute error was 3.58%, the minimum absolute error was 0.01%and the mean error was 0.53%.

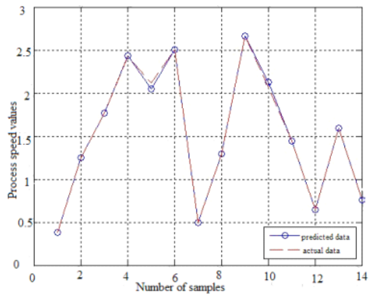

Fig.6 Curve of the actual data and fitting data

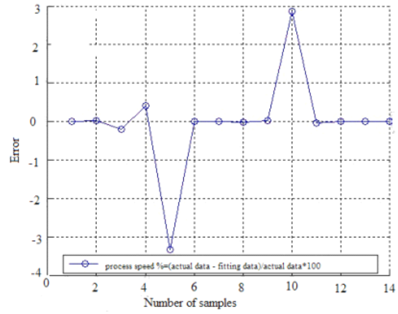

Fig.7 Error curve

Due to the randomness of the system itself and other factors ,the error between forecast data and actual data is inevitable.The value of model existence was not only illustrated by high fitting precision but also the ability of predicting unknown data.The simulation prediction was carried by two test data, the absolute error of two samples were 5.54% and 7.95% respectively, as shown in Fig 8.Therefore,the MMR model of EDG honeycomb ring (GH3536) was established to meet the requirements of generalization ability and can be used for guiding the actual production.

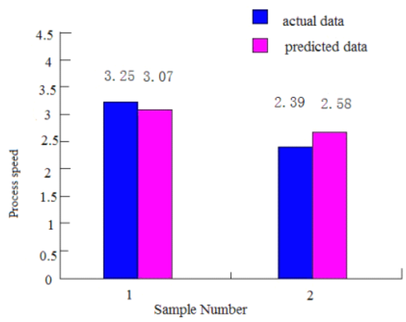

Fig.8 Samples prediction

4. Conclusions

（1）The processing mechanism of EDG honeycomb ring was complex and influenced by numerous factors .GRA results indicated that pulse-on time， pulse-off time， peak current and peak voltage were the significant machining parameters ranked by $I_p > U_e > t_{on} > t_{off}$ .It was consistent with the actual production.

（2）The MMR model of EDG honeycomb ring (GH3536) was established based on GNNM ,the prediction results with the maximum absolute error 3.58％, the minimum absolute error 0.01％ and the mean error 0.53％ confirmed the success of the prediction model.

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