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Electrode Wear Prediction in Milling Electrical Discharge Machining Based on Radial Basis Function Neural Network

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Abstract: Milling electrical discharge machining (EDM) enables the machining of complex cavities using cylindrical or tubular electrodes. To ensure acceptable machining accuracy the process requires some methods of compensating for electrode wear. Due to the complexity and random nature of the process, existing methods of compensating for such wear usually involve off-line prediction. This paper discusses an innovative model of electrode wear prediction for milling EDM based upon a radial basis function (RBF) network. Data gained from an orthogonal experiment were used to provide training samples for the RBF network. The model established was used to forecast the electrode wear, making it possible to calculate the real-time tool wear in the milling EDM process and, to lay the foundations for dynamic compensation of the electrode wear on-line. This paper demonstrates that by using this model prediction errors can be controlled within 8%.
Key words: milling electrical discharge machining (EDM), electrode wear prediction, radial basis function (RBF) neural network
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Introduction

Within the scope of electrical discharge die machining, milling electrical discharge machining (EDM) is an important technology. Traditional EDM sees the production of a female cavity in the work piece which is produced using a male electrode of corresponding shape. An unavoidable side-effect of the electro pulse power removing material from the work piece is the simultaneous removal of material from the tool. Normally, this undesirable electrode wear cannot be eliminated completely. This tool wear is a critical issue, as any wear in the electrode directly affects the shape and accuracy of the final work piece.

Milling EDM differs from traditional EDM which it is very similar to computer number control (CNC) machining. A simple rotating electrode, usually tubular or cylindrical, is used. This electrode follows a programmed path to obtain the desired shape on the work piece. This eliminates the need to utilize the shaped electrode tools typical of traditional EDM. This paper deals specifically with laminated milling EDM using a tubular electrode. This process is particularly efficient as the tubular electrode injects pressurized dielectric into the gap between the tool and the work piece intensifying the removal of the electrically eroded material from the surface of the product. The work piece is machined layer-by-layer, which means that the majority of the electrical discharge is generated between the end face of the electrode and the work piece.

Subsequently, wear of this type of electrode is uniform and the original shape is retained. This simplifies the measures that are taken to counteract wear.

1 General Wear Measure Methods and Radial Basis Function (RBF) Wear Measurement System

1.1 Current Methods for Measuring Wear in Milling EDM

In milling EDM, axial compensation of the electrode is sufficient[1], as shown in Fig. 1.

In the process of layer by layer milling EDM the final shape of the work piece is directly affected by the electrode wear. Therefore the accuracy of milling EDM is highly dependant upon the tool wear detection and compensation[2]. These are the key technologies to optimize the accuracy of the milling EDM.

Electrode wear is usually referred to in terms of relative electrode wear K,

$$K = V_{\mathrm{e}}/V_{\mathrm{w}}, \tag{1}$$

where V_{e} is the capacity of electrode wear, V_{w} is the capacity of the work piece corroded.

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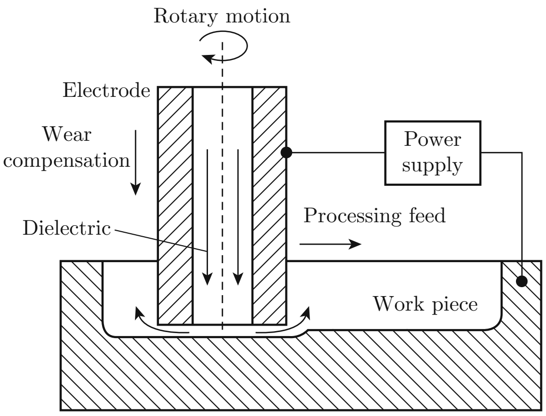

Fig. 1 Diagram of milling EDM process

It is possible to measure wear of the electrode using either on-line or off-line methods. The on-line method, not requiring additional detection equipment, is applied based on processing parameters. For example, pulse evaluation (used to calculate electrode wear), which is subsequently compensated for with linear path correction i.e. down-motion of the electrode[3-4]. However, with the on-line method, it is difficult to establish an accurate mathematical model to calculate wear because of the random nature of the milling EDM process.

The standard off-line method calculates the change in length of the electrode after machining each layer. The current length is measured each time the electrode makes contact with a conference point which triggers a short circuit. A CNC system is used to calculate the difference in length between readings and the difference is compensated for accordingly[5].

Mizugaki *et al*[6] used laser range sensors to measure electrode wear. These sensors consisted of a laser projector array part and a linear detector array part. During processing the electrode is intermittently placed between the projector and detector in order that the electrode length can be measured.

High accuracy can be obtained using these off-line methods, however the process must iteratively pause to measure the length of the electrode which is detrimental to process efficiency. The frequency of measuring depends upon required accuracy of work piece. In addition, the wear detection equipment employed, like used in Ref. [6], is expensive.

1.2 Possibilities for Development of a RBF Wear Measurement System

As intelligent technologies have become the subject of more development and wider application, artificial neural network (ANN) technologies have received increasing interest amongst the scientific community. ANN technology simulates the human brain, processing information with astonishing self learning, thinking, reasoning and judgment functions. However, ANN is not without drawbacks. The widely used classical gradient decent based on back propagation (BP) training strategy of the multi-layer ANN results in a very slow convergence and can easily get stuck at the local minimum[7].

RBF network uses representative basis functions such as Gaussian functions. It is distinctive because its weight parameters can be estimated by linear calculations[8-9]. This approach features rapid learning based on the local character input space and other vantages. In 1990s, RBF network models have drawn attention in many fields such as system identification and adaptive control[10].

The remainder of this paper will apply the RBF neural networking to establish a milling EDM electrode wear prediction model. This will lay the foundations for calculating electrode wear on-line and realizing dynamic wear compensation in the milling EDM process.

2 Research Methodology

With regards to the milling EDM, the working status has close relationships with many of the processing parameters including peak current, pulse width, pulse interval, polarity, open voltage, dielectric pressure, electrode cross sectional area and machining depth. Each of the parameters has a different and varying effect on the wear experienced by the electrode. Considering the possibility of creating a system that can replicate the complexity of the relationships between these variables would be such that training time would be unfeasibility long. Moreover, not every one of the parameters has a significant effect on tool wear. The orthogonal experiment was used to find parameters which had the most pronounced effect on tool wear.

Data gained from the orthogonal experiment was used to provide training samples for the RBF network. The model established was used to forecast the electrode wear, making it possible to calculate real-time tool wear in the milling EDM process, and to lay the foundations for dynamic compensation of the electrode wear on-line.

2.1 Experimental Method

The experiments supporting the research presented in this paper were carried out on low carbon steel using an EA8 die-sinking EDM machine manufactured by Mitsubishi Electric Co. Kerosene, injected through the tubular electrode that was used as a high pressure dielectric.

Through combinations of various process parameters experimental data was obtained. Six parameters were selected as the factors which influenced electrode wear. These were also used as the input vectors for the RBF network. Each factor was assigned 3 levels, which were usually used in experiments, as shown in Table 1.

The orthogonal method was applied to arrange the experiments and analyze these data. Relative electrode wear was measured and the results were recorded in

Table 1 Factors and levels of the electrode wear

Factor	Level		
	1	2	3
Peak current ($I_{\rm p}$)/A	14	16	22
Pulse width ($\tau_{\rm w}$)/μs	360	750	1 400
Pulse interval ($\tau_{\rm i}$)/μs	130	255	510
Dielectric pressure ($p_{\rm d}$)/MPa	0.05	0.10	0.18
Electrode cross sectional area (S)/mm^2	58.875	294.375	686.875
Machining depth (d)/mm	0.8	1.0	1.2

Table 2.

2.2 Results and Discussion

Results from the orthogonal analysis were similar to those of the actual process. With regards to current and pulse width, the higher the value, the more energy will be generated in the gap between work piece and tool. Consequently, the work piece will be machined more rapidly, but the tool will wear faster. The pulse interval eliminates ionization to avoid electrical arc generated in gap. A little pulse interval cannot get rid of ionization totally, and a large one decreases the energy in the gap in one unit processing time. So a proper pulse interval benefits process stability, machining velocity and electrode wear rate. Dielectric pressure favors process stability, however, a high pressure can inhibit the build up of carbon ions on the surface of the electrode, which removes the effect of the phenomena that occurs when the electrode is connected to the anode. If the tool is connected to the anode, polarity has an effect on generation of free carbon ion in the gap between tool and work piece. These carbon ions can build up on the surface of the electrode and consequently reduce the wear. In addition, it is possible for the electrode to experience negative wear when the molten particles and carbon ions adhere to the surface of the electrode. This explains the negative wear results.

The data shown in Table 2 are arranged according to the principles of orthogonal experimentation. These data have been used as inputs to the RBF network to ensure a fair representation of the experiment data whilst utilizing as few training samples as possible. And equalization between factors and levels is in favor of the artificial neural network training.

Range analysis was used to calculate the comparative influence of the 6 machining parameters on tool wear as shown in Table 3. $K_{\rm sum1}$, $K_{\rm sum2}$ and $K_{\rm sum3}$ denote the sum of relative electrode wear of levels 1, 2 and 3 on each factor respectively. The range, or the difference between the maximum and minimum values of $k_{{\rm sum}n}$ ($k_{{\rm sum}n} = K_{{\rm sum}n}/9$), reflects the impact of each corresponding factor on the electrode wear. The higher the range value is, the more impact the specific factor has on tool wear.

It can be seen from Table 3 that the range values, and hence the influence of the each of the 6 processing parameters over tool wear are, in descending order: electrode cross sectional area, peak current, dielectric pressure, pulse width, machining depth and finally, with least influence, the pulse interval. This concurs with

Table 2 Orthogonal experiment data

Experiment No.	$I_{\rm p}$/A	$\tau_{\rm w}$/ms	$\tau_{\rm i}$/μs	$p_{\rm d}$/MPa	S/mm^2	d/mm	K/%
1	14	0.36	130	0.05	58.875	0.8	15.54
2	14	0.36	255	0.10	294.375	1.0	0.60
3	14	0.36	510	0.18	686.875	1.2	−1.79
⋮							
25	22	1.40	130	0.10	58.875	0.8	44.53
26	22	1.40	255	0.18	294.375	1.0	15.74
27	22	1.40	510	0.05	686.875	1.2	−2.81

Table 3 Analysis results of orthogonal experiment

Parameter	$K_{\rm sum1}$	$K_{\rm sum2}$	$K_{\rm sum3}$	$k_{\rm sum1}$	$k_{\rm sum2}$	$k_{\rm sum3}$	Range
$I_{\rm p}$	23.100	129.280	229.110	2.567	14.364	25.457	22.890
$\tau_{\rm w}$	170.160	151.870	84.660	18.907	16.874	9.407	9.500
$\tau_{\rm i}$	126.800	154.470	125.420	14.089	17.163	13.936	3.228
$p_{\rm d}$	35.530	172.720	198.440	4.948	19.191	12.049	18.101
S	317.700	86.970	2.020	35.300	9.663	12.049	35.076
d	149.310	101.360	156.020	16.590	11.262	17.336	6.073

actual processing experience.

3 Neural Network Modeling

The data gained from orthogonal experiment were provided as training sample for RBF artificial neural network. The network was used to model the connection between 6 processing parameters and tool wear in the milling EDM process, making it possible to calculate the real-time relative electrode wear and lay the foundation for dynamic compensation of the electrode wear on-line.

3.1 Overview of RBF

RBF networks have a special neural network architecture, which consists of three layers namely, the input, hidden and output layers. A RBF network of n-h-m structure is shown in Fig. 2. $\boldsymbol{P} = (p_1, p_2, \cdots, p_n)$ are the input vector, $\boldsymbol{C}_j = (c_j^1, c_j^2, \cdots, c_j^n)$ are the centre vector of the jth node of the hidden layer, $||\boldsymbol{P} - \boldsymbol{C}_j||$ is the Euclidean distance, and $\boldsymbol{T} = (t_1, t_2, \cdots, t_m)$ are the output vector.

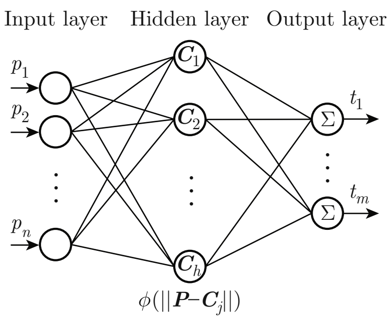

Fig. 2 Structure of RBF neural network

The input layer connects the network to its environment whilst the neural cells in the hidden layer use radial basis functioning as the activation function. The architecture of a single cell with n-inputs is shown in Fig. 3.

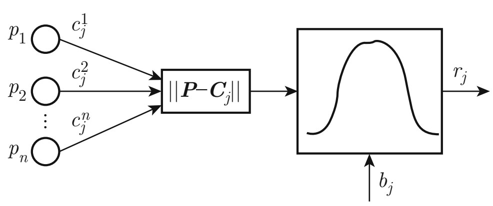

Fig. 3 Neural cell architecture with n-inputes

The neural cells in the hidden layer associate with centers which are vectors of dimension equaling to the number of inputs in the network. Every input vector of the neural cell connects with the neural node through the centre, $\boldsymbol{C}_j$, which is a vector with dimensions equal to the number of inputs to the cell.

The response of a hidden node is produced by passing the node activity, which is defined as the Euclidean distance between the input vector and the node centre, through a radial basis function, such as the Gaussian function[11-12] used in this research. This is shown in

$$r_j = \exp(-||\boldsymbol{P} - \boldsymbol{C}_j||^2/b_j^2), \quad j = 1, 2, \cdots, h, \tag{2}$$

where r_j is the output of the jth node of the hidden layer, b_j is the threshold parameter of the jth node and b_j determines the working scope of the basis function of the responding node. The outputs of the RBF network are linear combinations of the output of the hidden layer, as shown in the following equation

$$\begin{aligned} t_i &= \sum_{k=1}^{m} w_{j(k)} r_j, \\ j &= 1, 2, \cdots, h, \\ i &= 1, 2, \cdots, m, \end{aligned} \tag{3}$$

where t_i is the output of the ith node of the output layer and $w_{j(k)}$ is the weight value of the kth node of the output layer.

As shown in Eqs. (2) and (3), the mapping from the input to the hidden layer is nonlinear because the transformation function in the hidden layer is nonlinear. Where a normal BP network is trained using back propagation with a gradient decent algorithm, a RBF network is trained layer by layer. Firstly, the centre weight vectors $\boldsymbol{C}j$ and the threshold b_j of the hidden layer are confirmed using centre adjustment. Finally, the output weight vectors are updated to be confirmed. Because these two procedures are relatively independent and the parameters are linearly adjusted, the RBF network offers the advantage of faster convergence which, makes the RBF network suitable for identification and control of the real time system[13].

3.2 Establishment a Neural Network Model

The RBF network model construction includes sample data acquisition, data preprocessing and network training.

(1) Sample data acquisition. As shown in Table 1, three of the experimental data of each of the 6 factors known to affect electrode wear were selected and combined according to an orthogonal table $L_{27}(3^6)$. 27 groups of experimental data were considered as training samples for the RBF network model as shown in Table 2.

(2) Data preprocessing. Generally, when data are dispersed and the difference between values is large, a normalization process is needed to help reduce the training time of the model. But the RBF network is a feedforward network without a feedback layer, and the experimental data was selected using the orthogonal method so, the training samples in this paper were not treated with any normalizing process.

(3) Network Training. The RBF network model for prediction of electrode wear was trained using peak current, pulse width, pulse interval, dielectric pressure,

electrode cross sectional area and machining depth as the input factors of the model. Relative electrode wear was the output of the model, as shown in Fig. 4.

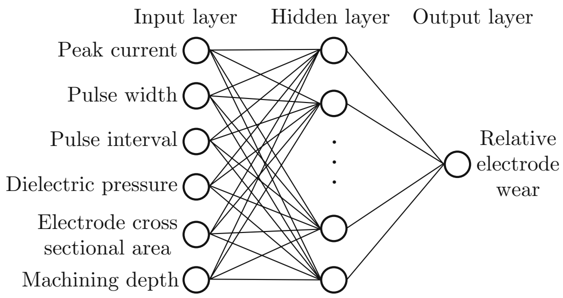

Fig. 4 Demonstrates the structure of the neural network model

In Matlab, the RBF network can be designed and trained using the newgrnn function. It is called in the following way:

$$\text{net} = \text{newgrnn}(\boldsymbol{T}_1, \boldsymbol{T}_2, C_{\text{spread}}). \quad (4)$$

The function newgrnn converts matrices of input vectors, $\boldsymbol{T}_1$ and $\boldsymbol{T}_2$ target vectors and a spread constant parameter C_{spread} into a network of centers and weights vectors. According to theory, the smaller C_{spread} is, the more precise the approximation of the function will be and the rougher the approximation process is. The value of C_{spread} has great impact on the final approximation accuracy, so it should be adjusted to achieve the ideal precision during the procedure of designing a network. After training, the model can be used to predict and calculate the electrode wear. The command can be called as follows

$$K_{\text{p}} = \text{sim}(\text{net}, \boldsymbol{T}_{\text{p}}), \quad (5)$$

where K_{p} is the result of the prediction wear and the $\boldsymbol{T}_{\text{p}}$ is the prediction sample. To achieve the best prediction results C_{spread} was set at 0.4. The following section discusses the analysis of the prediction results achieved.

3.3 Analysis of a Neural Network Model

Table 4 details the tool wear results predicted by the RBF network.

Figure 5 shows the results predicted by the RBF and BP network and compares them with the actual wear results K_{a}. The abscissas shows the actual value of relative electrode wear obtained from the experiments and the marked coordinate points show the predicted value of electrode wear obtained using the RBF network. The dispersion of marked coordinates reflects the relationship between the actual and predicted values if relative electrodes wear according to the same process parameters. The goodness of fit demonstrates the conformity of the predicted results with the actual results. These results correspond with the data presented in Tables 2 and 3.

Table 4 Prediction results of RBF network

I_{p}/A	τ_{w}/ms	τ_{i}/µs	p_{d}/MPa	S/mm^2	d/mm	K/%		
						Actual value	Prediction value	Prediction error
14	1.4	510	0.18	294.375	0.8	0.42	0.45	−7.14
16	1.4	510	0.10	58.875	1.0	25.83	26.48	−2.52
16	1.4	510	0.18	686.875	1.0	−2.85	−2.75	−3.51
22	1.4	510	0.10	686.875	1.2	−2.71	−2.79	2.95
22	1.4	510	0.05	58.875	1.2	28.85	26.65	7.63

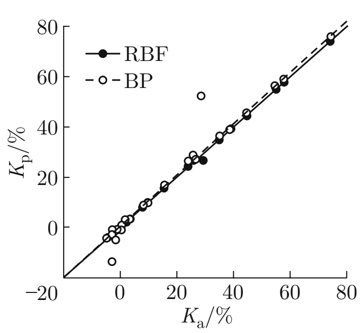

Fig. 5 Prediction effect of RBF and BP network

In BP prediction network, it can be seen that the goodness of fit is superior. RBF is an improved method of predicting relative tool wear. Another clear benefit of using the RBF network rather than the BP network is the shorter training time, particularly when the scale of the training sample is large.

The prediction errors of the RBF network model in this paper are controlled within 8%. The error distribution depends on stability of the process system. Additionally, with an increased training sample it is thought that the error could be reduced significantly.

Generally, the electrode wear prediction model based upon RBF and established in this paper can reflect the process laws of milling EDM, and accurately predict the relative electrode wear, which lays the foundation for the dynamical compensation of the electrode wear milling EDM on-line.

4 Conclusion

In this work, the features of multiple factors impacting on the milling EDM process were analyzed and, a novel milling EDM electrode wear prediction model based on a RBF neural network was presented. There are many factors impacting upon the electrode wear in the milling EDM process. According to the orthogonal experiment, it is found that 6 factors have significant effects on electrode wear. The descending order in which these parameters influence the process is as follows: electrode cross sectional area, peak current, dielectric pressure, pulse width, machining depth and, pulse interval. This demonstrates good agreement of theoretical and experimental results.

The electrode wear prediction model based on the RBF neural network can accurately reflect the processing laws of the milling EDM. The forecasting errors of the model established in this work are controlled within 8%, which lays the foundation for dynamical compensation of the electrode wear in milling EDM on-line. Compared with the conventionally used BP neural network, the RBF neural network model established in this work has the merits of short training time and high prediction accuracy.

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