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Parameter optimization model in electrical discharge machining process*

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Abstract: Electrical discharge machining (EDM) process, at present is still an experience process, wherein selected parameters are often far from the optimum, and at the same time selecting optimization parameters is costly and time consuming. In this paper, artificial neural network (ANN) and genetic algorithm (GA) are used together to establish the parameter optimization model. An ANN model which adapts Levenberg-Marquardt algorithm has been set up to represent the relationship between material removal rate (MRR) and input parameters, and GA is used to optimize parameters, so that optimization results are obtained. The model is shown to be effective, and MRR is improved using optimized machining parameters.

Key words: Electrical discharge machining (EDM), Genetic algorithm (GA), Artificial neural network (ANN), Levenberg-Marquardt algorithm

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INTRODUCTION

Electrical discharge machining (EDM) is a well-established machining option for manufacturing geometrically complex or hard material parts that are extremely difficult-to-machine by conventional machining processes. Its unique feature of using thermal energy to machine electrically conductive parts regardless of hardness has been its distinctive advantage in the manufacture of mould, die, automotive, aerospace and surgical components (Ho and Newman, 2003). The exact mechanism of metal erosion during sparking is still debatable. The model for correlating the process variables and material removal rate (MRR) is hard to be established accurately (Tsai and Wang, 2001; Das *et al.*, 2003). At present EDM parameter selection is still one experience process in the industry. In some cases, selected parameters are conservative and far from the optimum, and at the same time selecting optimization parameters requires many costly and time consuming experiments. Many researchers tried to optimize the machining performance by adapting different optimization techniques.

Artificial neural network (ANN) is an effective method to solve non-linear problem. There are many ANN applications in EDM. Predictions of surface finish for various work materials with the change of electrode polarity were compared based upon six different ANN models (Tsai and Wang, 2001). An ANN forecasting project was presented based on Web for EDM technology (Yang and Zhao, 2005). A tool wear prediction model was established based on ANN (Li *et al.*, 2004). A method that can optimize the processing parameters was presented in the EDM sinking process with the application of ANN (Cao and Yang, 2004).

Genetic algorithm (GA) possesses advantages that do not require any gradient information and inherent parallelism in searching the design space, thus

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making it a robust adaptive optimization technique (Rao, 1991). Some researchers investigated GA application in EDM. Mandal *et al.*(2007) used a multi-objective optimization method, non-dominating sorting genetic algorithm-II to optimize the process. Kuriakose and Shunmugam (2005) presented a multiple regression model to represent the relationship between input and output variables and a multi-objective optimization method based on a Non-Dominated Sorting Genetic Algorithm to optimize Wire-EDM process. Yang (2002) provided an optimization model based on genetic algorithms for EDM parameters to imitate a decision.

In the present work, ANN and GA are used together to establish parameter optimization model. An ANN model has been established to represent the relationship between MRR and input variables (current, pulse on time and pulse off time), which adapts Levenberg-Marquardt algorithm. GA has been used to obtain an optimal combination of parameters.

OPTIMIZATION MODEL

In EDM process, material is removed by erosive effects from a series of electrical sparks generated between tool and work-piece material with constant electric field emerging in a dielectric environment. EDM is a complicated process, and it is very hard to use traditional method to describe or optimize its parameters. To improve production rate and to decrease dependence on experience, it is necessary to establish an optimization model.

The problem in this paper can be described as: How to select proper machining parameters to get higher MRR.

Mathematical model

$$M = Op(f(I, T_{\text{on}}, T_{\text{off}}, \boldsymbol{W})), \quad (1)$$

$$4 \le I \le 18, \quad (2)$$

$$23 \le T_{\text{on}} \le 506, \quad (3)$$

$$23 \le T_{\text{off}} \le 186, \quad (4)$$

where I, T_{on}, T_{off} are current, pulse on time and pulse off time respectively, $\boldsymbol{W}$ is the weight matrix that is evaluated in the network training process, f represents the function relationship between MRR and three variables, Op is GA which is adapted to optimize machining parameters.

Flow chart, parameters of GA

The flow chart is shown in Fig.1, and the procedure steps are as follows:

(1) Adapt binary code. There are three variables, with different span. For current, its span is between 8 and 18 A; bit length is taken as 3; 000, 001, 010, 011, 100, 101, 110, 111 represent current of 4, 6, 8, 10, 12, 14, 16, 18 A, respectively. For pulse on time, bit length is also taken as 3; 000, 001, 010, 011, 100, 101, 110, 111 represent pulse on time 23, 58, 166, 256, 316, 376, 416, 506 μs, respectively. For pulse off time, bit length is taken as 4; 0000, 0001, 0010, 0011, 0100, 0101, 0110, 0111, 1000, 1001, 1010, 1011, 1100, 1101 represent pulse off time 23, 29, 38, 48, 56, 59, 80, 96, 118, 128, 138, 148, 170, 186 μs respectively. When

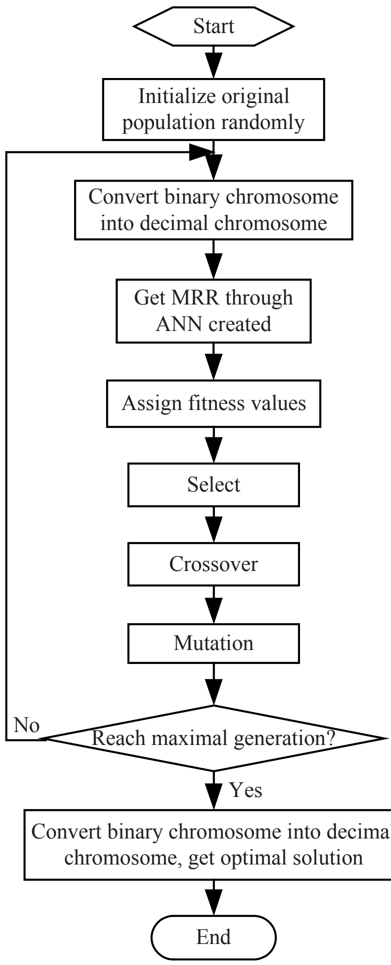

Fig.1 Optimization flow chart

1110 or 1111 occurs, the random number generation is invoked till they are among the range of [0000 1101]. So, the total bit length of a chromosome is 3+3+4=10.

(2) Objective function value is MRR, which comes from ANN model.

(3) The population size is taken as 300, and the original population is generated randomly.

(4) Convert binary value to decimal values according to rules of Step (1).

(5) Simulate the network created, get objective function value (ANN will be introduced in detail in the next section); the value is MRR.

(6) Assign fitness values according to objective function values, and return a column vector containing the corresponding individual fitness.

(7) Perform selection with stochastic universal sampling. Generation gap, namely rate of individuals to be selected is taken as 0.9.

(8) Then perform single-point crossover between pairs of individuals and return the current generation after mating. Crossover probability P_c=0.8.

(9) Mutate each element with given probability and return the resulting population; mutated chromosomes will be returned to Step (4) when generation maximum is not met; mutation probability P_m= 0.07.

(10) Procedure will stop when generation maximum is met; otherwise, recycle from Step (4). Generation maximum is taken as 250.

(11) Convert binary chromosome to decimal value.

ANN model

Some researchers find three layer networks can be used to approximate almost any function, if having enough neurons in the hidden layers. So in this paper, we select a three-layer network.

The hidden layer activation function is hyperbolic tangent sigmoid transfer function, shown as follows:

$$f(n) = \tan\mathrm{sig}(n) = \frac{2}{1-\mathrm{e}^{-2n}} - 1. \tag{5}$$

The output layer activation function is linear transfer function.

Performance function used for training feed forward neural networks is the mean sum of squares of the network errors (MSE).

The neural network architecture is 3-26-1.

Data pre-processing, before training, normalizes the input variables and MRR, so that they always fall into the span [0.1, 0.9].

It is assumed that $\boldsymbol{X}$ is the vector to be scaled.

$$y = \frac{0.9-0.1}{x_{\max}-x_{\min}}x + \left(0.9 - \frac{0.9-0.1}{x_{\max}-x_{\min}}x_{\max}\right), \tag{6}$$

where $x_{\max}$, $x_{\min}$ are maximum and minimum of vector $\boldsymbol{X}$ respectively, x is one element of vector $\boldsymbol{X}$.

After simulation, convert outputs back into the original values. Algorithm is the inverse function of Eq.(6).

All data are divided into two parts, one is training data, as shown in Table 1, and another is checking data, which checks the generalization performance, as shown in Table 2. Experiment was performed with normal polarity, and experiment data come from (Mandal *et al.*, 2007). Experiment condition: Electrode is copper, work piece is C40 steel, dielectric fluid is rustlick™ EDM oil of grade EDM 30, flushing pressure is 0.25 kg/cm^2, experiment was performed with normal polarity.

Table 1 Part of training data (experiment result with various machining parameters)

No.	I (A)	T_{on} (μs)	T_{off} (μs)	MRR (mm^3/min)
1	4	58	59	0.638462
2	6	58	59	1.330037
3	8	58	59	2.660256
4	12	58	59	5.842308
5	14	58	59	5.860465
…	…	…	…	…
57	4	416	118	2.323077
58	8	416	118	19.807690
59	12	416	118	39.378210
60	16	416	118	58.622220
61	18	416	118	69.488000
…	…	…	…	…
70	16	376	80	68.652990

Table 2 Checking data (experiment result with various machining parameters)

No.	I (A)	T_{on} (μs)	T_{off} (μs)	MRR (mm^3/min)
1	16	58	59	6.072564
2	10	166	128	9.005128
3	12	256	138	20.531860
4	14	58	23	7.185897
5	14	256	48	38.186330
6	16	476	170	53.802560
7	18	376	80	75.443590

Figs.2 and 3 give the linear regression between the network response (prediction values) and the target (experiment values). The correlation coefficient (R-value) is a measure of how well the variation in the output is explained by the target, if it is equal to 1, then there is perfect correlation between targets and outputs. The network outputs are plotted versus the targets as open circles. From them, it is clear that the two outputs seem to track the targets reasonably well, and R-value is 0.99995 and 0.99983 respectively. The best linear fit is indicated by the solid line, and the perfect fit by the dashed line. In these figures, it is difficult to distinguish the best linear fit line from the perfect fit line, which indicates a good fit.

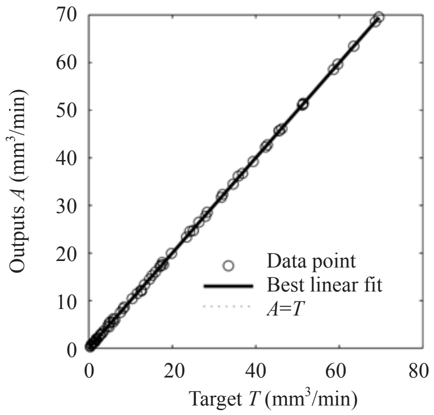

Fig.2 Regression analysis between train MRR and their prediction

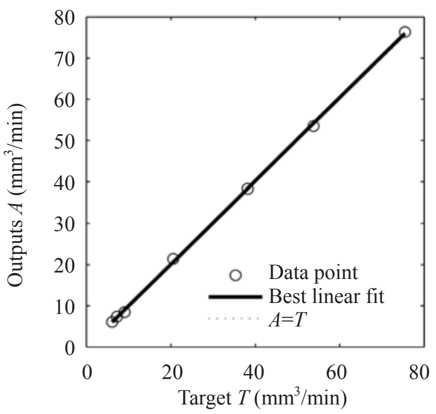

Fig.3 Regression analysis between check MRR and their prediction

Fig.4 gives prediction relative error of checking data. It is clear that the net has better generalization performance, the maximum of prediction relative error is 6.15% and the minimum is 0.29%, mean of relative error is 2.16%.

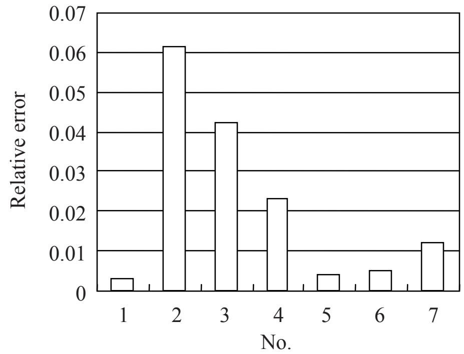

Fig.4 Prediction relative error

Optimization model will use ANN model to get MRR value.

RESULT AND DISCUSSION

Because original chromosomes are given randomly, this may induce getting different solution set, so the procedure was repeated many times. The result shows that although the set are slightly different, all of them can get the same maximum of MRR, and corresponding parameters are also the same.

Table 3 shows one group solution set evolved after 250 generations. Parameters listed in number 8 lead to the optimal solution; MRR values are 78.0370 mm^3/min, where current, pulse on time and pulse off time are 18 A, 416 μs, 59 μs respectively. Compare them with maximal MRR in Table 1, namely number 61, MRR is 69.488 mm^3/min, where current, pulse on time and pulse off time are 18 A, 416 μs, and 118 μs respectively, it is clear that MRR is improved using optimized parameters.

Table 3 Solution set of EDM process

No.	I (A)	T_{on} (μs)	T_{off} (μs)	MRR (mm^3/min)
1	18	376	80	76.3736
2	18	376	118	69.9391
3	14	376	186	42.5051
4	18	376	170	73.0987
5	12	376	59	44.4698
6	14	416	80	55.3284
7	18	416	96	72.3048
8	18	416	59	78.0370
9	12	416	96	40.7023
10	14	416	96	51.3540

Number 1 in Table 3, and number 7 which is experiment value in Table 2 have the same machining parameters, namely MRR of the former is 76.3736 mm^3/min, and that of the latter is 75.443590 mm^3/min; they only have slight difference. It means that optimized value is close to experiment value.

CONCLUSION

In this paper, one method to optimize EDM process parameters is introduced, which uses Levenberg-Marquardt algorithm and GA together. An ANN model was set up to represent the relationship between MRR and input parameters, which adapted Levenberg-Marquardt algorithm and its network architecture was 3-26-1. It shows that the net has better generalization performance, and convergence speed is faster.

GA is used to optimize parameters. MRR is improved by using optimized parameters; it is close to experiment result. With the increase of current, MRR can be improved. MRR can also be improved when we set proper pulse on time and pulse off time with the same current.

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