iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 3 **Issue:** II **Month of publication:** February 2015

DOI:

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Optimization of machining parameters in wire electrical discharge machine process by combination of genetic algorithm and artificial neural network

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Abstract: Wire electrical discharge machining (WEDM) has become an important non-traditional machining process. Wire Electrical discharge machining (WEDM) 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, the main objective is to select proper machining parameters to get high Material Removal Rate (MRR).
Keywords: Electrical discharge machining (EDM), Genetic algorithm (GA), Artificial neural network (ANN), Levenberg-Marquardt algorithm

I. 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). Wire electrical discharge machining (WEDM) has become an important non-traditional machining process. It is widely used in the aerospace, nuclear, and automotive industries. This is because WEDM provides an effective solution for machining hard materials (like titanium, molybdenum, zirconium, tungsten carbide, etc.) with intricate shapes and profiles that are difficult to machine using conventional methods [1–4]. The product quality produced by WEDM is always affected by process parameters such as the pulse on and off times, peak current, arc on and off times, polarity, servo voltage, no load voltage, duty factor, dielectric constant, feed rate override, wire feed rate, wire tension, water pressure, etc. Cutting velocity and surface roughness are important output parameters. These determine the production efficiency and quality of WEDM 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.

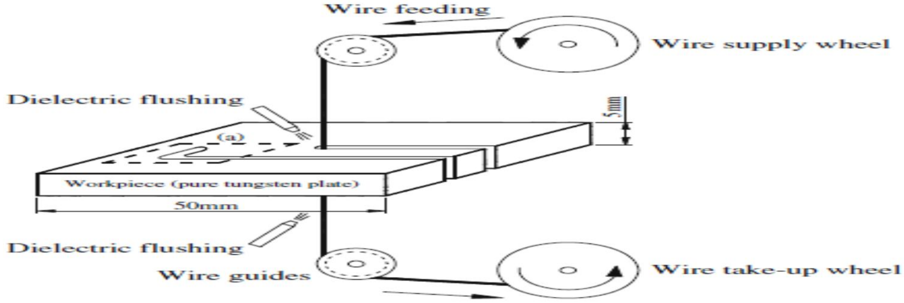

Fig. 1 Scheme of the WEDM process

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A. Artificial neural network

Artificial neural network (ANN) is an effective method to solve non-linear problem. There are many ANN applications in EDM. Software computing techniques like artificial neural networks (ANN) are highly flexible modelling tools with the capabilities of learning the mapping between input and output for any complex nonlinear system. 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.

TABLE 1
SINGLE POINT CROSSOVER PROCESS

1 Parent	$A_1\ A_2 \ldots A_n$	$A_{n+1} \ldots A_k$
2 Parent	$B_1\ B_2 \ldots B_n$	$B_{n+1} \ldots B_k$
1 Child	$A_1\ A_2 \ldots A_n$	$B_{n+1} \ldots B_k$
2 Child	$B_1\ B_2 \ldots B_n$	$A_{n+1} \ldots A_k$

TABLE 2
DOUBLE POINT CROSSOVER PROCESS

1 Parent	A	B	C
2 Parent	D	E	F
1 Child	A	E	C
2 Child	D	B	F

TABLE 3
UNIFORM CROSSOVER PROCESS

1 Parent	A_1	A_2	A_3	A_4
2 Parent	B_1	B_2	B_3	B_4
	1	0	0	1
1 Child	B_1	A_2	A_3	B_4
2 Child	A_1	B_2	B_3	A_4

TABLE 4
MUTATION PROCESS

Original child 1	1101111000011110
Original child 2	1101100100110110
Child with mutation 1	1100111000011110
Child with mutation 2	1101101100110110

B. Genetic Algorithm

GA, which imitates the evolution mechanism of nature, is used for finding a particular data in a dataset [19]. Ga produces ever-improving solutions based on the rule 'the best one survives'. For this purpose, it uses a fitness function that selects the best and operators like regeneration and mutation to produce new solutions. Another feature of GA is that it involves a group solution. By the way optimum solutions among other ones could be picked and disqualified ones are eliminated. The most important feature that distinguishes GA from other algorithms is selection. Fitness of a solution increases the chance for it to be selected.

ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

However, it does not guarantee that. Formation of first group in selection is random. However, fitness of solutions determines the chance of being selected in that random selection [19–21]. GA passes through three phases to form a new generation: Evaluating the value of fitness for each individual in the old generation, selecting individuals based on their value of fitness (using fitness function) and continuing generations with selected individuals using operators such as crossover and mutation. The aim of crossover process is to produce child chromosomes by changing the locations of main chromosome genes and hence to obtain chromosomes having even higher value of fitness from the ones with high values of fitness. There are three types of mostly used crossover for binary coding in the literature [20]. Single point, double point, and uniform crossover processes were explained in order and following tables are helpful [19–21] (Tables 1 and 2). In the uniform crossover, in order to determine displacing genes, the numbers 0 and 1 are generated randomly. In this manner, the same numbers of genes are generated. In Table 3 the string '1001' is a randomly generated number string. For number of '1' genes will be displaced, but for number of '0' will not be displaced (Table 3).The purpose of this process is to form a new chromosome by changing the place of one or more genes of an\ existing chromosome. As a consequence of permanent regeneration, the chromosomes in coming generations might start to repeat each other after some period of time and thus, production of different chromosomes might halt or decrease drastically. For this reason, some of the chromosomes are subject to mutation in order to increase the diversity of them. Mutation process is as indicated in Table 4.

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.

II. OPTIMIZATION MODEL

In WEDM 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. WEDM 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.

A. *Mathematical model*

$M \;\; Op(f (I, Ton , Toff , \boldsymbol{W}))$, (1)

$4 \leq I \leq 18$, (2)

$23 \leq Ton \leq 506$, (3)

$23 \leq Toff \leq 186$, (4)

where I, Ton, Toff 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.

III. 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 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

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0.9.
(8) Then perform single-point crossover between pairs of individuals and return the current

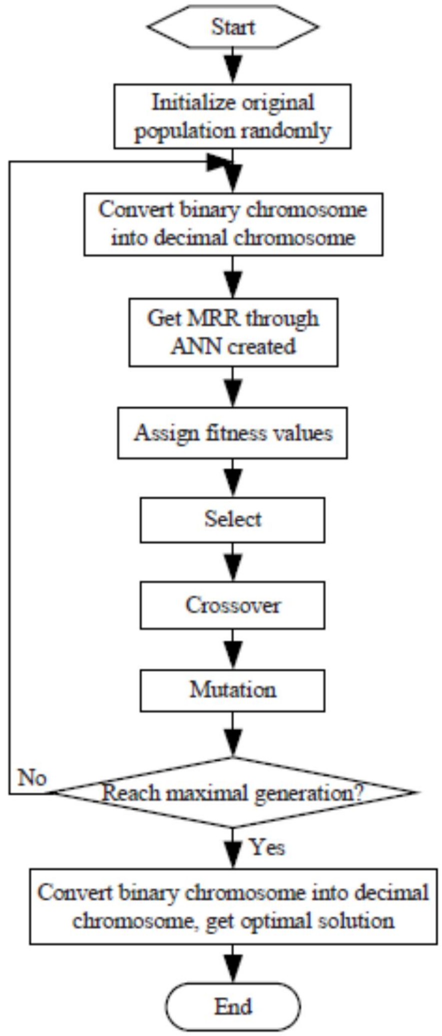

Fig.2 Optimization flow chart

generation after mating. Crossover probability Pc=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 Pm= 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.

IV. 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:

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

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

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MRR, so that they always fall into the span [0.1, 0.9]. It is assumed that ***X*** is the vector to be scaled.

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

where *x*max, *x*min are maximum and minimum of vector ***X*** respectively, *x* is one element of vector ***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. Experiment condition: Electrode is copper, work piece is C40 steel, dielectric fluid is rustlickTM EDM oil of grade EDM 30, flushing pressure is 0.25 kg/cm2, experiment was performed with normal polarity.

TABLE 5
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 6
CHECKING DATA (EXPERIMENT RESULTWITHVARIOUSMACHINING 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.3 and 4 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.

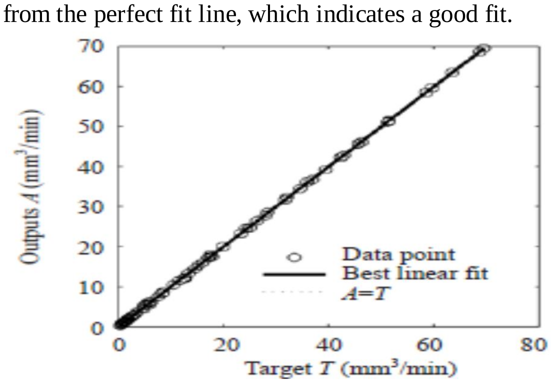

Fig.3 Regression analysis between training MRR and their prediction

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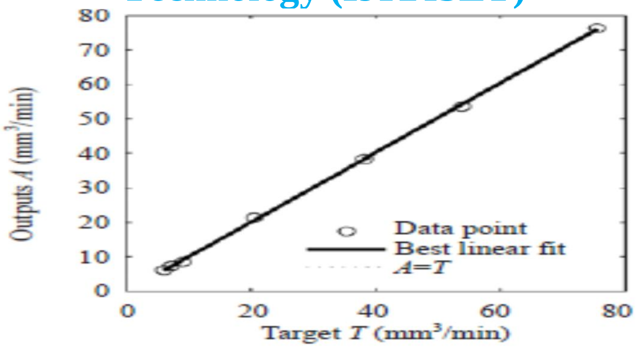

Fig.4 Regression analysis between check MRR and their prediction

Fig.5 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%.

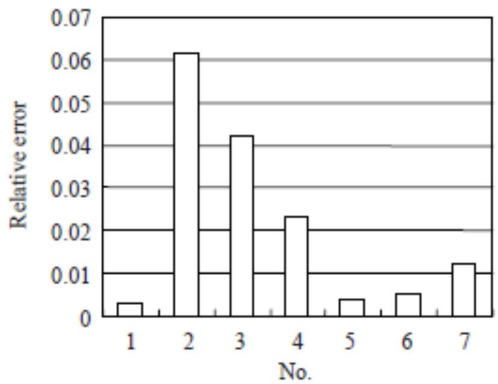

Fig.5 Prediction relative error

Optimization model will use ANN model to get MRR value.

V. 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. Table7 shows one group solution set evolved after 250 generations. Parameters listed in number 8 lead to the optimal solution; MRR values are 78.0370 mm3/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 5, namely number 61, MRR is 69.488 mm3/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 7
SOLUTION SET OF WEDM 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 Table7, and number 7 which is experiment value in Table 6 have the same machining parameters, namely MRR of the former is 76.3736mm3/min, and that of the latter is 75.443590 mm3/min; they only have slight difference. It means that optimized value is close to experiment value.

VI. 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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