Artificial Neural Network Modeling and Optimization using Genetic Algorithm of Machining Process

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***Abstract*— In the present work an attempt is made to model and optimize the complex wire electric discharge machining (WEDM) using soft computing techniques. The purpose of this research work is to develop the artificial neural network (ANN) model to predict the cutting width (kerf) during WEDM. Genetic algorithm (GA) was used to optimize the process parameters. Experiments were carried out over a wide range of machining condition for training and verification of the model. In this work four input parameters namely servo voltage, pulse-on time, pulse-off time and wire feed rate were used to develop the ANN model. Training of the neural network model was performed on 29 experimental data points.**

***Index Terms*—Wire electric discharge machining, Artificial neural network, Genetic algorithm**

I. Introduction

WEDM process is a thermo-electric process in which material is eroded from the work-piece by a series of discrete sparks between the work-piece and the wire electrode (tool) separated by a thin film of dielectric fluid which is continuously forced in to the machining zone to flush away the eroded particles [1]. Dimensional and geometrical accuracies of the cut profile depend on the accuracy of wire control mechanism. Selection of process parameters is crucial to the overall performance of the WEDM process. Modeling of machining process is also an effective way of solving tedious problems of relating the process parameters to the performance measures, but literature survey reveals that works done so far have not been incorporated into any modeling activity [2]. Cutting width (kerf) is the important performance measures in WEDM process. kerf determines the dimensional accuracy of the finishing part, which is of extreme importance as WEDM is usually used for profile finishing. The internal corner radius of the cut produced in WEDM process is also limited by the kerf. According to the literature survev, this parameter has not been given due importance in the area of modeling through soft computing techniques during development of process model of WEDM.

Comprehensive, qualitative and quantitative studies of machining processes and expanding effective prediction models with high degree of accuracy for machining performances are important in understanding of the processes, parametric optimization, process simulation, parametric analysis, and verification of the experimental results [3].

Artificial neural network (ANN) approach on the other hand is an effective exploratory technique to predict process parameters for optimal process performance [4]. GA is an optimization technique effectively employed for machining process [5]. As well, it is considerably used by the previous researchers to determine optimal values of premise and consequent parameters in the model. This optimization is done by directly maximizing the training accuracy [6]. In this paper modeling technique based on ANN and GA is employed to model kerf during WEDM.

II. Experimental Methods and Test Conditions

The experiments were conducted on the ECOCUT WEDM Machine (Electronica India Make) on 6061 aluminum based metal matrix composite work pieces of rectangular shape (6.0 mm thickness, 15 mm length and 10 mm width), made by stir casting having 10% SiC particles (by weight) as reinforcement. As four input process parameters namely servo voltage *(SV)*, pulse-on time *(T_{ON})*, pulse-off time *(T_{OFF})* and wire feed rate *(WF)* affect WEDM process performance and hence were chosen as input variables to investigate their effects on kerf during machining as response parameters. Other details of experimental setup are given in Table I. The ranges of input parameters were selected on the basis of literature survey, machining capability of the machine and preliminary experiments conducted by using one-variable-at-a-time approach as shown in Table II [7]. The response parameter kerf was measured using the stereo microscope, and is expressed as sum of wire diameter and twice of wire-work piece gap as given in following equation.

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$$kerf = d+2Wg \qquad (1)$$

where d is the wire diameter and Wg is the wire workpiece gap in which spark produce during the machining.

TABLE I. EXPERIMENTAL CONDITIONS

Wire	Diffused brass wire Φ 0.25 mm
Workpiece material	10% SiC_p/6061 Al MMC
Workpiece thickness	6 mm
Length of cut	15 mm
Dielectric	Deionized water
Dielectric temperature	20 ℃

TABLE II. LEVELS OF PROCESS PARAMETERS

Process parameters	Levels		
	-1	0	+1
Voltage (V)	70	80	90
Pulse-on time (μs)	1	2	3
Pulse-off time (μs)	6	8	10
Wire feed (m/min)	5	7	9

III. NEURAL NETWORK ARCHITECTURE

An artificial neuron is a mathematical function conceived as a crude model, or the abstraction of biological neurons. Artificial neurons are the constitutive units in an artificial neural network. The typical neural networks architecture is shown in Fig. 1. The input layer, hidden layer and output layer, includes several processing units known as neurons. The path connecting two neurons is associated with a certain variable weight which represents the synaptic strength of the connection. The input to a neuron from another neuron is obtained by multiplying the output of the connected neuron by the synaptic strength of the connection between them. The artificial neuron than sums up all the weighted inputs coming to it. In the neural network model, the output of neurons on the input layer reach the jth neuron on the next layer and become its input as stated in equation 2 [8].

$$net_j = \sum_{j=0}^{N} WijXi \qquad (2)$$

where N = number of neurons of the inputs to the j-th neuron in the hidden layer
net_j = total or net input
Xi = input from the i-th neuron in the preceding layer
Wij = weight of between the i-th neuron on the intput layer and the j-th neuron on the next layer.

The output of the neuron for a given input can be controlled to a desired value by adjusting the synaptic strengths and the threshold values of the neuron. In ANN several neurons can be connected in variety of ways. Until today, many different neural network models have been developed. They include perceptrons, Kohonen, Hassoun, Yuille, Hebbian, Oja, Hopfields, back propagation and Kolmogorov networks [9], to mention a few of the better known network models. Among various neural network models, the feed forward neural network based on back-propagation is the best general-purpose model.

In the present work neural network model was developed for kerf. In model the network has four inputs rate and one output. The network consists of one input layer, one hidden layer and one output layer.

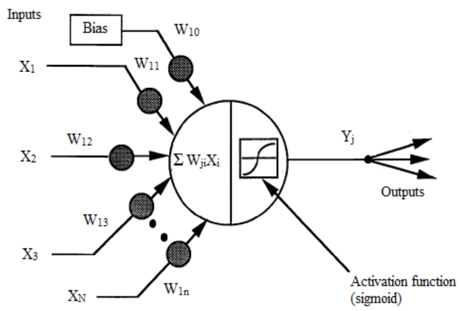

Figure 1. A typical neural network architecture

The selection of number of neurons in the hidden layer is usually modeled dependent. The number of hidden layer neurons is decided by trial and error method on the basis of the improvement in the error with increasing number of hidden nodes [10]. In the proposed model, hidden layer has fifteen neurons, where as input and output layers have four and one neurons, respectively. To train each network, learning rate (η) and momentum constant (α) of 0.05 and 0.9 respectively were used, the activation function of hidden and output neurons was selected as a hyperbolic tangent, and the error goal (mean square error, MSE) value was set at 0.0001, which means the training epochs continued until the MSE fell below this value.

TABLE III. EXPERIMENTAL DATA SET CONSIDERED FOR EXPERIMENTAL DESIGN

Exp. No.	V, (V)	T_{ON}, (μs)	T_{OFF}, (μs)	WF, (m/min)	kerf (mm)
1	0	1	0	-1	0.381
2	-1	0	0	-1	0.266
3	0	0	1	1	0.328
4	-1	0	1	0	0.287
5	0	-1	-1	0	0.359
6	1	0	0	-1	0.415
7	1	0	-1	0	0.438
8	0	0	0	0	0.424
9	0	0	0	0	0.387
10	1	0	0	1	0.308
11	0	0	1	-1	0.407
12	0	0	0	0	0.394
13	0	-1	0	1	0.342
14	0	0	0	0	0.426
15	0	1	0	1	0.302
16	0	0	0	0	0.422
17	1	0	1	-1	0.352
18	0	1	-1	-1	0.322
19	0	0	-1	1	0.368
20	0	-1	0	-1	0.372
21	0	0	-1	-1	0.334
22	0	-1	1	0	0.401
23	1	1	0	0	0.446
24	-1	0	-1	0	0.261
25	-1	1	0	0	0.274
26	-1	0	0	1	0.294
27	-1	-1	0	0	0.282
28	1	-1	0	0	0.432
29	0	1	1	0	0.316

To calculate connection weights, a set of desired network output values is needed (i.e. training dataset), which was obtained with the help of design of experiments (DOE). The desired network output values were obtained from experimental runs. kerf values corresponding to training data were obtained from experimental runs.

The experiment data set and training data set in this paper come from Shandilya *et al*. [11] is shown in Table III.

IV. Genetic Algorithm

Genetic algorithm is very efficient stochastic search technique that tries to emulate natural evolution. An important feature of GA is that it searches several paths simultaneously starting with initial population. Each individual element in the population is called a chromosome. Each chromosome can represent a feasible solution containing a sequence/string of binary or real numbers known as genes. During an evolution process, the current population is replaced by a new generation of chromosomes. The new population may contain both parent chromosomes and newly generated chromosomes called offsprings.

Operators like crossover, mutation etc. are used to generate the offspring chromosomes. The crossover operation is a process of merging two parent chromosomes and formation of one or two new chromosomes. Mutation refers to a process of modifying the structure of a selected chromosome by arbitrarily changing one or more genes. A fitness function representing the objective function is used to evaluate the chromosomes. The chromosomes with high fitness among the parents and offsprings will be selected for the next generation. This process repeats until the satisfaction of the stopping criteria that can be either a limited number of generations are reached or no further improvement in solutions [12].

V. Result and Discussions

A. ANN Predictions of Response Parameters

Training of the neural network model was performed on 29 experimental data points as explained in above section. Table IV shows the experimental and predicted values for kerf for the 29 training sets.

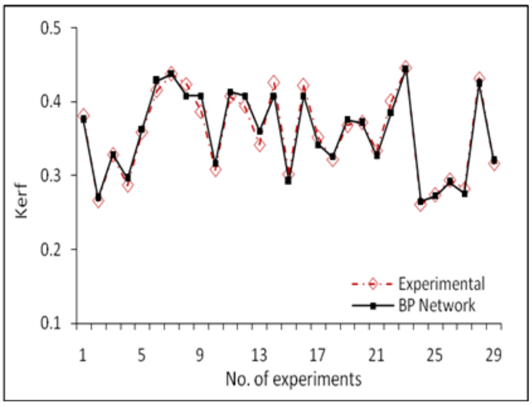

Figure 2. Comparison of ANN prediction with experimental results

Fig. 2 shows the comparison of experimental results and neural network prediction results for kerf. This figure indicates good agreement between neural network predictions and experimental values because the plot of the ANN predicted values is very similar to the plot of experimental values. Therefore, the adopted back-propagation neural network can be used to acquire a function that maps input parameters to the desired process outputs in a wide range of machining conditions during WEDM. Fig. 3 shows the convergence of the MSE with the number of epochs during the training of the best chosen back-propagation neural network. After 16213 epochs, the MSE requirement is met, training is stopped, and the weight values of the network are stored.

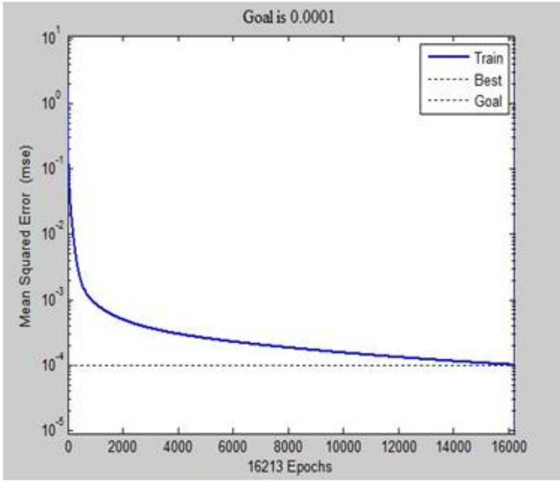

Figure 3. Learning behavior of the BP neural network model

For each input combination, the predicted values of responses were compared with the respective experimental values and the percentage absolute error is computed as follows:

$$\% \text{ Absolute error} = \left|\frac{Yj,expt - Yj,pred}{Yj,expt}\right| * 100 \qquad (3)$$

where *Yj,expt* is the experimental value and *Yj,pred* is the predictive value of the response for the *jth* trail by the ANN model.

Table IV shows the absolute percentage error for each input combination. According to this table the maximum percentage absolute error is 5.34. Thus it can be concluded that predictions are in good agreement with the experimental results because the maximum percentage absolute error of the predicted value with respect to the experimentally observed value for kerf is not high.

As a further step for studying the capabilities of the model in fitting all points in the input space, a linear regression between the network responses and the targets (experimental values) was performed. The correlation between the targets and the predicted values of ANN for the testing patterns are represented in the form of scatter diagrams, as illustrated in Fig. 4 for kerf. The value of correlation coefficient is 0.9843. From statistical point of view, the closer value of correlation coefficients (R) to 1, the more powerful the network in correlating the input space to output space.

TABLE IV. EXPERIMENTAL AND PREDICTED VALUES FOR KERF

Test Numbers	Experimental values (mm)	ANN predicted values (mm)	% absolute error
1	0.381	0.3753	1.4960
2	0.266	0.2697	1.3909
3	0.328	0.3285	0.1524
4	0.287	0.2959	3.1010
5	0.359	0.3628	1.0585
6	0.415	0.4283	3.2048
7	0.438	0.4379	0.0228
8	0.424	0.4077	3.8443
9	0.387	0.4077	5.3488
10	0.308	0.3162	2.6623
11	0.407	0.4134	1.5724
12	0.394	0.4077	3.4771
13	0.342	0.3595	5.1169
14	0.426	0.4077	4.2957
15	0.302	0.2922	3.2450
16	0.422	0.4077	3.3886
17	0.352	0.3419	2.8693
18	0.322	0.3254	1.0559
19	0.368	0.3758	2.1195
20	0.372	0.3715	0.1344
21	0.334	0.3266	2.2155
22	0.401	0.3853	3.9152
23	0.446	0.445	0.2242
24	0.261	0.265	1.5325
25	0.274	0.2727	0.4744
26	0.294	0.2907	1.1224
27	0.282	0.276	2.1276
28	0.432	0.4242	1.8055
29	0.316	0.32	1.2658

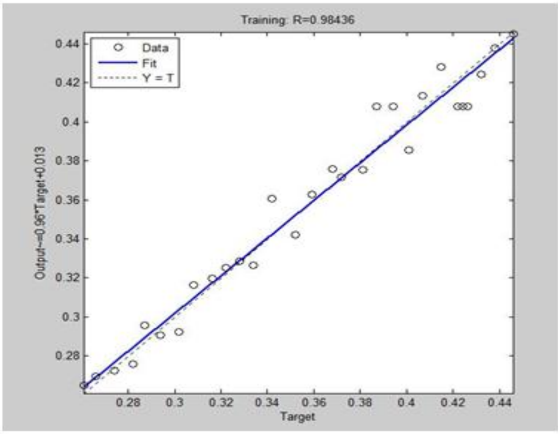

Figure 4. Linear regression analysis between neural network output and experimental results

B. GA Optimization

In the present study, GA is used as an optimization technique for solving a bound-constrained optimization problem. The problem can be formulated as given below. The main aim is to minimize the kerf value.

So, the objective functions:

$$Minimize\ Z = W \times (kerf)$$

(Conversion of multi-objective to single-objective)

W is arbitrarily chosen parameters to represent the importance of each response parameter and taken as 1.

Subjected to,

$$70 \leq V \leq 90;$$

$$1 \leq T_{ON} \leq 3;$$

$$6 \leq T_{OFF} \leq 10;$$

$$5 \leq WF \leq 9.$$

The optimization is carried out in GA Tool box of MATLAB (Version: 7.6.0.324) environment.

The GA parameters used for parametric optimization are as follows:

Population type: Double vector; Population size: 100; Number of generation: 200; Number of stall generation: 50; Fitness function: Rank scalling; Selection function: Roulette wheel, Crossover function: Two point; Crossover fraction: 0.8; Mutation function: adaptive feasible; Migration: Forward, Migration fraction: 0.2.

By solving the optimization problem, the GA reduces the kerf from 0.261 to 0.245 by about 6.13% compared to the initial cutting condition. The best (optimum) cutting condition leading to the minimum kerf is shown in Table V. An experiment was carried out at the optimal parametric settings for kerf so that targeted value of response parameter can be obtained. Table V shows the predicted value of kerf obatined from the GA and experimental result with the parameteric optimal setting as obtained from GA. Prediction are in good agreement with the experimental results because the percentage error of the predicted value with respect to the experimentally observed value for kerf is not high.

TABLE V. THE OPTIMUM VALUES FOR PROCESS PARAMETERS

Optimize value of input parameters				Predicted value (mm)	Experimental value (mm)	% error
SV	T_{ON}	T_{OFF}	*WF*			
70	3	6	5	0.245	0.251	2.39

VI. CONCLUSIONS

Present study reports on the development of process model using ANN for the prediction of kerf during WEDM and optimization of process parameters using GA. From the investigations, the following conclusions can be drawn.

ANN modeling of response parameter indicates good agreement between neural network predictions and experimental values because the plots of the ANN predicted values are very similar to the plot of experimental values.

Maximum percentage absolute error between the experimental value and ANN predicted value is 5.34. This result validates the prediction accuracy of ANN model because the maximum percentage absolute error of the predicted value with respect to the experimentally observed value for kerf is not high.

The value of correlation coefficient of ANN model is 0.9843. From statistical point of view, the closer value of correlation coefficients to 1, the more powerful the network in correlating the input space to output space.

The developed mathematical model was further coupled with a developed GA to find out the optimum conditions leading to the minimum kerf value. Minimum kerf value, which was 0.261 mm before optimization, was reduced to 0.245 mm after optimization. GA improved the kerf value by an amount of 6.13%. The predicted optimum cutting condition was validate with an experimental measurement. The maximum percentage absolute error between the experimental value and GA predicted value is 2.39%. This result validates the prediction accuracy of GA, because the maximum percentage absolute error of the predicted value with respect to the experimentally observed value for kerf is not high.

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