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Optimization of electrical discharge machining process using combined artificial neural networks and heuristic algorithm

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Abstract
In this paper the effect of input electrical discharge machining process variables on AISI2312 hot worked steel is modeled and optimized. The objective is to find a combination of process variables to minimize tool wear rate and surface roughness and maximize material removal rate simultaneously. In order to establish the relationships between the input and the output parameters, back propagation neural network used. In the last section of the study, particle swarm optimization algorithm has been employed for optimization of the multiple response characteristics. Using the proposed optimization procedure, proper levels of input parameters for any desirable group of process outputs can be identified. The results indicate that the proposed modeling technique and PSO algorithm are quite efficient in modeling and optimization of the process variables in order to the desired outputs.

Keywords: Electrical discharge machining (EDM) process, Design of experiments (DOE), Optimization, Back propagation neural network (BPNN), Particle swarm optimization (PSO) algorithm.

Introduction

In EDM process, electrical energy through sparking frequency is used to remove the material. This machining method could eliminates mechanical stresses and chatters vibrations during the machining process because the machining process since it does not involves contact process between the tool electrode and specimen. During the machining process, the tool electrode moves towards the specimen and the gap will be reduced to a very short distance (about 25 micrometer). Then, when current flows, the dielectric fluid breaks down, the gap is ionized and electrons are emitted from the specimen. The impact between atoms will increase the concentration of electrons. Thus, plasma channel will starts to form. The spark then will occurs between the tool electrode and specimen and temperature will increases at the spark point on the specimen. Thus, small quantities of metal will melt and evaporate. During the machining process, small particles will be carried away by the circulated dielectric fluid which floods the gap [1-2]. The most influential process parameters of EDM process are discharge voltage, peak current, pulse duration (pulse on time and pulse off time), duty factor, polarity, type of dielectric flushing, spark gap, pulse frequency and corresponding performance measures are material removal rate (MRR), tool wear rate (TWR), surface roughness (SR), total machining time and etc.,. However, optimizing any of these measures alone has a limited value in real practice, due to the complex nature of the process where several different and sometimes contradictory objectives must be simultaneously considered [3]. Several attempts have been made to study the influence of different process parameters on the important performance measures of EDM process such as MRR, SR and TWR.

The success of optimization techniques depend on the establishment of proper relationships between input parameters and performance characteristics. But the stochastic and complex nature of the process makes it difficult to establish such relationship [4].

In recent years, artificial neural networks (ANNs) have demonstrated great potential in modeling of the input–output relationships of complicated systems. There are many types of artificial neural networks which vary in architecture, implementation of transfer functions and strategy of learning. In view of their universal approximation property, back propagation neural network (BPNN) has received considerable attention. The feature subsets, the number of hidden layers and the number of processing elements in hidden layers are the architectural factors of BPNN to be determined in advance for the modeling process [5, 6].

The aim is to find out the effect of parameters such as discharge current (I), pulse on time (T_{on}) and off time (T_{off}), voltage (V) and duty factor (η) on the responses, namely, MRR, TWR and SR. The purpose of this paper is to present an efficient and integrated approach for the determination of appropriate machining parameters yielding the objective of maximum MRR and minimum SR and TWR simultaneously. First, the experimental data are gathered based on L_{36} orthogonal array (OA) design of experiments (DOE). Then, the process is modeled using a BPNN. Finally, the model has been embedded into a PSO algorithm, to determine the best set of process parameter values to achieve maximum MRR, and minimum SR and TWR simultaneously. Finally, the article concludes with the verification of the proposed approach and a summary of the major findings.

Equipment Used

In this study AISI2312 hot worked steel parts have been applied since only a few researchers have done studies regarding this material using EDM process. The EDM process is performed on specimens having 5 mm thickness and 50 mm diameter ("Figure 1"). Based on the basis of these facts and literature survey, pure copper

(99% purity and 8.98 g/cm^3 density) were used as tools. The machining time for each test was 45 minutes. Furthermore, the experiments have been done in random order to increase accuracy. Die-sinking machine used is shown in "Figure. 2".

Figure 1. the specimen and tool electrode used

Figure 2. The EDM machine used for experiments

Design of Experiments and Assessing the Output Characteristics

Once the process variables and the limits are known, the next step is to select an appropriate design matrix for carrying out of the experiments. DOE approach facilitates the identification of the influence of individual parameters, establishing the relationship between process parameters and operational conditions, and finally establishing performance at the optimum levels. Taguchi is one of the effective techniques that can dramatically reduce the number of trails required to gather necessary data [7]. "Table 1" lists the machining parameters and their levels.

Table 1. Machining Parameters and their Levels

parameters	Symbol	Range	Level 1	Level 2	Level 3
Pulse off time (μs)	A	10-75	10	75	-
Pulse on time (μs)	B	25-200	25	100	200
Peak current (A)	C	6-30	6	18	30
Voltage (V)	D	50-60	50	55	60
Duty factor (S)	E	0.4-1.6	0.4	1	1.6

Taguchi's L36 has been selected to provide a well-balance design of the number of test runs ("Table 2"). It consists of 36 sets of coded conditions. Thus the 36 experimental runs allowed the modeling and effects evaluation of the process parameters on the machined specimens. The results of DOE are given in "Table 2".

Table 2. The L_{36} experimental design matrix and result

No	T_{off} (μs)	T_{on} (μs)	I (A)	η (Sec)	V (V)	SR (μm)	MRR (gr/min)	TWR (%)
1	1	1	1	1	1	3.6	0.35	11.4
2	1	2	2	2	2	7.2	3.04	2.6
3	1	3	3	3	3	3.2	0.33	0.6
4	1	1	1	1	1	7.2	2.08	9.0
5	1	2	2	2	2	13.0	6.84	3.3
6	1	3	3	3	3	3.8	0.45	0. 4
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
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.	.	.	.	.	.	.	.	.
31	2	1	3	3	3	6.6	0.44	42.0
32	2	2	1	1	1	8.8	4.26	2.3
33	2	3	2	2	2	5.0	0.85	0.7
34	2	1	3	1	2	5.4	0.64	47.0
35	2	2	1	2	3	9.2	5.13	1.6
36	2	3	2	3	1	3.2	0.91	0.2

Back Propagation Neural Network

The first model of the artificial neural network (ANN) was given by McCulloch and Pitts [7]. ANNs are simplified models of biological nervous system inspired by the computing performed by a human brain. Kohonen defined neural network as "massively parallel interconnected networks of simple usually adaptive elements and their hierarchical organizations which are intended to interact with the objects of the real world in the same way as biological nervous system do". ANNs have the capability to learn and thereby acquire knowledge and make it available for use [8].

Many researchers have proposed that multilayered networks are capable of computing a wide range of Boolean functions than networks with a single layer of computing units [9]. However, the computational effort needed for modeling a system increases substantially when more parameters and more complicated architectures are considered. The back propagation neural networks (BPNN) are found most appropriate for handling such large learning problems. This type of neural network is known as a supervised network because it requires a desired output in order to learn. A BPNN consists of multiple layers of nodes in a directed scheme, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function [10].

$$F_{i,j} = \frac{1}{1+\exp^{-P(W_{i,j-1},O_{i,j-1})}} \quad (1)$$

Where, for ith neuron in the jth layer, P ($W_{i,j-1}$, $O_{i,j-1}$) is given by:

$$P(W_{i,j-1}, O_{i,j-1}) = \sum_{j=1}^{m}\sum_{i=1}^{n} W_{i,j-1}.O_{i,j-1} \quad (2)$$

Where, n and m are number of hidden layers and neurons in each layer respectively. $W_{i,j-1}$ is the weight of the ith neuron in $(j-1)^{th}$.

One of the most important tasks in ANN modeling is to choose the best network architecture, namely the number of hidden layers and the number of neurons in each layer. Since the number of possible combinations may be very large, the trial-and-error approach is inefficient. In this study, in order to specify the best ANN architecture SA is employed. Usually the performance of the network will be checked by mean square error (MSE) between desired outputs (Y_k) and predicted outputs (y_k) which is expressed as:

$$MSE = \frac{1}{p}\sum_{k=1}^{p}(Y_k - y_k)^2 \quad (3)$$

Learning MSE and the generalization MSE, detect the two main characteristics of "learning" and "generalization" of ANN. The effectiveness of developed net depends on these features.

The appropriate neural network architecture for model development was tuned via SA. Number of hidden layers was varied from 1 to 4; hence a 5–n1–n2–n3–n4–1 structure was constructed; where n1, n2, n3 and n4 are the number of nods in the 1st to the 4th hidden layers. The training of a neural network implies finding desired net's architecture and weights that minimize error between the desired output and the predicted outputs ("Figure 3").

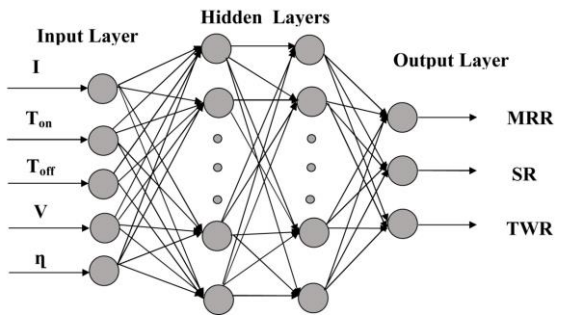

Figure 3. Configuration of the back propagation neural network (BPNN) model for the EDM process

Particle Swarm optimization Algorithm

Particle swarm optimization (PSO) algorithm, a population based stochastic optimization algorithm, has been proposed by Eberhart and Kennedy in 1995 inspired by social behavior of birds flocking [11]. The intelligence of swarm is based on the principle of social and psychological behavior of the swarm. The optimization procedure is initialized with a population of random solutions and searches for optima by updating generations. The potential solutions called particles fly through the problem space by following the current optimum particles. PSO is very easy to implement and there are few parameters to adjust. The algorithm can be explained based on the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in their search [23]. So the best strategy to attain the food is to simply follow the bird, which is nearest to the food. In optimization problems, each bird in the search space is referred to as 'particle'. All the particles are evaluated by the fitness function to be optimized and have velocities for the particles. The particles fly through the problem space by following the current optimum particles. The problem is initialized with a group of random particles and then searches for optima by updating generations [11]. Although conventional PSO can rapidly find out good solutions, it may be trapped in local minimum and fails to converge to the best position [12]. To obviate this problem and improve resolving capacity, an improved PSO algorithm with the rule of mutation is proposed. Using both the best and worst particle positions in the improved PSO algorithm accelerate the finding of the optimal solution. The particle positioning is accomplished by modifying the particle parameters including the speed and position (V_i and X_i) which are defined in the following expressions [12].

$$X_i(k+1) = X_i(k) + V_i(k+1) \quad (4)$$
$$V_i(k+1) = \gamma.V_i(k) + c_1 r_1(p_i - x_i(k)) + c_2 r_2(p_g - x_i(k))$$

Where c_1,c_2 and c_3 are acceleration parameters, r_1 and r_2 are random numbers ranged between 0 and 1, and γ represents the inertia weight which decreases linearly from 1 to near 0 while convergence of algorithm. p_i and p_g denote the best position of the ith particle and the best position of the colony respectively. Each evolutionary optimization algorithm has its own parameters that affect its performance and the quality of solution. In this study optimal value of parameters involved in algorithm is determined by large numbers of trials are conducted by varying different parameters to obtain the best performance of PSO.

Result of Process Optimization and Confirmation Runs

The proposed PSO algorithms have been applied to solve the EDM process problem for multiple response characteristics optimization. The BPNN model, considering the effects of main parameters and the process output constrains was used to model the objective function. Therefore, the BPNN model was used to define the objective function of the optimization problem where the minimum SR and TWR and maximum MRR is the optimum solution. "Figure. 4", shows the convergence of the proposed algorithm.

The optimum design parameter values obtained by using PSO algorithm are given in "Table 7". In order to evaluate the proposed method, four actual experiments (with different weights) was carried out based on the optimized process parameters and observed results ("Table 3"). Results show that the approach presented in this study can accurately predict the process. Furthermore, the developed optimization approach has

a desired performance in determining the optimal set of parameters.

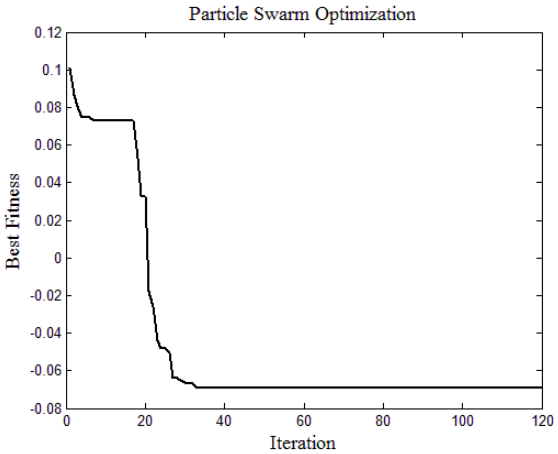

Figure 4. Convergence of proposed PSO algorithm

Table 3. Optimal parameters and observed responses

Process responses					Objective Function		
T_{on} (µs)	T_{off} (µs)	V (V)	I (A)	η (S)	Predict F	Experiment F	Error (%)
182	50	57	18	1	0.160	0.156	2.5
87	56	58	8	0.7	2.900	2.820	2.7
200	38	50	25	1.3	0.256	0.262	2.3
129	39	54	22	1.2	1.249	1.292	3.4

Conclusion

Hybrid modeling and optimization of process parameters and responses in EDM of AISI2312 hot worked steel parts have been implemented. Experimental data for process modeling obtained from conducted experiments by Taguchi methodology, a systematic design of experiments technique. The BPNN predicted responses in a proper agreement with the experimental data which illustrate the capability of the proposed model a tool for accurate estimation of process behavior. Correlation coefficient (R2adj) and mean square error (MSE) between the experimental and predicted values have been calculated. Results demonstrates that proposed neural network models the process efficiently; hence the proper process input parameters determined via PSO based on the developed model. Also the optimization results obtained by PSO were successfully verified with four confirmation tests; which the actual experiment outputs for optimal design compared to the model's simulated data. Good agreement of prediction of BPNN and absolute results Indicates that the proposed model coupled with the PSO algorithm can be effectively utilized to find out the optimal parameters of other manufacturing processes.

Nomenclature

EDM Electrical discharge machining
MRR Material removal rate
TWR Tool wear rate
SR Surface roughness
BPNN Back propagation neural network
PSO Particle swarm optimization
I Peak current
V Discharge voltage
T_{on} Pulse on time
T_{off} Pulse off time
η Duty factor
GA Genetic algorithm
OA Orthogonal array
DOE Design of experiments
RSM Response surface methodology
CCD Center composite design
ANN Artificial neural network
x_i Neuron input
w_i Neuron weight
f Neuron function
MLP Multi-Layer perceptron
c_i Acceleration parameter
r_i Random numbers
p_i The best position of the ith particle
p_g The best position of the group

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