Modeling and optimization of electrical discharge machining process based on combined artificial neural network and particle swarm optimization algorithm

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Abstract

In this study electrical discharge machining (EDM) process, extensively employed in different manufacturing processes such as mold/die making industries, has been modeled and optimized using artificial neural network (ANN) and particle swarm optimization (PSO) algorithm. Surface quality, material removed from the workpiece and tool erosion ratio have been considered as performance characteristics of the process. Objective of this study comprises of optimization of the process in order to find a combination of process input parameters to simultaneously minimize tool ware rate (TWR) and surface roughness (SR) and maximize material removal rate (MRR). Establishing the relations between the process input parameters and the output characteristics, neural network with back propagation algorithm (BPNN) has been used. In the last section of this research, PSO algorithm has been used for optimization of the process with multi-response characteristics. Verifying the accuracy of the proposed optimization procedure, a set of confirmation tests has been carried out. Results show that proposed modeling method (BPNN) can accurately simulate the authentic EDM process with less than 1\% error. Furthermore the optimization technique (PSO algorithm) is quite efficient in process optimization (with less than 4\% error).

Keywords Electrical/Electro discharge machining (EDM), Modeling, Artificial Neural Network (ANN), Neural network with back propagation algorithm (BPNN), Optimization, Particle swarm optimization (PSO) algorithm.

1. Introduction

These days, to cope with high alloy or hard to machining materials such as super alloys and hot worked steels, different advanced machining processes have been modified or developed. Producing parts with
complex shapes along with reasonable surface quality and machining speed/time is difficult to achieve by conventional machining processes [1]. EDM is an unconventional (advanced) machining process utilized for machining of hard to machining conductor materials which are difficult or sometimes impossible using traditional processes. Nevertheless, low removed material ratio from parts known as material removal rate (MRR) characteristic is the major restriction of the EDM process. It is, therefore, essential to improve this process characteristic without affecting other process measures including; tool erosion and surface quality known as tool wear rate (TWR) and surface roughness (SR) respectively [2]. This could be achieved using optimal machining parameters selection affecting the process characteristics (MRR, SR and TWR) to increase MRR and reduce TWR and SR [1, 2].

In EDM process, electrical energy through sparking frequency is used carrying out the process of machining. This machining method could eliminates mechanical stresses and chatters vibrations due to the unique feature of the machining process since it does not involve contact between the tool electrode and specimen (Figure 1) [1]. During the machining process, the tool electrode moves towards the specimen and the gap between them will be reduced to a very short distance (about 25 micrometer). Then, due to the increase of the current, the dielectric fluid breaks down, the gap is ionized and electrons are emitted from the specimen. The concentration of electrons will be increased by the impacts occurs between atoms and a plasma channel starts to form. Therefore, the spark will occurs between the tool electrode and specimen and temperature will increases at the spark point on the specimen. Consequently, small quantities of metal from the specimen will melted and evaporated. During the machining process, small particles removed from the specimen carried away by the circulated dielectric fluid which floods the gap [3].

Peak current (I), voltage of discharge (V), pulse on time and pulse off time (T_{on} and T_{off}), duty factor (\eta), frequency of pulse (F), machining gap (G), dielectric flushing type and polarity are the most significant EDM process parameters considered in different studies [3]. The most essential process measures are MRR, SR, TWR, and etc. Nonetheless, in real practice, optimization of these characteristics has limitations due to the complex nature of the process where several conflicting goals must be considered simultaneously [4]. To study the effect of different process input parameters on the significant performance characteristics of EDM process, many studies have been made as stated in the following section [2-14].

2. State of the art

The achievement of optimization techniques be influenced by the appropriate establishment of relations between process performance measures and input parameters [5]. As a result of the stochastic nature of
the process, establishment of such relationship is difficult. Consequently, initially, EDM process physical models based on the authentic mechanism were developed. As the process involves thermal, electrical and metallurgical variables, the relations between the process characteristics and input parameters cannot be established accurately using the physical models [6, 7]. Therefore, inability of these models due to large deviations from the actual process developed, data based models have been introduced [8]. To model the EDM process, various empirical, statistical and modeling based procedures have been employed [7]. When the number of input parameters is high, suitable curves to nonlinear data become complex. Thus, statistical procedures find restricted use in modeling of the EDM process. Regression modeling techniques also do not provide reasonable results, due to the existence of noise in the EDM process variables [4, 5].

Recently, for modeling of complicated systems input parameters and output measures relations, artificial neural networks (ANNs) have been extensively used [8]. Based on the learning strategy, architecture and application of transfer functions, there are different types of ANNs. Moreover, neural network with back propagation algorithm (BPNN) due to its distinctive features has been widely used [15]. For the modeling procedure, architectural factors of BPNN (number and processing elements of each hidden layer) has been determined in advance [10, 11, 15, 16].

Different studies with different approaches have been conducted to model and optimize EDM process. To model and optimize the EDM process parameters in machining of Inconel 718 super alloy specimens, a BPNN along with a heuristic algorithm (controlled elitist non-dominated sorting genetic algorithm (GA)) have been employed by Pushpendra et al [9]. Training of the network has been carried out based on experimental tests. Obtaining a set of Pareto optimal solutions, controlled elitist non dominated sorting GA in the trained network has been used. Next, the confirmation test has been carried out to verify the ability of forecasting of the proposed network. The average percentage error between empirical and ANN’s forecasted data was 4.67 and 4 for SR and MRR respectively. Based on the obtained results, the proposed network and algorithm were capable in modeling and optimizing of the process.

Estimation and optimization of MRR and SR for EDM process has been performed using BPNN models. Peak current, resistance, T\text{on} and T\text{off} considered as process input parameters. Moreover, the significant parameters and the percent of contribution of each input parameters on the process characteristics has been determined. Based on the obtained results, the most influential process parameter on the two machining responses was peak current [10].

EDM of silicon carbide has been modeled using ANN along with BP algorithm based on data extracted from empirical tests. Different NN architectures have been considered, and 3-5-5-2 was opted. A multi objective optimization technique has been used to optimize MRR and SR using GA. Results of confirmation tests validated that the model is quite proper for estimating the performance measures [11].
A method for optimization of input parameters of EDM (flushing pressure, pulse on time and current) in machining of Aluminum composite has been proposed by Radhika et al [12]. Minimum SR and TWR and maximum MRR has been considered as process objectives. A hybrid optimization technique (ANN-GA) has been used to carry out the multi objective optimization of the process. A decision maker can utilize a Pareto optimal solution set which offers a set of non-dominated solutions.

Influence of process parameters on dimensional tolerance, MRR, TWR and SR during EDM of AISI304 stainless steel parts has been studied by Panda et al, [13]. Predicting TWR, MRR and SR were developed by correlating the input parameters (I, T_on, T_off, and flow rate of dielectric) using mathematical models. Moreover, for each process responses, significant input parameters and the amount of importance have been identified. A method based on Taguchi-grey relational analysis has been used to check the adequacy of the developed models. Confirmation test also has been carried out to verify the proposed models. Based on the achieved results using response surface methodology (RSM), second order developed models for process characteristics representations (MRR, TWR and SR) have been selected. Optimization procedure of the proposed models has been carried out using modified PSO algorithm. As a result of using this approach, complicated multiple performance characteristics optimization has been simplified. Variable factors have been considered to decrease consuming costs and try and error time in the state of reducing production costs and developing quality.

A multi-objective optimization technique has been proposed determining the optimum machining conditions to improve the process performance for machining of 316LN stainless steel parts by Majumder [14]. The proposed technique consists of two stages. In stage one, polynomial regression models calculated to predict the EDM process measures (MRR and TWR). A desirability function based on fuzzy logic has been used to convert the multiple responses into a single response in stage two.

Modeling and optimization of gas metal arc welding (GMAW) process of steel sheets has been carried out using ANN and PSO algorithm [15]. In this study, geometry of weld bead and width of heat affected zone have been modeled and optimized. A set of parameters values and the work piece groove angle in such a way that a pre specified weld bead geometry is achieved while the width of heat affected zone is minimized using hybrid ANN-PSO. Results of confirmation tests verified that the proposed procedure (ANN-PSO) is efficient in modeling and optimization of the process.

An ANN model proposed and optimized by PSO algorithm to predict pure and impure minimum miscibility pressure (MMP) of oils. Finding the best initial weights and biases of NN, PSO algorithm has been used. Reservoir temperature, fluid composition and injected gas composition and MMP have been considered as adjusted input parameters using NN. Calculated results for common gas–oil MMP has been used to verify the performance of hybrid ANN–PSO. The results showed that the proposed model ended
in accurate gas–oil MMP with highest square of correlation coefficient ($R^2$) and lowest average absolute deviation [16].

To gather values needed for modeling procedure of MRR, TWR and SR of holes in EDM process, Box–Behnken design of experiments matrix and RSM have been implemented. Multi objective optimization has been considered using weighted sum method. It has been concluded that among the process input parameters pulse-off time was the least influencing ones, while pulse-on time and peak current has been determined as the dominating control parameters for stated objectives in the study [17].

EDM process has been employed for Hydroxyapatite-enriched coating on Mg-alloy by Prakash et al. [18]. Furthermore, effect of process input parameters on surface quality (SR) of EDMed specimens has been taken into account. To gather data needed for modeling the process, Taguchi method based on design of experiments has been used. Moreover, based on the results, SR and thickness of recast layer have been minimized and micro hardness has been maximized using PSO algorithm. Furthermore, it has been revealed that a hydroxyapatite (HA) layer with interconnected pores of 5–10 μm size on the specimens has been produced.

To optimize the input variables (duty cycle ($T_{du}$), pulse current ($I_p$), pulse on time ($T_{on}$), and gap voltage ($V$)) in EDM process carried out on AISI D2 steel parts, jaya algorithm (JA) has been used. MRR and SR has been considered as response functions of the process. Multiple regression modeling has been used to combine the responses as a single objective function. Then, a JA algorithm has been used to determine an optimal set to obtain the desired outputs (maximum MRR along with minimum SR simultaneously) [19].

The effect of EDM process input parameters namely; $T_{on}$ and $T_{off}$, current, and flushing pressure on output parameters including MRR and TWR have been studied. To design experimental matrix, Taguchi approach has been used. Furthermore, grey relational analysis (GRA) has been employed to optimize the micromachining process through finding the best level of process parameters. Furthermore, to reveal the percentage contribution of process input parameters on process characteristics, analysis of variance (ANOVA) has been applied. Based on the results, current was the most influencing EDM input parameter [20].

An extensive body of studies has been conducted to model and optimize the EDM process. However, there is no research in which modeling and optimization of EDM process has been carried out to obtain the maximum MRR and minimum SR and TWR using DOE approach and integrated ANN-PSO algorithm. Consequently, establishing the relations between process input parameters and output measures of EDM process, ANN has been developed. The proposed model (ANN) consist of five input parameters ($I$, $V$, $T_{on}$, $T_{off}$ and $\eta$) and three output measures (TWR, MRR and SR). In the proposed combined ANN-PSO method, multi objective optimization has been performed. These settings would result in maximum
MRR, and minimum SR and TWR. The proposed method has been carried out on AISI2312 hot worked steel parts, an alloy widely used in numerous industries including injection molding.

In this study, the data sets required for the ANN training and testing have been gathered using DOE attitude (orthogonal array (OA) Taguchi approach). Since much valuable information about the system under study with minimal number of trials could be provided, Taguchi scheme has been employed. Then, to simulate actual EDM process an ANN model has been developed and tested. Finally, the ANN model was embedded into a multi objective optimization algorithm (PSO) to specify the optimized process input parameters.

3. Experimental details and material used

In this study, hot worked AISI2312 steel alloy widely used in injection molding industry has been considered as the material used. In spite of having exclusive properties due to high costs of processing, the usage of this alloy is limited. The process has been conducted on specimens with dimension of 5 and 50 mm for thickness and diameter respectively (Figure 2). 45 minutes has been considered as time of machining. Moreover, to increase accuracy of the data, the tests have been carried out in random order.

A die sinking machine (Azerakhsh-304H model) has been used to carry out the experiments on (Figure. 3).

Several materials may be considered as tool electrode in EDM process (including brass, copper and tungsten alloys as well as graphite). Tool electrodes with brass and tungsten material have restricted usage. Graphite and copper are the most commonly used material as electrode in EDM process. Due to extremely high melting point of graphite its wear rate is less than copper. In contrast, very fine surface qualities can be produced using copper electrode. Furthermore, graphite has better machinability than copper [5, 6]. Thus, pure copper with 8.98 g/cm³ density and 99% purity were used as tools based on the literature survey. To increase the accuracy, the electrodes were replaced after each experiment. Besides, the tool electrode and work piece polarity were assigned as positive and negative respectively, as this status can make minimum tool wear along with stable sparks [1]. Commercial grade kerosene ejected as impulse side flushing through a nozzle was used as the dielectric liquid carrying out machining debris from the gap zone and cooling down the machining zone.

4. Design of experiments and assessing the output characteristics

One of the most powerful methods used for exploring any system or process, is design of experiments (DOE) [15]. This technique is primarily used for achieving information of the existing processes and/or optimizing the processes output measures. In performing DOE, to observe changes in the output
characteristics of the under study process, input parameters changed systematically. Modeling and optimization of the process could be carried out using the information achieved from properly planned and executed experiments. Orthogonal array (OA) Taguchi method, full factorial, center composite design (CCD) and response surface methodology (RSM) are the most common and popular design strategies used. Detailed information about DOE approach and its various applications may be found in the related literatures [14, 15].

Among various DOE strategies, Taguchi technique has been widely used in several engineering applications due to its distinct advantages. With fewer number of experiments (and hence lesser time and cost needed), Taguchi can provide much more useful information which, in turn, can be used for process modeling, analysis and optimization [16].

Once the process variables and the limits are known based on preliminary experimental tests and screening procedures, selecting an appropriate design matrix for conducting the experimental tests is the next step [15]. Using DOE technique facilitate different items including identification of the influence of each process input parameters on the output characteristics, creating the relation between process input and output parameters, and finally establishing performance at the optimum levels. One of the mostly used methods, which dramatically reduce the number of experiments needed for gathering essential data (for modeling and optimization) is Taguchi approach [16, 21].

Process/machining parameters and their considered levels has been listed on Table 1. Limitations of the equipment used may dictate a certain number of levels for some of the process input parameters. In this study, there were only two levels for $T_{off}$ (10 and 75 μs) on the die-sinking machine used.

To provide a well-balanced DOE, Taguchi’s $L_{36}$ has been opted (Table 2). It comprises of 36 sets of coded conditions. The experiments matrix based on Taguchi’s DOE is given in Table 2. In order to increase the accuracy of the tests they were conducted randomly.

In this research, MRR, TWR, and SR have been considered to evaluate the process performance. MRR is expressed as the specimen removal weight ($SRW$) in a determined machining time ($MT$) considered in minute obtained by Equation (1) [22].

$$\text{MRR} = \frac{SRW}{MT} \quad (1)$$

TWR, is defined by the ratio of the tool wear weight ($TWW$) to the specimen removal weight ($SRW$) and usually expressed as a percentage which is obtained using Equation (2) [22].

$$\text{TWR(\%)} = \frac{TWW}{SRW} \times 100 \quad (2)$$
The average roughness ($Ra$) used in this study as a representative of SR. $Ra$ is the area between the profile of roughness and its mean line, or the integral of the absolute value of the roughness profile height over the evaluation. This process characteristic is calculated using Equation (3) [22].

$$SR \approx Ra = \frac{1}{L} \int_{0}^{L} |A(x)| \, dx$$

(3)

Where, the sampling length shown as $L$, and the ordinate of the profile curve is shown with $A(x)$ [23].

Table 2, represents the Taguchi matrix used and resultant outputs.

5. Back propagation neural network

The first model for artificial neural networks (ANNs) has been proposed by McCulloch and Pitts [15]. ANN has been defined as “enormously parallel interrelated 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” by Kohonen. ANNs have the ability to learn and thereby obtain information and make it accessible for use [15].

ANNs are comprise of connecting processing units (named nodes/neurons). Each input parameter ($x_i$) is related with a weight ($w_i$) which indicates a portion of the input to the neuron for processing. The inputs and weights have been multiplied ($x_i \times w_i$) by neurons and inputs transformed into output (Figure 4) by transfer functions or activation functions (considered as ($f$)) [24, 25].

Assumptions for model simplifications are usually used for traditional modeling methods, and subsequently might lead to inaccurate results. In recent times, complex non-linear systems are modeled using ANN, a useful and powerful method. The foundation of ANN modeling consists of detention of underlying trend of the data set presented to it, in the form of a complex non-linear relation between input parameters and output characteristics [25]. Significant advantages of ANN are Learning, generalization, and parallel processing. These features make the ANN as a suitable tool for modeling of different machining processes such as EDM.

There are different ANN structures among which multi-layer perceptron (MLP) has been extensively used due to capability of solving different nonlinear problems and fairly accurate continuous functions. MLP structure includes an input layer, hidden layer/s (one or more), and an output layer, as illustrated by Figure 4. In the training stage, the modification of biases and weights is performed in a supervised way, providing a set of input and output data pairs, which allows the MLP to learn the relationships between the input parameters and the output characteristics. Back propagation (BP) algorithm is being used in the
training stage, in which error of the MLP for each input-output pair is calculated and then this error is propagated from the output (the last) layer to the input layer (the first), modifying the biases and weights of the MLP to the error devoted by its neuron proportionally [15]. The details in this regard are well documented in Refs. [24, 25].

In this study the suitable architecture for modeling development of NN was adjusted using PSO algorithm. The hidden layers number was diverse from 1 to 4; hence a 5–n₁–n₂–n₃–n₄–3 structure was constructed; where n₁, n₂, n₃ and n₄ are the number of nodes/neurons for the 1st to the 4th hidden layers respectively. The training of a NN denotes finding desired architecture and weights of net that leads to minimum error between the desired and predicted outputs (Figure 4).

Table 3 reports the process output characteristics and the simulated values using ANN. Based on the errors given the process is quiet well-organized for modeling of the EDM process.

6. Problem definition

Obtaining the best set of EDM process parameters to simultaneously maximize MRR and minimize TWR and SR is the main objective of this study. Consequently, process output measures (MRR, TWR and SR) could be considered together to build a multiple response characteristic in the optimization procedure. Therefore, the optimal design can be formulated as a multiple response characteristic optimization problem illustrated as Equation (4) [26]:

\[
\begin{align*}
\text{Maximum MRR} & = \text{MRR} \ (I, \ V, \ T_{\text{on}}, \ T_{\text{off}}, \ \eta) \\
\text{Minimum TWR} & = -\text{TWR} \ (I, \ V, \ T_{\text{on}}, \ T_{\text{off}}, \ \eta) \\
\text{Minimum SR} & = -\text{SR} \ (I, \ V, \ T_{\text{on}}, \ T_{\text{off}}, \ \eta)
\end{align*}
\] (4)

In this study, multi-response optimization comprises achieving low TWR and SR and high MRR simultaneously. Therefore, Multi-output measures are changed into a single measure using Equation (5), where \(w_1, w_2\) and \(w_3\) are weighting coefficients.

\[
\text{Minimize } \ F(I, \ T_{\text{on}}, \ T_{\text{off}}, \ \eta, \ V) = (W_1 \times \text{TWR}) + (W_2 \times \text{SR}) - (W_3 \times \text{MRR})
\]

Subjected to

\[
\begin{align*}
6 \leq I \leq 30 \\
25 \leq T_{\text{on}} \leq 200 \\
10 \leq T_{\text{off}} \leq 75 \\
0.4 \leq \eta \leq 1.6 \\
50 \leq V \leq 60
\end{align*}
\] (5)
7. Heuristic algorithm (particle swarm optimization) used

Particle swarm optimization (PSO) algorithm, a population based and stochastic algorithm, which is reminiscent of flocking birds’ social behavior, was first suggested by Eberhart and Kennedy [15, 18]. The optimization procedure is adjusted with a random answers population and searches by updating generations for targets. In optimization procedure, each bird in the search area called as particle. Furthermore, Particles are potential solutions following the current optimal particle by flying through the problem space. One of the advantages of the PSO algorithm is its easy implementation due to few parameters to adjust. The algorithm could be explained as the following setting: a bird’s flock is searching one piece of food (an answer) in an area (answer space) randomly. The food location is unknown for all the birds. Nonetheless, the birds know how far the food is in their search area [27-29]. Consequently, chasing the bird which is nearest to the food is the best approach. Fitness function is used to evaluate all the particles which have different velocities [20, 21]. Although, good solutions may be found rapidly, it might also end in converge failure being trapped in local minimum. A modified PSO algorithm (with the rule of mutation) has been proposed to avoid this phenomena. Optimal solution finding speeded up, using both particle positions (the best and worst) in the proposed modified algorithm. Modifying the particle parameters including the velocity ($V_j$) and position ($X_j$) which are defined in Equation (6) has been used to accomplish the position of particle [27].

$$X_j(k+1) = X_j(k) + V_j(k+1)$$

$$V_j(k+1) = \gamma \times V_j(k) + c_1 \times r_1 \times (p_j - X_j(k)) + c_2 \times r_2 \times (p_g - X_j(k)) \quad (6)$$

Where parameters of acceleration has been shown using $c_1$ and $c_2$ and random numbers (ranged between 0 and 1) $r_1$ and $r_2$. The inertia weight which decreases linearly during the optimization process from 1 to near 0 represents using $\gamma$ symbol. The best position of the $j^{th}$ particle and group have been shown using $p_j$ and $p_g$ respectively. The performance of an evolutionary optimization algorithm and is being affected by its own distinctive adjusting parameters. The details of the PSO performance are well documented in Refs [26-29].

The adjusting parameters used for controlling the PSO algorithm performance is shown in Table 4.

8. Result of process parameters optimization and confirmation tests

The use of the modified multi-response characteristics optimization method and proposed combinatory model of BPNN-PSO is reported for EDM of hot worked steel parts (AISI2312). To solve the EDM process problem for multi-response characteristics optimization, the PSO algorithm has been proposed. To model the objective function, the BPNN model, considering the effects of main parameters and the
process output constraints was used. 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 desired. The convergence of the proposed PSO algorithm has been well illustrated in Figure. 5.

Using PSO algorithm, the optimum design parameter values obtained. In order to evaluate the proposed method, four actual experiments (with different weights) based on the optimized process input parameters and observed results have been performed (Table 5). Based on the proposed approach results, the process characteristics can be precisely predicted.

9. Conclusion

Empirical values needed for modeling of EDM process on AISI2312 hot worked steel parts gathered using Taguchi methodology. The multi objective optimization technique comprises finding a certain combination of process input parameters to achieve maximized MRR and minimized SR and TWR simultaneously. A BPNN has been used for modeling of the process. A proper agreement has been shown between the BPNN based predicted responses model used and the experimental values (with less than 0.8% error for the three outputs) which illustrates the capability of the proposed model as a tool for accurate estimation of process behavior. Therefore, results demonstrate that proposed NN model the process proficiently; hence the suitable process adjusting (input) parameters have been selected using PSO algorithm. Furthermore, the optimization results obtained by PSO were successfully verified with four experimental tests. Confirmation results show the efficiency of the hybrid proposed procedure (BPNN-PSO) in multi-response modeling and optimization of EDM process. Good agreement of BPNN prediction indicate that the proposed BPNN-PSO algorithm procedure could be effectively employed finding out the optimum input parameters of other manufacturing processes.

References


**Biographies**

**Farhad Kolahan** was born in September 1965 in Mashhad, Iran. He acts as an associate professor at the Department of Mechanical Engineering, Faculty of Engineering, Ferdowsi University of Mashhad (FUM), I.R. Iran. He obtained his B.Sc. degree from Tabriz University, I.R. Iran, in Production and Manufacturing Engineering. He continued his postgraduate studies and graduated in 1999 with a Ph.D. degree in Industrial and Manufacturing Engineering from Ottawa University, Canada. His research interests include scheduling and production planning, optimization of manufacturing processes and applications of evolutionary algorithms for industrial optimization.

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**List of Captions**

**Table Captions**

*Table 1. Machining Parameters and Their Feasible Intervals and Levels*

*Table 2. Taguchi L36 experimental design and corresponding results of tests carried out*
Table 3. Comparison of normalized experimental and BPNN simulated results of the process characteristics (TWR, MRR and SR)

Table 4. Control parameters of PSO algorithm used

Table 5. Optimal process parameters settings and corresponding measures

**Figure Captions**

Figure 1. Schematic representation of electrical discharge machining process [1]

Figure 2. The specimen and tool electrode used

Figure 3. The EDM machine used for conducting experiments

Figure 4. Configuration of artificial neural network (ANN) model used for EDM process

Figure 5. Convergence trend of the proposed optimization algorithm (PSO)

**Table list**

Table 1. Machining Parameters and Their Feasible Intervals and Levels

<table>
<thead>
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Table 2. Taguchi L$_{36}$ experimental design and corresponding results of tests carried out

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Table 3. Comparison of normalized experimental and BPNN simulated results of the process characteristics (TWR, MRR and SR)
Table 4. Control parameters of PSO algorithm used

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Table 5. Optimal process parameters settings and corresponding measures

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Figure List
Figure 1. Schematic representation of electrical discharge machining process [1]

Figure 2. The specimen and tool electrode used
Figure 3. The EDM machine used for conducting experiments

Figure 4. Configuration of artificial neural network (ANN) model used for EDM process
Figure 5. Convergence of the proposed PSO algorithm

Nomenclature

Acceleration parameter ($c_i$)
Artificial neural network (ANN)
Center composite design (CCD)
Design of experiments (DOE)
Discharge voltage (V)
Duty factor ($\eta$)
Electro/Electrical discharge machining (EDM)
Genetic algorithm (GA)
Machining time (MT)
Material removal rate (MRR)
Multi-Layer perceptron (MLP)
Neural network with back propagation algorithm (BPNN)

Neuron function ($f$)

Neuron input ($x_i$)

Neuron weight ($w_j$)

Orthogonal array (OA)

Particle swarm optimization (PSO) algorithm

Peak current (I)

Pulse off time ($T_{off}$)

Pulse on time ($T_{on}$)

Response surface methodology (RSM)

Specimen removal weight (SRW)

Specimen removal weight (SRW)

Surface roughness (SR)

The best position of the group ($p_g$)

The best position of the $j^{th}$ particle ($p_j$)

Tool electrode wear rate (TWR)

Tool electrode wear weight (TWW)

Uniform random numbers ($r_i$)