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

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Optimization;
Particle Swarm Optimization (PSO) algorithm.

Abstract. In this study, the Electrical Discharge Machining (EDM) process, which is extensively employed in different manufacturing processes such as mold/die making industries, was 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 were considered as the performance characteristics of this process. The objective of this study comprises the optimization of the process in order to find a combination of process input parameters to simultaneously minimize Tool Wear Rate (TWR) and Surface Roughness (SR) and maximize Material Removal Rate (MRR). By establishing a relationship between the process input parameters and the output characteristics, a neural network with back propagation algorithm (BPNN) was used. In the last section of this research, PSO algorithm was used for the optimization of the process with multi-response characteristics. By verifying the accuracy of the proposed optimization procedure, a set of confirmation tests was carried out. Results showed that the proposed modeling method (BPNN) could 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).

1. Introduction

These days, to cope with high-alloy or hard-to-machine 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]. Electrical Discharge Machining (EDM) is an unconventional (advanced) machining process that is utilized for machining hard-to-machine conductor materials, which is difficult or sometimes impossible to do by traditional processes. Nevertheless, the low ratio of materials removed from parts known as a Material Removal Rate (MRR) characteristic is a major limitation of the EDM process. It is, therefore, essential to improve this process characteristic without affecting other process measures such as 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 affecting the process characteristics (MRR, SR and TWR) to increase MRR and reduce TWR and SR [1,2].

In the EDM process, electrical energy through

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sparking frequency is used for carrying out the process of machining. This machining method could eliminate mechanical stresses and chatter 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 is reduced to a very short distance (about 25 micrometers). 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 increase with the impact that occurs between atoms and a plasma channel starts to form. Therefore, the spark occurs between the tool electrode and specimen and temperature increases at the spark point on the specimen. Consequently, a small quantity of metal from the specimen melts and evaporates. During the machining process, small particles removed from the specimen are carried away through 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 (η), frequency of pulse (F), machining gap (G), dielectric flushing type, and polarity are the most significant EDM process parameters that are considered in different studies [3]. The most essential process measures include MRR, SR, TWR, etc. Nonetheless, in real practice, the 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 the EDM process, many studies have been made, as stated in the following section [2-14].

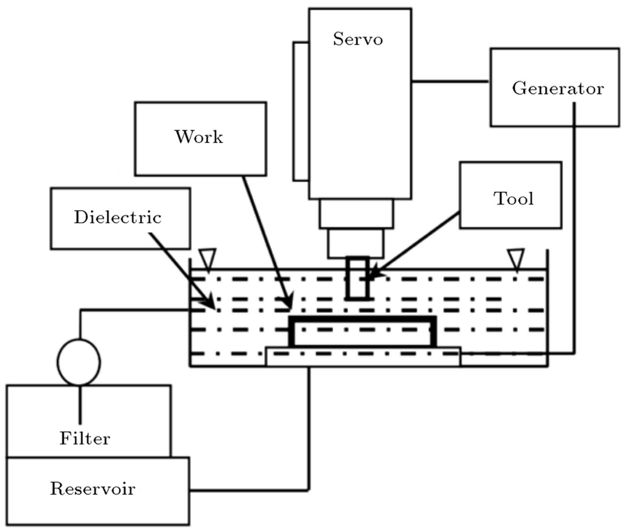

Figure 1. Schematic representation of the electrical discharge machining process [1].

2. State of the art

The achievement of optimization techniques is influenced by the appropriate establishment of a relationship between process performance measures and input parameters [5]. As a result of the stochastic nature of the process, the establishment of such a relationship is difficult. Consequently, initially, physical models of the EDM process are developed based on the authentic mechanism. Since 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]. Since these models are incapable and inaccurate due to large deviations from the actual process developed, data-based models were introduced [8]. To model the EDM process, various empirical, statistical, and modeling-based procedures were employed [7]. When the number of input parameters is high, fitting suitable curves to nonlinear data becomes complex. Thus, statistical procedures have a restricted use in modeling the EDM process. Regression modeling techniques do not provide reasonable results due to the existence of noise in the EDM process variables [4,5].

Recently, for modeling the relations between input parameters and output measures of complicated systems, 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, the architectural factors of BPNN (number and processing elements of each hidden layer) have been determined in advance [10,11,15,16].

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

The estimation and optimization of MRR and

SR for the EDM process were carried out by BPNN models. Peak current, resistance, T_{on}, and T_{off} were considered as process input parameters. Moreover, the significant parameters and the contribution percentage of each input parameter with respect to the process characteristics were determined. Based on the obtained results, the most influential process parameter for the two machining responses was peak current [10].

The EDM of silicon carbide was modeled using ANN along with BP algorithm based on the data extracted from empirical tests. Different NN architectures were considered and 3-5-5-2 was selected. A multi-objective optimization technique was used to optimize MRR and SR using GA. Results of the confirmation tests confirmed that the model was quite proper for estimating the performance measures [11].

A method for optimizing input parameters of EDM (flushing pressure, pulse on time, and current) in the machining of aluminum composite was proposed by Radhika et al. [12]. Minimum SR and TWR and maximum MRR were considered as process objectives. A hybrid optimization technique (ANN-GA) was used to carry out the multi-objective optimization of the process. A decision-maker can utilize a Pareto optimal solution set that offers a set of non-dominated solutions.

The effect of process parameters on dimensional tolerance, MRR, TWR, and SR during the EDM of AISI304 stainless steel parts was studied by Panda et al. [13]. The prediction of TWR, MRR, and SR was developed by correlating the input parameters (I, T_{on}, T_{off}, and flow rate of the dielectric) using mathematical models. Moreover, for each process response, significant input parameters and the amount of importance were identified. A method based on Taguchi-grey relational analysis was used to check the adequacy of the developed models. The confirmation test was 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) were selected. The optimization procedure of the proposed models was implemented using a modified Particle Swarm Optimization (PSO) algorithm. As a result of applying this approach, the optimization of the complicated multiple performance characteristics was simplified. Variable factors were considered to reduce consumption costs and trial-and-error time in the state of reducing production costs and developing quality.

A multi-objective optimization technique was proposed for determining optimum machining conditions to improve the process performance for machining 316LN stainless steel parts by Majumder [14]. The proposed technique consists of two stages. In stage 1, polynomial regression models were calculated to predict the EDM process measures (MRR and TWR). A desirability function based on fuzzy logic was used to convert multiple responses into a single response in stage 2.

The modeling and optimization of Gas Metal Arc Welding (GMAW) process of steel sheets was carried out using ANN and PSO algorithm [15]. In this study, the geometry of weld bead and width of the heat-affected zone were modeled and optimized. A set of parameters' values and the work piece groove angle are presented such that a prespecified weld bead geometry can be achieved while the width of the heat-affected zone is minimized using hybrid ANN-PSO. Results of the confirmation tests verified that the proposed procedure (ANN-PSO) was efficient in the modeling and optimization of the process.

An ANN model was proposed and optimized by PSO algorithm to predict pure and impure Minimum Miscibility Pressures (MMP) of oils. By determining the best initial weights and biases of NN, PSO algorithm was used. Reservoir temperature, fluid composition, and injected gas composition and MMP were considered as adjusted input parameters using NN. Calculated results of common gas-oil MMP were used to verify the performance of hybrid ANN-PSO. The results showed that the proposed model produced accurate gas-oil MMP with the highest square of correlation coefficient (R^2) and the lowest average absolute deviation [16].

To gather values required for the modeling procedure of MRR, TWR and SR of holes in the EDM process, Box-Behnken design of experiments matrix, and RSM were implemented. Multi-objective optimization was considered by the weighted sum method. It was concluded that pulse-off time was the least influencing parameter among process input parameters, while pulse-on time and peak current were found to be the dominating control parameters for the stated objectives in [17].

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

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

The effects of the EDM process input parameters including T_{on} and T_{off}, current, and flushing pressure on output parameters including MRR and TWR were studied. To design an experimental matrix, Taguchi approach was used. Furthermore, Grey Relational Analysis (GRA) was employed to optimize the micro-machining process by determining the best level of the process parameters. Furthermore, to assess the effect of process input parameters on process characteristics in percentage unit, analysis of variance (ANOVA) was applied. Based on the results, current was the most influencing EDM input parameter [20].

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

In this study, the datasets required for the ANN training and testing were collected using Design Of Experiments (DOE) attitude (Orthogonal Array (OA) Taguchi approach). Since a large portion of valuable information about the system under study with a minimal number of trials could be provided, Taguchi scheme was employed. Then, to simulate the actual EDM process, an ANN model was 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

This study considers the hot-worked AISI2312 steel alloy and is widely used in the injection molding industry as the material used. Despite featuring a number of exclusive properties due to high costs of processing, the application of this alloy is limited. The process was conducted on specimens with a dimension of 5 and 50 mm for thickness and diameter, respectively (Figure 2). Machining operational time is set to 45 minutes. Moreover, to increase the accuracy of the data, the tests were carried out in random order.

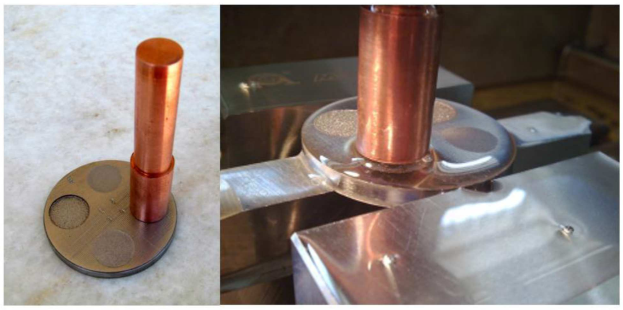

Figure 2. The specimen and tool electrode used.

A die sinking machine (Azerakhsh-304H model) was used to carry out the experiments (Figure 3). Several materials may be considered as tool electrodes in the EDM process (including brass, copper, tungsten alloys, and graphite). Tool electrodes with brass and tungsten materials have restricted usage. Graphite and copper are the most commonly used materials as electrodes in the EDM process. Due to the extremely high melting point of graphite, its wear rate is less than that of copper. In contrast, very fine surface qualities can be produced by the copper electrode. Furthermore, graphite has better machinability than copper [5,6]. Thus, pure copper with a density of 8.98 g/cm^3 and a purity of 99% was used as tools based on the literature survey. To increase the accuracy, the electrodes were replaced after each experiment. Besides, the tool electrode and workpiece polarity were assigned as positive and negative, respectively, since this status could ensure minimum tool wear and 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.

Figure 3. The EDM machine used for conducting experiments.

4. DOE and assessment of the output characteristics

One of the most powerful methods used for exploring any system or process is the DOE [15]. This technique is primarily used for obtaining information about the existing processes and/or optimizing the process output measures. In performing DOE, to observe changes in the output characteristics of the under-study process, input parameters change systematically. The modeling and optimization of the process could be carried out by 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 is widely used in several engineering applications due to its distinct advantages. Characterized by fewer experiments (hence, shorter time and lower cost needed), Taguchi can provide much more useful information to facilitate process modeling, analysis, and optimization [16].

Once the process variables and the limits are determined based on preliminary experimental tests and screening procedures, selecting an appropriate design matrix for conducting the experimental tests becomes the next step [15]. The application of DOE technique facilitates different objectives including the identification of the role of each process input parameter in the output characteristics, creation of the relationship between process input and output parameters, and the establishment of performance at optimum levels. One of the most used methods that dramatically reduces the number of experiments required for gathering essential data (for modeling and optimization) is Taguchi approach [16,21].

Process/machining parameters and their considered levels are listed in 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 are only two levels for T_{off} (10 and 75 μs) on the die-sinking machine used.

To provide well-balanced DOEs, Taguchi's L_{36} was opted (Table 2). It comprises 36 sets of coded conditions. The experiment 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 were considered to evaluate the process performance. MRR is expressed as the Specimen Removal Weight (SRW) in a determined Machining Time (MT) measured in minute unit, obtained through Eq. (1) [22]:

$$MRR = \frac{SRW}{MT}. \tag{1}$$

TWR is defined by the ratio of the Tool Wear Weight (TWW) to the Specimen Removal Weight (SRW) and is usually expressed as a percentage obtained through Eq. (2) [22]:

$$TWR(\%) = \frac{TWW}{SRW} \times 100. \tag{2}$$

The average roughness (Ra) is used in this study as 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 through Eq. (3) [22]:

$$SR \approx Ra = \frac{1}{L}\int_0^L |A(x)|\,dx, \tag{3}$$

where the sampling length is denoted by L and the ordinate of the profile curve by $A(x)$ [23].

Table 2 represents the Taguchi matrix used and resultant outputs.

5. Back propagation neural network

The first model for ANNs was proposed by McCulloch and Pitts [15]. Kohonen defined ANN 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". ANNs have the ability to learn and, thereby, obtain information and make it accessible for use [15].

Table 1. Machining parameters and their feasible intervals and levels.

Process parameters	Symbol	Range	Level 1	Level 2	Level 3
Pulse on time (μs)	T_{on}	25–200	25	100	200
Pulse off time (μs)	T_{off}	10–75	10	75	–
Voltage (V)	V	50–60	50	55	60
Duty factor (S)	η	0.4–1.6	0.4	1	1.6
Peak current (A)	I	6–30	6	18	30

Table 2. Taguchi L_{36} experimental design and the corresponding results of tests carried out.

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
7	1	1	1	2	3	8.8	5.52	6.7
8	1	2	2	3	1	13.0	2.83	2.7
9	1	3	3	1	2	4.6	0.56	0.7
10	1	1	1	3	2	7.6	1.56	5.3
11	1	2	2	1	3	13.4	10.64	3.8
12	1	3	3	2	1	5.0	1.70	0.7
13	1	1	2	3	1	8.4	2.53	35.9
14	1	2	3	1	2	6.4	0.88	7.5
15	1	3	1	2	3	4.8	1.28	1.1
16	1	1	2	3	2	10.2	2.24	36
17	1	2	3	1	3	6.0	1.14	6.6
18	1	3	1	2	1	4.4	0.57	0.8
19	2	1	2	1	3	7.0	2.99	35.1
20	2	2	3	2	1	6.4	0.85	11.0
21	2	3	1	3	2	4.6	1.20	1.2
22	2	1	2	2	3	8.4	4.43	39.2
23	2	2	3	3	1	5.8	0.37	7.9
24	2	3	1	1	2	5.8	2.00	2.7
25	2	1	3	2	1	5.8	0.77	46.5
26	2	2	1	3	2	11.2	1.74	1.3
27	2	3	2	1	3	4.6	1.84	0.6
28	2	1	3	2	2	4.4	0.67	44.6
29	2	2	1	3	3	11.6	1.91	1.5
30	2	3	2	1	1	5.2	1.57	0.5
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

ANNs are comprised of connecting processing units (named nodes/neurons). Each input parameter (x_i) is related to a weight (w_i), which indicates a portion of the input to the neuron for processing. The inputs and weights are 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 concerning model simplifications are usually used for traditional modeling methods and, subsequently, might produce inaccurate results. In recent times, complex non-linear systems have been modeled using ANN, a useful and powerful method. The foundation of ANN modeling consists of detention of the underlying trend of the dataset presented to it in the form of a complex nonlinear relationship between input parameters and output characteristics [25]. Significant advantages of ANN include learning, gen-

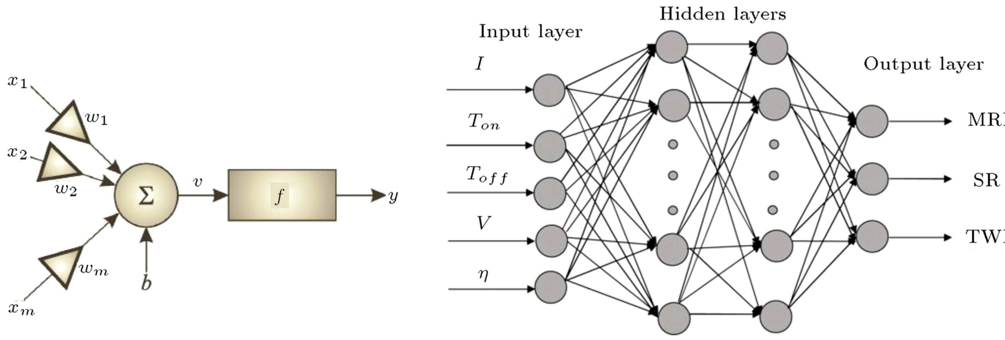

Figure 4. Configuration of the Artificial Neural Network (ANN) model used for the EDM process.

eralization, and parallel processing. These features make the ANN a suitable tool for modeling different machining processes such as EDM.

There are different ANN structures, among which Multi-Layer Perceptron (MLP) is extensively used due to the 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 in Figure 4. In the training stage, the modification of biases and weights is performed under supervision and provides a set of input and output data pairs, allowing the MLP to learn the relationships between the input parameters and the output characteristics. Back Propagation (BP) algorithm is used in the training stage, in which the error of the MLP for each input-output pair is calculated and, then, 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 to its neuron proportionally [15]. The details in this regard are well documented in [24,25].

In this study, a suitable architecture for the modeling development of NN was adjusted using PSO algorithm. The number of the hidden layers varies from 1 to 4; hence, a $5-n_1-n_2-n_3-n_4-3$ structure was constructed, where n_1, n_2, n_3, and n_4 are the number of nodes/neurons for the 1st to 4th hidden layers, respectively. The training of a NN involves finding the desired architecture and weights of the net, leading 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 quite well organized for modeling the EDM process.

6. Problem definition

The best set of EDM process parameters is used 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, as illustrated in Eq. (4) [26]:

$$\begin{aligned} &\text{Maximum} \quad MRR = MRR(I, V, T_{on}, T_{off}, \eta), \\ &\text{Minimum} \quad \text{TWR} = -\text{TWR}(I, V, T_{on}, T_{off}, \eta), \\ &\text{Minimum} \quad \text{SR} = -\text{SR}(I, V, T_{on}, T_{off}, \eta). \end{aligned} \tag{4}$$

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

$$\begin{aligned} \text{Minimize} \quad & F(I, T_{on}, T_{off}, \eta, V) = (W_1 \times TWR) \\ & + (W_2 \times SR) - (W_3 \times MRR). \end{aligned}$$

Subjected to:

$$\begin{aligned} &6 \le I \le 30, \\ &25 \le T_{on} \le 200, \\ &10 \le T_{off} \le 75, \\ &0.4 \le \eta \le 1.6, \\ &50 \le V \le 60. \end{aligned} \tag{5}$$

7. Heuristic algorithm (particle swarm optimization) used

Particle Swarm Optimization (PSO) algorithm as a population-based and stochastic algorithm, which is reminiscent of flocking birds' social behavior, was first suggested by McCulloch and Pitts [15] and Kennedy and Eberhart [18]. The optimization procedure is adjusted with a population-based random search algorithm by updating generations for targets. In the optimization procedure, each bird in the search area

Table 3. Comparison of normalized experimental and BPNN simulated results of the process characteristics (TWR, MRR, and SR).

No.	Real TWR	SIM TWR	Error (%)	Real MRR	SIM MRR	Error (%)	Real SR	SIM SR	Error (%)	Mean error
1	0.242553	0.242776	0.000919	0.032995	0.039460	0.195939	0.284672	0.297249	0.044181	0.080346
2	0.055319	0.070400	0.272619	0.285956	0.266111	0.069399	0.518248	0.498391	0.038316	0.126778
3	0.012766	0.010799	0.154081	0.629019	0.661913	0.052294	0.985401	0.975175	0.010377	0.072251
4	0.191489	0.242776	0.267833	0.03088	0.03946	0.277850	0.233577	0.297249	0.272595	0.272759
5	0.070213	0.070400	0.002663	0.195431	0.266111	0.361662	0.50365	0.498391	0.010442	0.124922
6	0.008511	0.010799	0.268829	0.642978	0.661913	0.029449	0.927007	0.975175	0.051961	0.116746
7	0.142553	0.143816	0.008859	0.042301	0.061558	0.455237	0.277372	0.297998	0.074362	0.179487
8	0.057447	0.058041	0.010340	0.519036	0.452180	0.128808	0.613139	0.620450	0.011924	0.050357
9	0.014894	0.015395	0.033638	0.266074	0.287632	0.081023	0.912409	0.927070	0.016068	0.043576
10	0.112766	0.112311	0.004035	0.052453	0.063952	0.219220	0.321168	0.311810	0.029137	0.084132
11	0.080851	0.082315	0.018107	0.146785	0.162411	0.106455	0.554745	0.405427	0.269165	0.131243
12	0.014894	0.015671	0.052169	1.000000	0.981862	0.018138	1.000000	0.957226	0.042774	0.037694
13	0.763830	0.764077	0.000323	0.159898	0.147688	0.076360	0.350365	0.353623	0.009299	0.028661
14	0.159574	0.160442	0.005439	0.237733	0.236932	0.003369	0.591241	0.593366	0.003594	0.004134
15	0.023404	0.023343	0.002607	0.082910	0.080105	0.033832	0.452555	0.458949	0.014129	0.016856
16	0.765957	0.761345	0.006021	0.120135	0.087411	0.272393	0.335766	0.310760	0.074474	0.117630
17	0.140426	0.14032	0.000755	0.210660	0.189678	0.099601	0.729927	0.726316	0.004950	0.035101
18	0.017021	0.016849	0.010105	0.107022	0.106917	0.000981	0.423358	0.425266	0.004507	0.005198
19	0.746809	0.747469	0.000884	0.053723	0.069749	0.298308	0.357664	0.297421	0.168434	0.155875
20	0.234043	0.234442	0.001705	0.280880	0.293022	0.043228	0.510949	0.503742	0.014105	0.019679
21	0.025532	0.02488	0.025537	0.079949	0.086297	0.079401	0.474453	0.404145	0.14*8187	0.084375
22	0.834043	0.784038	0.059955	0.112944	0.072682	0.356478	0.350365	0.297683	0.150363	0.188932
23	0.168085	0.167378	0.004206	0.416244	0.415021	0.002940	0.635036	0.63519	0.000243	0.002462
24	0.057447	0.029321	0.489599	0.034687	0.063013	0.816617	0.445255	0.442145	0.006985	0.437734
25	0.989362	0.987137	0.002249	0.187817	0.191153	0.017762	0.401460	0.412985	0.028708	0.016240
26	0.02766	0.027741	0.002929	0.072335	0.069609	0.037686	0.423358	0.403649	0.046550	0.029056
27	0.012766	0.012798	0.002507	0.163706	0.201459	0.230615	0.810219	0.768059	0.052035	0.095052
28	0.948936	0.94786	0.001134	0.173012	0.172198	0.004705	0.357664	0.331382	0.073482	0.026440
29	0.031915	0.032041	0.00395	0.063029	0.067283	0.067493	0.335766	0.406429	0.210453	0.093965
30	0.010638	0.011326	0.064673	0.179357	0.169052	0.057455	0.846715	0.820007	0.031543	0.051224
31	0.893617	0.892343	0.001426	0.147631	0.164972	0.117460	0.357664	0.354617	0.008519	0.042469
32	0.048936	0.050112	0.024031	0.041455	0.037185	0.103003	0.459854	0.454185	0.012328	0.046454
33	0.014894	0.014521	0.025044	0.400592	0.40547	0.012177	0.642336	0.687756	0.070711	0.035977
34	1.000000	0.992453	0.00755	0.079949	0.089591	0.120602	0.357664	0.325585	0.089690	0.072613
35	0.034043	0.034221	0.005229	0.060068	0.064882	0.080143	0.401460	0.403891	0.006055	0.030476
36	0.004255	0.005563	0.307403	0.482234	0.490790	0.017742	0.715328	0.700266	0.021056	0.115401

is called a particle. Furthermore, particles become potential solutions after the existing optimal particle by flying through the problem space. One of the advantages of the PSO algorithm is its ease of implementation, since it has only few parameters to adjust. The algorithm can be explained as in the following setting: A flock of birds searches for 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 intended food is in their search area [27–29]. Consequently, chasing the bird, somewhere nearest to the food, is the best approach. Fitness function is used to evaluate all the particles that have different velocities [20,21]. Although good solutions can be found quite quickly, this may lead to the convergence failure trapped in a local minimum. A modified PSO algorithm (with a rule of mutation) has been proposed to avoid this phenomenon. The optimal solution finding has accelerated by both particle positions (the best and worst) in the proposed modified algorithm. The modification of the particle parameters, including the velocity (V_j) and position (X_j), that are defined in Eq. (6) has been made to determine the position of the 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 the parameters of acceleration are denoted by c_1 and c_2 and random numbers (ranging between 0 and 1) by r_1 and r_2. The inertia weight, which decreases linearly during the optimization process from 1 to almost 0, is denoted by symbol γ. The best positions of the jth particle and group are denoted by p_j and p_g, respectively. The performance of an evolutionary optimization algorithm is affected by its own distinctive adjusting parameters. The details of the PSO performance are well documented in [26–29].

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

Table 4. Control parameters of the PSO algorithm used.

PSO algorithm	Values
Number of dimensions	5
Population size	50
Inertia weight	0.7
Personal cognition coefficient	1
Social cognition coefficient	1
Iterations	35

8. Result of process parameters optimization and confirmation tests

The application of the modified multiple response characteristics of the optimization method and the proposed combinatory model of BPNN-PSO to the EDM of hot-worked steel parts (AISI2312) was reported. To solve the EDM process problem for the optimization of multiple response characteristics, the PSO algorithm was proposed. To model the objective function, the BPNN model was used, considering the effects of the main parameters and the process output constrains. Therefore, the BPNN model was used to define the objective function of the optimization problem, where the minimum SR and TWR and maximum MRR were found to be desired. The convergence of the proposed PSO algorithm is well illustrated in Figure 5.

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

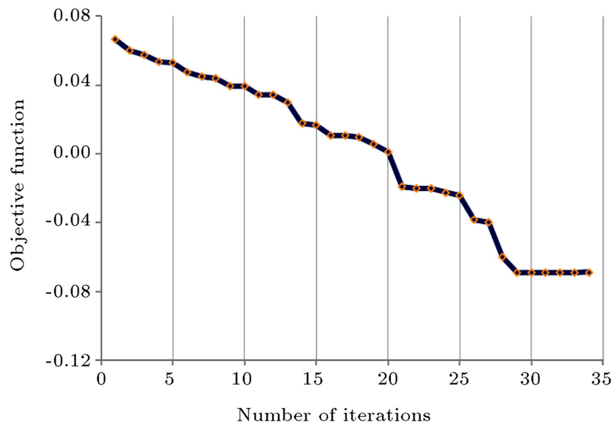

Figure 5. Convergence trend of the proposed Particle Swarm Optimization (PSO) algorithm.

Table 5. Optimal process parameters settings and corresponding measures.

Optimal process input parameters setup	Process characteristics					Weighting coefficients			Objective function		
	T_{on} (μs)	T_{off} (μs)	V (V)	I (A)	η (S)	W_1	W_2	W_3	Predicted F	Experimental F	Error (%)
Setting 1	182	50	57	18	1	0.750	0.125	0.125	0.160	0.156	2.5
Setting 2	87	56	58	8	0.7	0.125	0.750	0.125	2.900	2.820	2.7
Setting 3	200	38	50	25	1.3	0.125	0.125	0.750	0.256	0.262	2.3
Setting 4	129	39	54	22	1.2	0.333	0.333	0.333	1.249	1.292	3.4

9. Conclusion

The empirical values needed for modeling the EDM process on AISI2312 hot-worked steel parts were determined by Taguchi methodology. The multi-objective optimization technique was used to find a certain combination of process input parameters to achieve maximized MRR and minimized SR and TWR simultaneously. A BPNN was used for the modeling of the process. Proper agreement between the BPNN-based predicted model responses was used and the experimental values was observed (with less than 0.8% error for the three outputs), illustrating the capability of the proposed model as a tool for an accurate estimation of the process behavior. Therefore, results demonstrated that the proposed NN modeled the process proficiently; hence, the suitable process adjusting (input) parameters were selected using PSO algorithm. Furthermore, the optimization results obtained by PSO were successfully verified with four experimental tests. Confirmation results showed the efficiency of the hybrid proposed procedure (BPNN-PSO) in the multi-response modeling and optimization of the EDM process. The aforementioned good agreement indicates that the proposed BPNN-PSO algorithm procedure can be effectively employed for determining the optimum input parameters of other manufacturing processes.

Nomenclature

c_j	Acceleration parameter
ANN	Artificial Neural Network
CCD	Center Composite Design
DOE	Design Of Experiments
V	Discharge voltage
η	Duty factor
EDM	Electro/Electrical Discharge Machining
GA	Genetic Algorithm
MT	Machining Time
MRR	Material Removal Rate
MLP	Multi-Layer Perceptron
BPNN	Neural network with back propagation algorithm
f	Neuron function
x_i	Neuron input
w_j	Neuron weight
OA	Orthogonal Array
PSO	Particle Swarm Optimization
I	Peak current
T_{off}	Pulse off time
T_{on}	Pulse on time
RSM	Response Surface Methodology
SRW	Specimen Removal Weight
SRW	Specimen Removal Weight
SR	Surface Roughness
p_g	The best position of the group
p_j	The best position of the jth particle
TWR	Tool electrode Wear Rate
TWW	Tool electrode Wear Weight
r_i	Uniform random numbers

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