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Using an Integrated Artificial Neural Network and Heuristic Algorithms Approach for Optimization of EDM Process

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Abstract
In the present study artificial neural network (ANN) along with particle swarm optimization (PSO) and simulated annealing (SA) algorithms have been employed for modeling and optimization of electrical discharge machining (EDM) process of AISI2312 hot worked steel parts. The process input parameters considered here include voltage (V), peak current (I), pulse off time (T_{off}), pulse on time (T_{on}) and duty factor (η). The process quality measures are surface roughness (SR), tool wear rate (TWR) and material removal rate (MRR). The objective is to determine a combination of process parameters to minimize TWR and SR and maximize MRR independently (as single objective) and also simultaneously as multi-criteria optimization. The experimental data are gathered based on Taguchi L_{36} orthogonal array design of experiments. The three performance characteristics (MRR, TWR and SR) obtained from experimental tests. Then, the outputs are used to develop the artificial neural network (ANN) model. Next, in order to determine the best set of process parameters values for a desired set of process quality measures the developed ANN model is embedded into heuristic algorithms (SA and PSO) and their derived results have been compared. Validation of the results has been carried out through a series of experimental test run under the optimal machining conditions. It is evident that the proposed optimization procedure is quite efficient in modeling and optimization of EDM process parameters.

Keywords: Electrical discharge machining (EDM), Taguchi technique, Design of experiments (DOE), artificial neural network (ANN), simulated annealing (SA) algorithm, particle swarm optimization (PSO) algorithm.

Introduction
Electrical discharge machining (EDM) is the most widely and successfully applied for the machining of difficult-to-cut alloys amongst the several non-conventional processes. In EDM process, the primarily cutting mechanism is material erosion that makes use of electrical energy in the form of a series of discrete electrical discharges occurring between the two electrodes (tool and workpiece). Both electrodes are immersed in a dielectric fluid (Figure 1). The electrical energy discharges generates a channel of plasma between the workpiece electrode and the tool electrode resulting a substantial amount of heat that, in turn, melts and evaporates the material at the surface of workpiece. When the pulsating current supply is turned off, the plasma channel breaks down causing a sudden reduction in the temperature and allowing the dielectric fluid to implore the plasma channel and flush the molten material from the electrodes surfaces in the form of microscopic debris (chips). This process of melting and evaporating of the workpiece surface is in complete contrast to the conventional machining processes, as chips are not mechanically produced. This unique feature of using thermal energy to machine electrically conductive parts is its distinctive advantage in the manufacturing of molds, dies, aerospace and surgical components [1].

In EDM, like other machining processes, proper parameters setting is the key to reduce production cost and to enhance product quality. There are several input parameters in EDM, out of which the most influential ones are discharge voltage (V), peak current (I), pulse on time (T_{on}), pulse off time (T_{off}) and duty factor (η). In turn, the corresponding quality measures are material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR). 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. As a result, in recent years multi-criteria process optimization has received more attention by researchers in this field [2].

To develop appropriate EDM process models, it is required to understand how performance measures depend on input parameters. Similarly, the successful implementations of optimization methods depend on the proper establishment of relationships between input parameters and the corresponding performance measures. But the stochastic nature of such complex process as EDM makes it difficult to establish such relationships [3, 4]. The early attempts to develop physical models could not establish the relationships between input parameters and performance measures accurately as the process involves thermal, electrical and metallurgical variables. Thus, the shortcomings of physical models have led the researchers to develop experiential or data based model of EDM process. As a result, many experiential, statistical and regression modeling techniques have been used for modeling the EDM process [3, 5]. However, the regression based techniques find limited application in modeling EDM process, as these techniques do not provide reasonable results due to the high degree of nonlinearity and the presence of noise in the system variables [6].

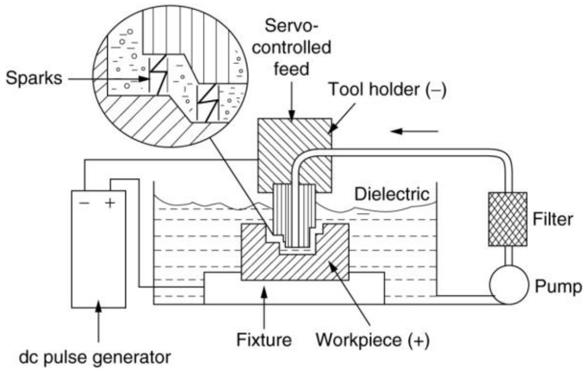

Figure 1 Schematic illustration of EDM process

In recent years, Artificial Neural Networks (ANNs) have demonstrated ample potential in modeling of the input–output relationships of complicated nonlinear systems such as EDM process. 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 of the process under consideration [7].

Along this line, BPNN models have been used by Mohana et al [8] to determine the settings of pulse on time, pulse off time, peak current and resistance for the estimation and optimization of MRR and SR. Furthermore, the effect of each input parameters on the process characteristics has been studied. Based on their results, peak current has the most influence on the two machining responses. BPNN algorithm has been developed to model the EDM process for machining of Silicon Carbide [9]. Various ANN architectures were examined and 3-5-5-2 was selected. They have optimized MRR and SR by a non-dominating sorting genetic algorithm (NSGA II). Testing results demonstrated that the model is suitable for predicting the response parameters. Bharti et al [10], have employed BPNN and controlled elitist non-dominated sorting genetic algorithm (GA) to optimize the EDM process for Inconel 718. The proposed ANN has been trained with the experimental data set. Then, the controlled elitist non-dominated sorting genetic algorithm has been used in the trained network and a set of pareto-optimal solutions was obtained. The reported results pointed out that the proposed procedure is quite capable in modeling and optimization of EDM process parameters.

As mentioned, the efficiency of ANN and heuristic algorithms to model and optimize process parameter setting of EDM process has been proved by the previous studies. This study proposes a hybrid approach composed of ANN and heuristic algorithms (SA and PSO) to undertake the single objective and multi-criteria modeling and optimization in EDM of AISI2312 hot worked steel parts. The purpose of this study is to present an efficient and integrated approach for the determination of appropriate parameters setting yielding the objective of maximum MRR and minimum SR and TWR independently and also simultaneously. Then, the results derived from heuristic algorithms has been compered. To the best of our knowledge, there is no published work to study the EDM process of AISI2312 steel through the proposed method. First, the experimental data are gathered based on L36 orthogonal array (OA) Taguchi design matrix. Then, the process is modeled using a back propagation neural network (BPNN). Finally, the BPNN models have been embedded into heuristic algorithms to determine the best set of process parameters in order to achieve maximum MRR, and minimum SR and TWR as single and multi-criteria optimization. Finally, the performance of the proposed algorithms have been compared. Moreover, the article concludes with the verification of the computational results and a summary of the major findings.

Experimental setup

The experiments were carried out on AISI2312 hot worked steel parts. The 40 × 20 mm specimens have been cut out of a plate with 10 mm thickness. Various materials such as brass, copper and tungsten alloys as well as graphite may be used as tool electrode in EDM process. Based on the literature survey conducted, copper electrodes, with 99% purity and 8.98 g/cm^3 density, were used as tools in our experiments [5]. An Azerakhsh-304H die-sinking machine, shown in Figure 2, has been employed to carry out the experiments. Table 1 illustrates the technical specification of the EDM machine tool used for conduction the experiments. The machining time for all tests was set at 45 minutes. The dielectric was pure kerosene.


Figure 2 Azerakhsh-304H EDM machine used

Table 1 Detailed technical specifications of the Azerakhsh-304h die-sinking machine

Specification	Size
Work Table Size	500×300 mm
Cross Travel Y	250 mm
Spindle Travel & Head Stock Travel	180+200 mm
Maximum Electrode weight	50 kg
Loading Capacity of Table	500 kg
Work Table Size	500×300 mm

Design of experiments (DOE)

A powerful technique used for exploring any systems or processes under study is design of experiments (DOE). This technique is mainly used for gaining knowledge of the existing processes and/or optimizing the processes quality measures. In carrying out DOE, structural and systematic changes are made to the input parameters of the system in order to observe changes in the output measures [11].

Among various DOE strategies, Taguchi technique has been widely used in various engineering applications due to its distinct advantages. With fewer number of experiments (and hence lesser cost), Taguchi can provide much useful information which, in turn, can be used for process modeling and analysis. In this study, attempt has been made to find optimum parameters of EDM process on AISI2312 hot worked steel parts to minimize TWR and SR and maximize MRR using Taguchi matrix and BPNN integrated with heuristic algorithms.

Firstly, some preliminary tests were performed to determine the stable domain of the input parameters of the process and also the different ranges of them [10]. Based on literature surveys, preliminary test results and working characteristics of the EDM process, peak current (I), voltage (V), pulse off time (T_{off}), pulse on time (T_{on}), and duty factor (η) were chosen as the independent input parameters. During these experiments, by altering the values of the input parameters to different levels, stable states of the machining conditions have also been specified. Preliminary experiments were performed for the wide range of pulse-on-time, discharge current and gap voltage. Reasonable results were obtained for 6-30A, range of peak current. Below 6A, MRR was very low and beyond 18A, MRR was good but SR was very poor. Similar observations were made for specified range of pulse on and off time, gap voltage and duty factor. Therefore, L_{36} (21×34) design of experiments matrix has been used to carry out experiments. The limitations of test equipment may also dictate a certain number of levels for some of the process parameters. In our case, the die-sinking EDM machine used for experiments had only two settings for pulse off time - T_{off} (10 and 75 μs).Out of five, one factor has 2 levels and the rest of the factors have 3 levels each. Consequently, this study has been carried out to investigate the effects of peak current (I), voltage (V), pulse off time (T_{off}), pulse on time (T_{on}), and duty factor (η) on material removal rate (MRR) tool wear rate (TWR) and surface roughness (SR). Table 2 lists the machining parameters and their corresponding levels.

Table 2 Machining parameters and levels

parameters	Range	Level 1	Level 2	Level 3
peak current (A)	6-30	6	18	30
Voltage (V)	50-60	50	55	60
pulse on time (μs)	25-200	25	100	200
pulse off time(μs)	10-75	10	75	-
duty factor (S)	0.4-1.6	0.4	1	1.6

Evaluation of the process quality measures

In this study MRR, SR, and TWR are used to evaluate EDM machining process of AISI2312 hot worked steel parts. These measures of performance are calculated as follows [11]:

Material removal rate (MRR) is a measure of machining speed and is expressed as the work piece removal weight (WRW) in a predetermined machining time (MT) in minute.

$$\mathrm{MRR} = \frac{\mathrm{WRW}}{\mathrm{MT}} \tag{1}$$

The TWR, usually expressed as a percentage, and is defined by the ratio of the tool wear weight (TWW) to the workpiece removal weight (WRW) which is obtained using Equation (2).

$$\mathrm{TWR}(\%) = \frac{\mathrm{TWW}}{\mathrm{WRW}} \times 100 \tag{2}$$

In machining processes, surface quality is usually measured in terms of surface roughness (SR). The average roughness (Ra) is the area between the roughness profile and its mean line, which is defined by Equation (3).

$$\mathrm{Ra} = \frac{1}{L}\int_0^L \left| Z(x) \right| \, dx \tag{3}$$

In the above, Ra is the arithmetic average deviation from the mean line, L the sampling length, and Z(x) is the ordinate of the profile curve.

Table 3, shows the L_{36} experimental design matrix and their corresponding results.

Table 3 The L_{36} experimental design matrix and results

No	V(V)	η (sec)	I(A)	Ton (μs)	Toff (μs)	MRR (gr/min)	TWR (%)	SR (μm)
1	1	1	1	1	1	0.0078	11.4	3.9
2	2	2	2	2	1	0.0676	2.6	7.1
3	3	3	3	3	1	0.1487	0.6	13.5
4	1	1	1	1	1	0.0073	9.0	3.2
5	2	2	2	2	1	0.0462	3.3	6.9
6	3	3	3	3	1	0.1520	0.4	12.7
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
30	1	1	2	3	2	0.0424	0.5	11.6
31	3	3	3	1	2	0.0349	42.0	4.9
32	1	1	1	2	2	0.0098	2.3	6.3
33	2	2	2	3	2	0.0947	0.7	8.8
34	2	1	3	1	2	0.0189	47	4.9
35	3	2	1	2	2	0.0142	1.6	5.5
36	1	3	2	3	2	0.1140	0.2	9.8

Model development - back propagation neural network (BPNN)

Traditional modeling methods are mostly relied on assumptions for model simplifications, and consequently may lead to imprecise results. Recently, ANN has become a powerful and useful method to model complex non-linear systems. The basis of ANN modeling is to capture the underlying trend of the data set presented to it, in the form of a complex nonlinear relationship between the input parameters and the process quality measures. Learning, generalization, and parallel processing are important advantages of ANN that make them suitable for EDM process modeling.

ANNs are built by connecting processing units, called nodes or neurons. Each of the input (X_i) is associated with some weight (W_i) which takes a portion of the input to the node for processing. The node combines the inputs (X_iW_i) and produces net input which in turn is transformed into output with the help of transfer function/activation function.

Many researchers have proposed that multilayered networks are capable of computing a wider ranges of nonlinear functions than the networks with a single layer [9-10]. However, the computational effort needed for modeling a system increases substantially when 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 process quality measures in order to learn.

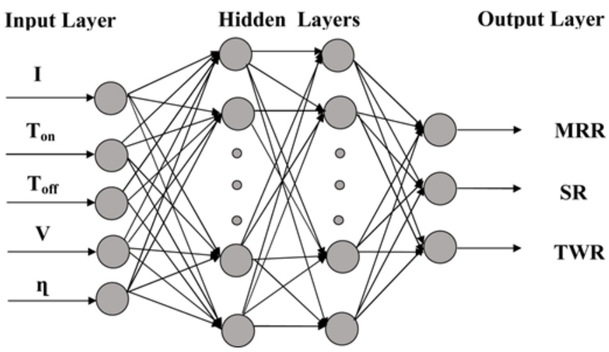

Figure 3 Architecture of proposed artificial neural network used for single objective modeling

Simulated annealing algorithm

Simulated annealing (SA) algorithm, first proposed by Kirkpatrick in 1983, is an optimization process whose operation is strongly reminiscent of the physical annealing of crystalline compounds such as metals. In condensed matter physics, annealing is a physical process that is used to reconstruct the crystal structure of a solid with a low energy state. In annealing process a metallic part is first heated up to a temperature close to its melting point. At this temperature, all particles of the solid are in violent random motion. The temperature of the part is then slowly lowered down so as the atoms rearrange themselves toward low energy state. As the cooling of the particle is carried out sufficiently slowly, lower and lower energy states are obtained until the lowest energy state is reached.

A standard SA procedure begins by generating an initial solution at random. At initial stages, a small random change is made in the current solution. Then the objective function value of new solution is calculated and compared to that of the current solution. A move is made to the new solution if it has better value or if the probability function, implemented in SA, has a higher value than a randomly generated number.

Simulated annealing algorithm has diverse applications in various engineering problems [8, 9]. In this study SA algorithm has been used in the optimization of EDM process parameters. In this stage, the proposed ANN model is implanted into a SA procedure to find the optimal set of EDM process parameters in order to maximize the MRR and minimize the TWR and SR simultaneously.

Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) algorithm is a population based stochastic optimization procedure developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of birds flocking [9]. The optimization process is initialized with a population of random solutions and searches for optima by updating generations. The potential solutions named particles fly through the problem space by following the current optimal particles. PSO algorithm is implemented easily and there are few parameters to adjust. The algorithm can be illustrated 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 [10]. So the best approach to achieve 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. In all the iterations, each particle is updated by following two 'best' values. The best solution achieved so far among the particle is called as 'particle best' termed as pbest and the best solution obtained so far in the population are called as 'global best' termed as gbest.

EDM process optimization results

Single objective optimization

In this section, the developed BPNN model has been embedded into SA and PSO algorithms to maximize MRR and minimize TWR and SR independently. The results of optimization has been shown in Table 4.

Table 4 Result of single objective optimization

Output	Algorithm	Parameters					Predicted	experiment	Error (%)
		I	η	T_{off}	T_{on}	V			
MRR	SA	27	1.6	12	200	50	0.27	0.26	3.8
MRR	PSO	30	1.6	10	200	50	0.27	0.26	3.8
SR	SA	8	0.4	71	25	60	2.82	2.71	4.0
SR	PSO	6	0.4	75	25	60	2.80	2.8	2.7
TWR	SA	6	1.4	32	200	60	0.123	0.126	2.4
TWR	PSO	6	1.5	29	200	60	0.120	0.116	3.4

Multi-criteria optimization

As these objectives (MRR, TWR and SR) are conflicting, they have been converted into a single measure for multi-criteria optimization. To maximize MRR and minimize TWR and SR, the process parameters values should be found in such a way that minimize the following equation.

$$
\begin{aligned}
&\text{Minimize} \quad f\,(I,\ T_{on},\ T_{off},\eta,\ V) = W_1TWR + W_2SR - W_3MRR \\
&\text{Subjected to} \\
&6 \le I \le 30 \\
&25 \le T_{on} \le 200 \\
&10 \le T_{off} \le 75 \\
&0.4 \le \eta \le 1.6 \\
&50 \le V \le 60
\end{aligned}
\qquad (4)
$$

Where, W_1, W_2 and W_3 are the weights considered for TWR, SR and MRR respectively.

The algorithms were run from different starting points and with various parameters settings. The best results obtained from the optimization procedure are reported in Tables 5 and 6.

In complementary section, in order to evaluate the accuracy of the predicted values, a set of experimental experiment was carried out based on the optimized process parameters. Moreover, the obtained experimental responses derived from SA and PSO algorithms were compared. The results which are presented in Tables 5 and 6 for equal (0.333) and different (0.75) weighing of each process characteristics, show that the hybrid model can improve quality characteristics of the process.

Table 5 Optimal EDM parameters and corresponding process quality measures for equal weighing

Output	Algorithm	Parameters					Predicted	experiment	Error (%)
		I	V	T_{on}	T_{off}	η			
MRR	SA	19	53	118	33	1.2	0.243	0.236	2.9
SR	SA						3.70	3.57	3.6
TWR	SA						0.19	0.20	5
MRR	PSO	22	54	129	39	1.2	0.249	0.240	3.75
SR	PSO						3.80	3.60	5.55
TWR	PSO						0.20	0.19	5.26

Table 6 Optimal EDM parameters and corresponding process quality measures for 75% weighing for each output

Output	Algorithm	Parameters					Predicted	experiment	Error (%)
		I	V	T_{on}	T_{off}	η			
MRR	SA	22	50	200	43	1.3	0.25	0.242	5.7
MRR	PSO	22	50	200	41	1.3	0.25	0.248	3.2
SR	SA	9	58	95	53	0.7	2.9	2.8	3.4
SR	PSO	8	57	95	56	0.7	2.9	2.8	3.4
TWR	SA	18	56	176	51	0.96	0.17	0.18	5.5
TWR	PSO	18	57	182	50	1	0.16	0.15	5.0

Figure 4 illustrates the convergence trends for the heuristic algorithms used for TWR (W1=0.75 and W2=W3=0.125). By the same token, Figures 5, 6 and 7 show the convergences of the proposed algorithms for SR (W2=0.75 and W1=W3=0.125), MRR (W3=0.75 and W1=W2=0.125) and the equal weighing (W1= W2=W3=0.33) corresponding. As shown, PSO converges quicker than SA. However, the optimized values are approximately the same. The termination factor has been considered time (30 sec).

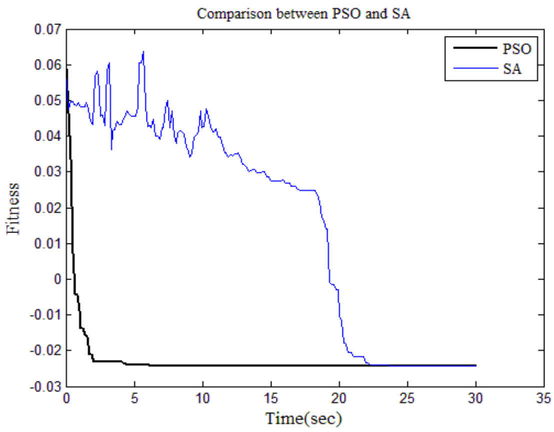

Figure 4 convergence of the heuristic algorithms for TWR (W1=0.75)

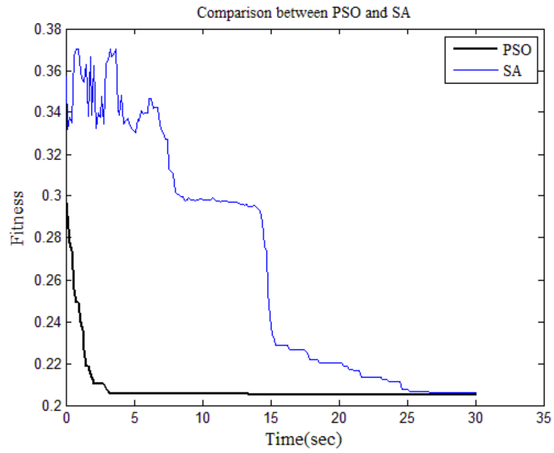

Figure 5 convergence of the heuristic algorithms for SR (W2=0.75)

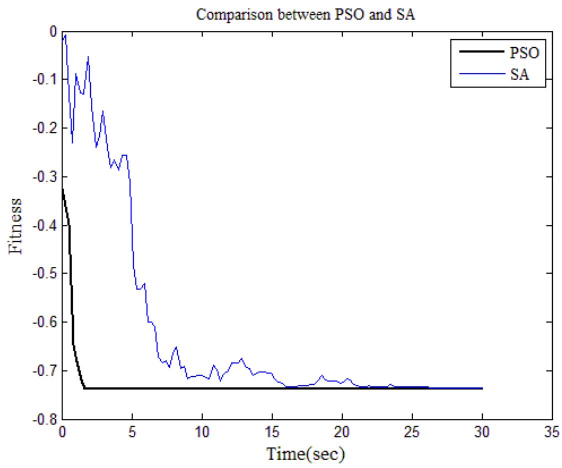

Figure 6 convergence of the heuristic algorithms for MRR (W3=0.75)

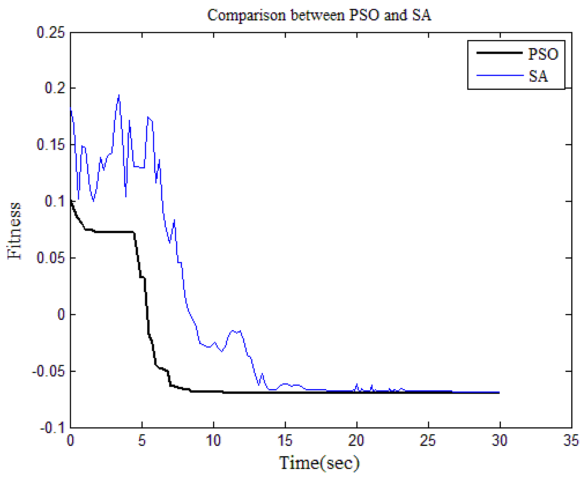

Figure 7 convergence of the heuristic algorithms for the equal weighing (W1= W2= W3= 0.333)

Conclusions

The selection of process parameters levels is significantly affects the quality of final product in EDM. On the other hand, the interactions of these parameters call for simultaneous selection of their optimal values. In this research the problem of modeling and multi-criteria optimization of EDM for AISI2312 hot worked steel alloy has been addressed. The process modeling has been carried out using experimental data gathered as per L36 Taguchi design matrix. First, to combine three important process characteristics including material removal rate (MRR), surface roughness (SR) and tool wear rate (TWR), into an equally weighed single measure; called weighted normalized grade (WNG). Next, the back propagation neural network (BPNN) was developed to establish accurate relationships between input process parameters and multiple performance characteristics. In the next stage, the developed BPNN model has been implanted into heuristic algorithms (SA and PSO) algorithms to find the optimal set of EDM process parameters in order to maximize MRR and minimize SR and TWR independently and simultaneously. Then, the algorithms performances have been compared. The derived results manifests that the performance for both algorithms in single objective optimization are approximately the same. Furthermore, the results of the optimization illustrates that the PSO algorithm converges quicker than the SA algorithm.

The proposed modeling and optimization approach, with minor changes, can be applied to other manufacturing process. The study can also be extended using other modeling methods like response surface methodology (RSM), and other heuristic algorithms such as genetic algorithm (GA) and etc.

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