Chapter

Nature Inspired Metaheuristic Approach for Best Tool Work Combination for EDM Process

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Abstract

As the modern day, the technologies are approaching with high accuracy at the same time with low material costing, non-traditional machining is very much essential to sustain in this modern manufacturing system. In this present research work Electric Discharge Machining (EDM) is used with different types of tools like Copper, Aluminium, and Brass are used while machining High Carbon High Chromium (HCHCr), Hot Die Steel (HDS) and Oil Hardened Nitride Steel (OHNS) workpiece material. This research work is aimed to find out the most efficient tool material for different workpiece materials while satisfying the contradictory objectives of high material removal rate (MRR) and low Tool Wear Rate (TWR). The experimental data are trained and validated by using Artificial Neural Network (ANN). Finally, the results obtained through Genetic Algorithm are hybridized with a Fuzzy- Multi Criteria Decision Making (MCDM) technique to obtain a single parametric combination of the process control parameters which satisfies these two contradictory objectives function simultaneously.

Keywords: EDM, ANN, Genetic Algorithm, Fuzzy, MDCM

1. Introduction

The progressive growth in the advanced manufacturing process is aimed to achieve a finished material with a complex shape having very high accuracy. This precise manufacturing leads the industries to modern non-traditional machining processes. Electric Discharge Machining (EDM) is one such wieldy used non-traditional machining, where material removal takes place by the control erosion through spark discharge from the cathode tool on the anode workpiece. The conductive tool and the workpiece are submerged in flowing dielectric fluid and are separated by a small gap, known as a spark gap. The temperature of the spark varies from 8000°C to 12000°C which melts and vaporizes the workpiece material instantly. This electric discharge process is used to manufacturing complex part of a metal mould, tool and die, industrial instruments, aerospace's instruments, etc. The main advantage of EDM is that this process can machine hard material accurately [1]. EDM is a complex machining process which depends upon several interrelated control parameters; hence it is important to find an optimal control parameter setting so that the machining can be optimized for a better output. In the modern era, the optimization techniques are mostly nature inspired metaheuristics process. Artificial Neural Network (ANN) is one such nature-inspired technique where the results are trained, validated and finally tested within an artificial network. In 1940, D.O. Hebb first introduced neural plasticity-based learning and then finally backpropagation is developed by Werbos in 1975 [2].

Previous research works which have been carried out to optimize the process control parameters either analytically or by simulation is presented here. Bose and Pain [3] have studied the effect of EDM on different types of tool material used in plastic industries and they have concluded different process control parameters for different material. Ho and Newman [4] have experimented on different types of an electric spark in EDM and have designed a simplified electrode to increase the performance index of the process. Zhou et al. [5] studied on minimum variance and pole placement coupled controller along with two-step prediction controllers to stabilize the machining in EDM. Equbal and Sood [6] have discussed the various parameters of the EDM process. They have also elaborated the future scope of EDM in industries. Choudhary and Jadoun [7] has experimented various types of EDM fluid in order to optimize machining productivity. They have developed die-sinking EDM, dry EDM, powder mixed EDM and also water-based EDM process. Abulais [8] has researched on various types of EDM like ultrasonic vibration dry EDM, powder-based EDM, and also used water as the dielectric fluid. Lin et al. [9] used Grey Neural Network on EDM and verified that the data are very similar to the actual experimental result. Ni [10] has discussed the various type of application of the Artificial Neural Network (ANN) in various uneasy condition and achieved a key technology for this application.

The experimental results are optimized by Genetic Algorithm (GA). Contradictory responses during machining like high Material Removal Rate (MRR) and low Tool Wear Rate (TWR) can be optimized by applying Fuzzy- Multi-Criteria Decision Making (MCDM) techniques. The objective of this research work is to identify the best tool work combination which will satisfy the contradictory responses of high MRR and low TWR.

2. Experimental design

The present research study is done on the Die Sinking EDM (Electronica make). In this research work the workpiece material, tool material, current and pulse on time (POT) are varied simultaneously. The tools considered here are Copper, Aluminum, and brass. While the workpiece material used are High Carbon High Chromium (HCHCr) steel, Hot Die Steel (HDS) and Oil Hardened Nitride Steel (OHNS). During experimentation, the current is varied in three levels as 10 amps, 15 amps and 20 amps and the Pulse on Time (POT) are varied in three levels as 800 μsec, 1600 μsec, and 2000 μsec respectively. Other parameters which have a significant effect on the process are kept constant. Here kerosene is used as the dielectric fluid, voltage is kept at 85 Volts, pulse off time is set at 800 μsec, depth of cut considered is 2 mm and spark gap is 5 mm. During the experimental run, various parameters are varied simultaneously by following the L9 Orthogonal Array (OA) so that the experimental time and as well as experimental cost can be reduced to a great extent. To analyze the data statistically the tool materials and also workpiece materials are expressed by their respective density as in **Table 1**.

From the experimental run the regression equitation is obtained for the MRR, where a1, b1, c1 and d1 are constant terms:

$$\begin{aligned} MRR = {} & a1 + b1 * \text{Tool Density} + c1 * \text{W/P Density} + d1 * \text{Current} + e1 * \text{POT} \\ & + f1 * \text{Machining Time} \end{aligned} \tag{1}$$

Materials	Symbols	Density (g/cm^3)
Tool Materials	Cu	8.96
	Al	2.78
	Br	8.73
Work Materials	HCHCr	7.7
	HDS	7.75
	OHNS	8.67

Table 1.
Density of the tool and workpiece materials.

From the same experimental run Tool Wear Rate (TWR) is obtained where a2, b2, c2 and d2 are constant terms:

$$\begin{aligned} \text{TWR} = {} & \text{a2} + \text{b2} * \text{Tool Density} + \text{c2} * \text{W/P Density} + \text{d2} * \text{Current} + \text{e2} * \text{POT} \\ & + \text{f2} * \text{Machining Time} \end{aligned} \tag{2}$$

Here Artificial Neural Network (ANN) is utilized to test and validate the experimental data. Then the responses Material Removal Rate (MRR) and Tool Wear Rate (TWR) are optimized by Genetic Algorithm (GA) in 'MATLAB R2015a' environment. The global optimal solution is then calculated by the Multi-Criteria Decision Making (MCDM) technique by applying Fuzzy set theory. Finally, the calculated data are analyzed by actual experimentation to validate the final result.

3. Artificial Neural Network

Artificial Neural Network (ANN) is the replica of the actual neural network system and there working principle is quite similar to the biological neural network [11]. Outer nodes collect the input responses. The other nodes are inter-connected, and finally, nodes give the responses to the input responses. In a neuron, there are synapses, they multiply each input by the weighted value, only if this value receded the threshold value, then these responses transfer to the next neuron. The interconnected inner layer of the neuron is known as a hidden layer. Eq. (3) shows the input calculation for each hidden layer of the neuron.

$$\mathrm{I}I_i = \sum_{i-1}^{n} W_i X_i \tag{3}$$

The output responses are defined by sigmoid function as shown in Eq. (4).

$$O_i = f(I_i) = \frac{1}{1 + e^{-I_i}} \tag{4}$$

The working principle of an artificial neuron is shown in **Figure 1**.
There are generally three types of architectures in case of Neural Network.

- Feedforward-neural networks
- Feedback-neural networks

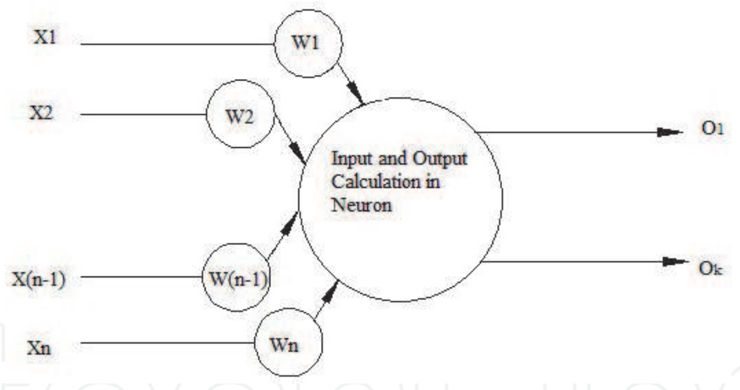

Figure 1.
Schematic diagram of an artificial neural.

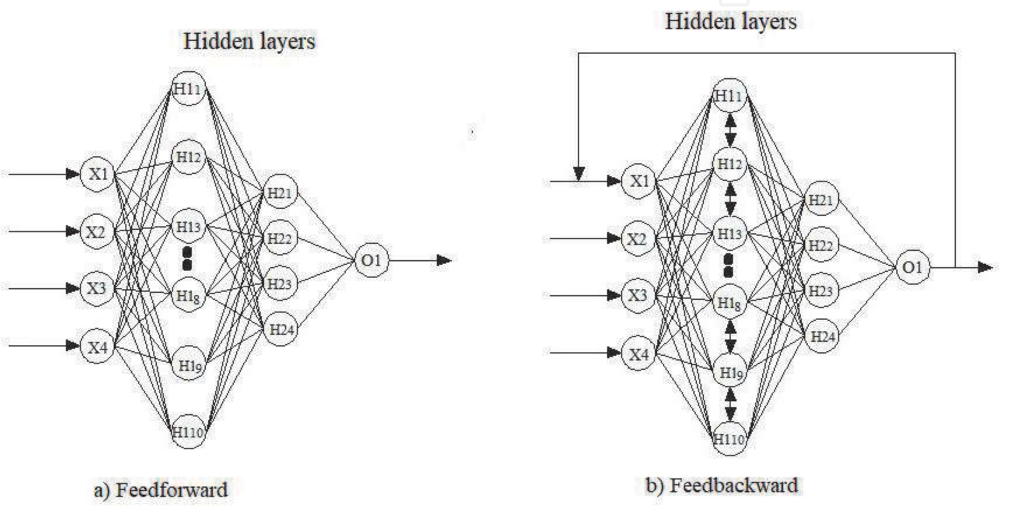

Figure 2.
The architecture of general ANN.

- Self-organizing-neural networks

Figure 2 displays the general structure of ANN.

3.1 Analysis of the experimental result

In this research work, the analysis of the experimental results is analyzed by dividerand function, in using Matlab R2015a. The backpropagation method is used in this analysis because this backpropagation method gives the feedback while training the data for calculation. The individual responses are evaluated using the Simulink model in ANN considering all those five parameters. Also, ten number of hidden layers are used to optimize the responses. **Figure 3** shows the Simulink diagram used in ANN.

In ANN responses are trained then validated and finally tested to find out that is there any linear relationship between control parameters and responses. The continuous line is the best fit linear regression line of output versus targets. While the value of regression (R) is 1 represents the linear relation between control and response parameters.

3.1.1 Analysis to maximize MRR

For calculating 50%, 25% and 25% of the date have been used for training, testing and validation, respectively. MSE has been achieved after 5 successful

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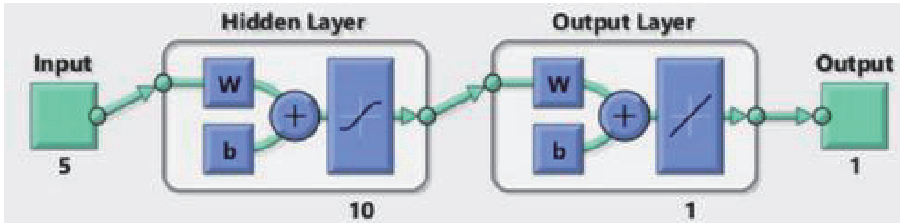

Figure 3.
Simulink diagram of ANN.

iteration and as a result the training has been terminated. It has been programmed in such a way that in case the gradient falls below 1.00×10^{-7}, the training will terminate. In this experiment the gradient is 5.01×10^{-8}. Here the number of successive iterations performed for validation checks is 2. **Figure 4** represents the neural network training performance progress.

Best validation performance is 5.0748×10^{-7} at epoch 3, which is a low prediction error measured with MSE shown in **Figure 5**. This graph does not show any main problems with the training. The validation and test curves are very similar to each other up to 3 epochs.

In this case, the values of R for training, testing and validation are 0.85099, 1 and 1, respectively. So, from the **Figure 6** it is evident that the value of overall R is 0.77755. As the values of R for validation and testing both has the values more than 0.9 the training shows a good result.

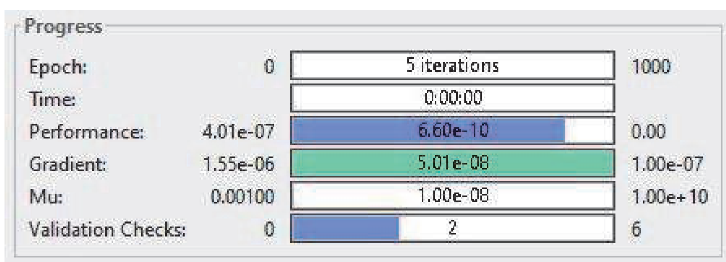

Figure 4.
Training performance progress for MRR.

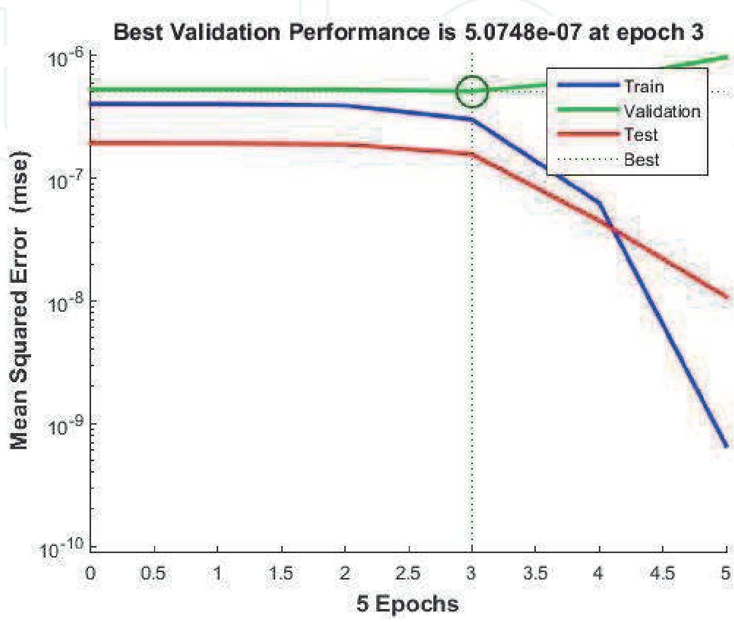

Figure 5.
Performance plot for MRR.

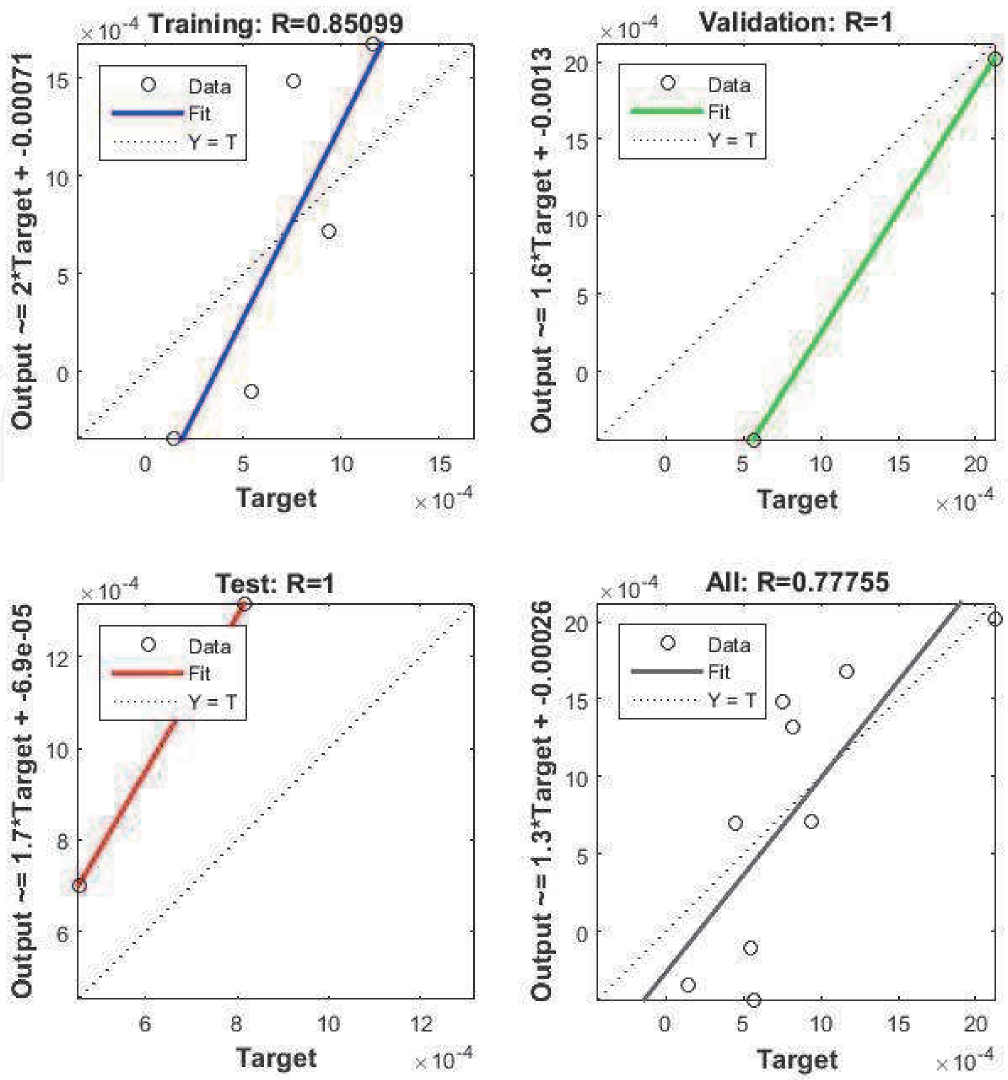

Figure 6.
Regression plot of MRR.

3.1.2 Analysis to minimize TWR

For calculating 55%, 25% and 20% of the date have been used for training, testing and validation, respectively. MSE has been achieved after 4 successful iteration and as a result the training has been terminated. It has been programmed in such a way that in case the gradient falls below 1.00x10^{-7}, the training will terminate. In this experiment the gradient is 7.63x10^{-8}. **Figure 7** represents the neural network training performance progress.

Best validation performance is 206859x10^{-5} at epoch 4, which is a low prediction error measured with MSE shown in **Figure 8**. This graph does not show any main problems with the training. The validation and test curves are very similar to each other.

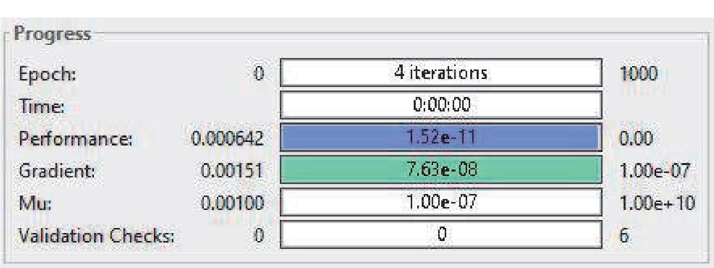

Figure 7.
Training performance progress for TWR.

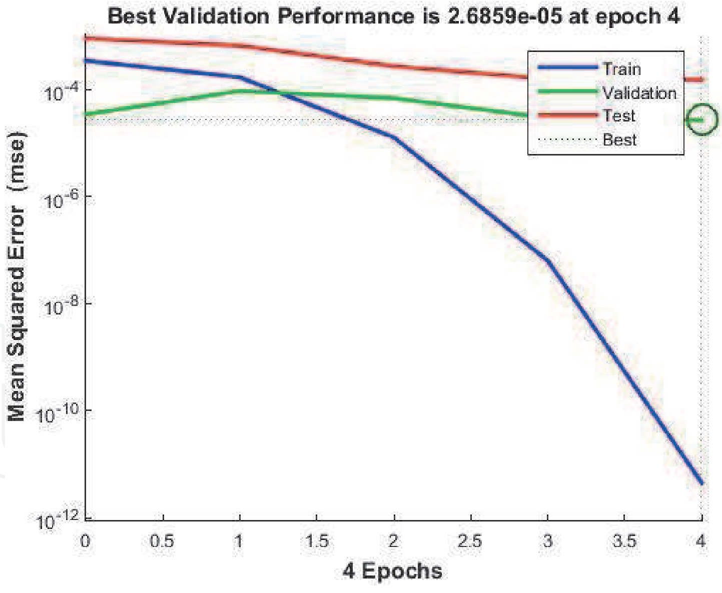

Figure 8.
Performance plot for TWR.

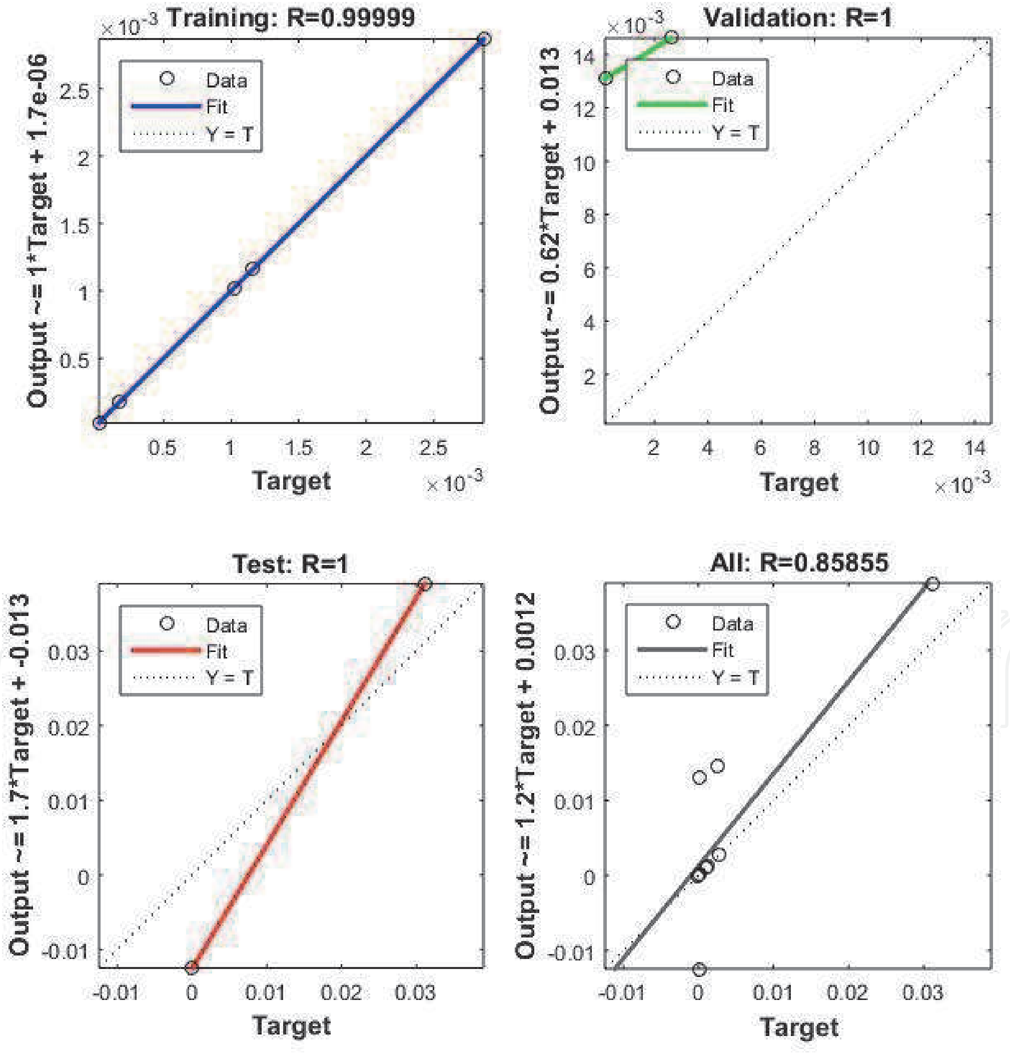

Figure 9.
Regression plot of TWR.

In this case, the values of R for training, testing and validation are 0.99999, 1 and 1, respectively. From the **Figure 9**, the value of overall R is 0.85855. As the values of

R for validation and testing both has the values more than 0.9 the training shows a good result.

4. Genetic Algorithm (GA)

Genetic Algorithm is a similar approximation method as survival of the fittest. This nature-inspired metaheuristic process follows some fundamental rules [12].

- Every living being in any ecosystem struggle for food and mates.
- Those victorious individuals will compete and fittest offspring will be produced. Those individuals also are known as 'King' in the system.
- A good individual will reproduce again and again and will survive in nature for a long time than those week individuals.

Each fitness functions are considered as individual chromosome and they are the various sequence of binary alphabets (1 and 0). This algorithm is very useful to find out the global solution to a problem set.

On average, better new generations are formed with better genes. Every successive generation will have a 'partial better solution' than the previous generations. Ultimately, when the newly created offspring does not have a noticeable difference from the previous generations, then the algorithm will terminate at a converged solution.

4.1 Results using the Genetic algorithm

It has been aimed to find out the single parametric combination for this contradictory parameters by using multi-response optimization. In order to find out the two contradictory parameters like high MRR and low TWR. The boundary condition for this genetic algorithm is used as follows:

- Population

  Population type: Double vector

- Stopping Criteria

  Generations: 100 x number of variables

  Time limit: infinity

  Stall generations: 100

  Function tolerance: $1x10^{-4}$

  Constrain tolerance: $1x10^{-3}$

Here the total number of iterations required for optimization is 127 and which gives 16 combinations for the control parameters along with responses. Optimization terminated as the average change in the spread of Pareto solutions has been reached to its tolerance value. Based on the conflicting nature of the objectives, multi-response optimization is carried out in order to achieve the goal by a single parametric combination. As the EDM process is complex machining, it can have two general situations while it is used for commercial purposes. In one case the

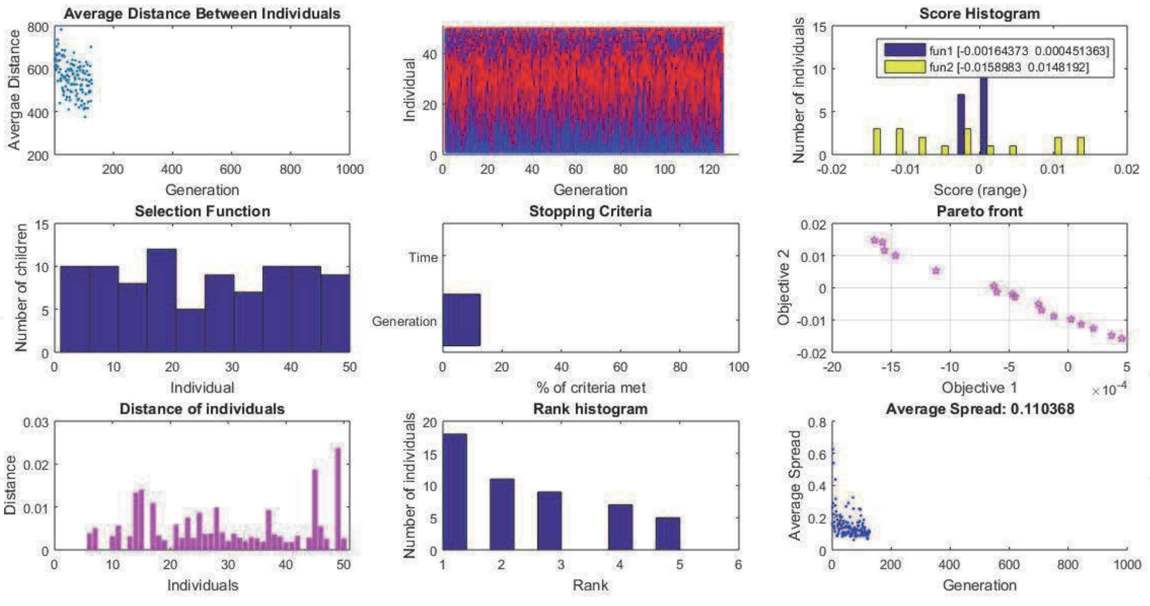

Figure 10.
Plot functions for GA.

primary objective is to achieve maximum MRR. It can be used for rough cutting. In another case for finishing operation, more emphasis should be given on TWR instead of MRR. In this condition, the tool wear can highly affect the final geometry of the product. As the genetic algorithm is generally subjected to minimizing the function, so in the case of maximizing the MRR the negative sign have been neglected. In **Figure 10** the two contradictory objectives are simultaneously optimized by using GA have been plotted. From this plot, the boundary condition for

Exp. No	Tool Density (g/cm^3)	W/P Density (g/cm^3)	Current (Amp)	POT (μSec)	Machining Time (min)	MRR (cm^3/min)	TWR (gm/min)
1	4.5	15.90	88.58	864.64	101.16	1045.33	1216.031
3	16.4	14.82	89.36	771.19	198.54	1436.91	149.4018
4	0.2	9.78	87.15	859.08	126.59	1100.34	961.2881
5	15.7	14.17	86.24	783.69	199.16	1437.78	149.4643
6	15.6	11.71	88.01	774.51	194.3	1167.08	185.9447
7	2.2	7.04	86.72	826.90	158.6	1074.93	1057.663
8	4.5	2.85	88.46	819.28	151.4	1201.48	827.6156
9	2.5	5.09	88.50	828.50	102.9	1145.31	683.333
10	6.3	0.67	88.23	800.79	119.1	1233.71	531.6255
11	2.1	12.68	88.31	849.67	123.3	1070.92	1178.077
12	6.0	1.13	88.41	828.16	150.9	1154.8	633.3167
13	4.7	1.85	88.44	814.21	158.9	1305.47	875.2726
14	1.1	11.47	88.40	860.27	129.6	1072.24	1070.531
15	3.7	14.69	88.50	863.51	101.2	1049.99	1138.689
16	11.2	5.36	88.51	786.64	175.8	1111.97	461.5821
17	1.2	8.81	88.59	851.90	158.6	1074.93	1057.913

Table 2.
Combination of factors and responses.

MRR and TWR can be found out. For MRR the range is between 1045.3295 cm^3/min to 1437.789 cm^3/min and for TWR, it varies between 149.402 gm/min to 1216.031 gm/min respectively. Therefore, in order to arrive at an optimal or near optimal parametric combination which will consecutively satisfy the contradictory nature of the responses Fuzzy Gray Relational Analysis is conducted.

The different parametric combinations with respective responses as obtained through GA are shown in **Table 2** below.

5. Multi objective solution using Grey Relation Analysis (GRA)

GRA can be employed to simultaneously find out the optimized solution for several contradictory responses [13]. This theory has been proposed by Deng in 1982's [14]. In modern research work, this theory is a very essential tool to design the model for the unknown of partially known or unspecified data.

GRA form the link between preferred (best/ideal) with real investigational data. The average of the grey coefficient is used to estimate the grey grade. This grade is generally varies between 0 and 1. When the value is close to 1, it signifies that the solution approaches the ideal condition. In the final acquired data set the parametric combinations which have the maximum grey relation grade, that combination will be termed as the optimized solution.

The normalized equation for the condition where the maximum value is required, like MRR that can be expressed as:

$$X_{ij} = \frac{Y_{ij} - Min\left[Y_{ij}, i = 1, 2, \ldots \ldots n\right]}{Max\left[Y_{ij}, i = 1, 2, \ldots \ldots n\right] - Min\left[Y_{ij}, i = 1, 2, \ldots n\right]} \tag{5}$$

If lower value for the better performance such as TWR then it is expressed as,

$$X_{ij} = \frac{Max\left[Y_{ij}, i = 1, 2, \ldots \ldots n\right] - Y_{ij}}{Max\left[Y_{ij}, i = 1, 2, \ldots \ldots n\right] - Min\left[Y_{ij}, i = 1, 2, \ldots n\right]} \tag{6}$$

To find out the single solution for these two contradictory processes the GRA is performed. When the grey grade is 1, that solution gives the optimized single parametric combination.

6. Fuzzy set theory

To find out the ambiguous solution in decision-making problem, the Fuzzy set theory can be used as a powerful tool. Instead of using numerical values, assign of weights for linguistic assessment is more useful [15]. During the consideration of the decision makers' fuzzy rating, fuzzy decision matrix can be achieved from a decision matrix and finally it can be converted into weighted normalized fuzzy decision matrix. A fuzzy set can be described by a membership function $\mu_{\hat{d}}(x)$ while converting X. A degree of membership of x in $\hat{d}$ can be plots individual element x in X to a real number in the period of 0 to 1. In this case triangular fuzzy number (TFN), can be defined as a triplet (d1, d2, … , dn) and the membership function is defined [16].

The translation method of fuzzy number into the non-fuzzy number, that is, a crisp value is identified as defuzzification. In this current research work 'centroid of area' technique for defining Best Non-Fuzzy Performance (BNP) value is applied.

7. Multi-criteria decision making (MCDM) analysis

In this chapter the two contradictory responses i.e. MRR and TWR have got a dissimilar level of rank. In this case the maximized MRR is the primary objective rather than the lower TWR.

Table 3 is tabulated by using the weightage from the fuzzy set theory.

The closed value to the 1 gives the ideal solution between the comparative sequences. In this case, 16 simulated data from the genetic algorithm have been used for further evaluation. In this case, the criteria for decision making have been set as Maximum MRR and minimum TWR.

7.1 Optimization of the parameters

The specified weights for MRR and TWR are 84.4% and 15.6% respectively as calculated by using Entropy method [17]. **Table 4** represents the grey relation coefficient and grades corresponding to parametric settings and responses for the material in **Table 2**.

Criteria	Linguistic terms	Fuzzy number	BNP
MRR	VH	0.9,1.0,1.0	0.844
TWR	ML	0.1,0.3,0.5	0.156

Table 3.
Weight criteria for deference responses.

Exp. No	Responses		Grey Co-efficient		Grey Grade	Rank
	MRR (cm^3/min)	TWR (gm/min)	MRR (cm^3/min)	TWR (gm/min)		
1	1045.330	1216.031	0.458	0.135	0.296	16
2	1436.914	149.402	0.997	1.000	0.999	2
3	1100.345	961.288	0.495	0.170	0.333	10
4	1437.789	149.464	1.000	1.000	1.000	1
5	1167.082	185.945	0.550	0.820	0.685	3
6	1074.937	1057.663	0.477	0.155	0.316	11
7	1201.488	827.616	0.584	0.197	0.390	8
8	1145.313	683.333	0.531	0.238	0.384	9
9	1233.717	531.626	0.619	0.303	0.461	4
10	1070.928	1178.077	0.474	0.139	0.307	14
11	1154.800	633.317	0.539	0.256	0.398	7
12	1305.472	875.273	0.715	0.186	0.451	5
13	1072.248	1070.531	0.475	0.153	0.314	13
14	1049.991	1138.689	0.461	0.144	0.302	15
15	1111.972	461.582	0.504	0.348	0.426	6
16	1074.937	1057.913	0.477	0.155	0.316	12

Table 4.
Grey relation co-efficient along with grades and ranks.

Settings Levels	Predicted result	Experimental result
MRR	1437.789	1385.74
TWR	149.464	256.84
Grey Grade	1.000	0.736
Improvement of the grey relation grade: 0.264		

Table 5.
Results of machining performance using the initial and optimal machining parameters.

Grey relation coefficient, relation grade, and the ranks have been displayed in **Table 4**. From this table, it is obvious that the experimental run number 4 has achieved maximum gray relation grade. As has been discuses earlier, this experimental run satisfies the condition for the optimized multi-response parameter. So, experiment 4, which have parametric combination Tool Density 15.7 g/cm^3, Workpiece density of 14.17 g/cm^3, Current 86.24 amp, POT 7836.89 μSec, and Machining time of 199.16 min is the best parametric combination for having high MRR and low TWR.

The confirmation experiment performed with the above optimal combination results in grey relational grade MRR and TWR is obtained as 1385.75 cm^3/min and 256.84 gm/min respectively. It is observed that MRR and TWR improve significantly by using optimal machining variables combinations. **Table 5** shows the validation results while machining at optimizing condition.

8. Conclusion

The experimental study indicates that while machining different workpieces like HCHCr, HDS, and OHNS using different EDM tools like Cu, Al, and Br, the responses are dependent on tool material, workpiece material, pulse on time, and machining time. While analyzing the response data individually applying, ANN considering four control parameters in order to achieve maximum MRR and minimum TWR the training, validation, and testing data indicates that the values of R, are almost 1.

A multi-objective response is developed which is optimized using GA. Since the objectives of the responses are contradictory in nature, therefore, using GA the optimum values of responses are obtained within a range. In the case of MRR varies from 1045.3295 cm^3/min to 1437.789 cm^3/min and TWR varies between 149.402 gm/min to 1216.031 gm/min respectively.

The GRA establishes the ranks of output for different variables combinations and establishes optimal combinations for a complex process like EDM process. For evaluating the optimum parametric combination during machining her Tool Density of 15.7 g/cm3, Workpiece density of 14.17 g/cm^3, Current of 86.24 amp, POT of 7836.89 μSec and Machining time of 199.16 min is the best among all the other combinations for having high MRR and low TWR. If any tool material and workpiece have the exact tool density as obtained from the GA that will give the best tool and workpiece combination for machining. As our research is limited to the three types of tool material and three types of the workpiece material, hence it can be concluded that Cu is the best tool for machining OHNS workpiece material by EDM when 20 amp current and POT is 800 μSec.

Therefore, this experimental analysis for estimating the optimum EDM parametric combination during machining with a different tool and work materials can act as valuable and an effective guideline for machining of die and mould.

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