MODELING ELECTRICAL DISCHARGE MACHINING PROCESS USING ARTIFICIAL NEURAL NETWORK FOR THE MACHINING OF SPECIAL STEEL WP7V

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Abstract

Electrical discharge machining (EDM) is a process for shaping hard conducting materials and forming intricate shaped holes by spark erosion. The special steel WP7V are highly promising materials for the applications in many steel industries for making various accessories like high wear loaded dies with flat impression, hot & cold shear knives, cutting sheet, highly stressed punches, profiling rolls and EDM is one of the most commonly used manufacturing processes for making intricate impression in any hard conducting materials. From literature review it has been found that less work has been done on the material WP7V. Due to stochastic nature of EDM process, perfect relationship between input and output parameters cannot be made. So modeling by artificial neural network (ANN) is adopted. This study addresses the modeling of machinability of WP7V. In the present work, a feed forward back propagation artificial neural network (ANN) is used to model the influence of current and time on material removal rate & surface roughness. Multilayer perception model has been constructed with feed forward back propagation algorithm using current and time as input parameters and MRR and average surface roughness (R_a) as the output parameters. The predicted results based on the ANN model are found to be in very in a very close agreement with the unexposed experimental data set. The modeling results confirm the feasibility of the ANN and its good correlation with the experimental results. The ANN model, thus developed is then used to develop the response surfaces to investigate the effect of different input parameter.
Keyword: EDM, ANN, MRR, Surface Roughness

1. Introduction

Electrical discharge machining (EDM) is a thermal process where material is removed by the erosive action of spatially discrete high-frequency electrical discharges (sparks) of high power density between a tool and the work piece with a dielectric fluid in the gap between them ***(Khanra et. al.)***. The process has the capacity of producing complex three dimensional shapes on any material regardless of its hardness, strength and toughness. Different hard to machine materials, composites, ceramics and alloys are machined by this process ***(Thesen et. al)***. Different statistical and mathematical models have been developed for predicting the characteristic relationship between the input and response parameters of the process like response surface methodology (RSM), artificial neural network (ANN) model, Taguchi method etc ***(George et. al.).*** Some authors have analyzed the EDM process by Taguchi fuzzy-based Approach ***(Tzeng et. al.)***.

For the last few years, researchers have been using different optimization methods for optimizing the process parameters like genetic algorithm (GA), simulated annealing (SA) etc. ***(Keskin et. al.).*** Very few researchers have used simulated annealing for the optimization of the process as can be seen from the literature study. In the present investigation, therefore the modeling of the electrical discharge machining process was attempted using response surface methodology as well as artificial neural network method and subsequently simulated annealing process has been employed for both the models to get the pareto-optimal set of conditions for the process. In this experiments special steel WP7V has used as work-piece and copper as tool material.

2. Specification of material:

In our experiment we are using Special Steel WP7V as working material. The material contains carbon .5%, chromium 7.8%, Molybdenum 1.5% and vanadium 1.5%.The material has very high toughness, good compressive strength, high wear resistance also at high temperature. It is used to produced high wear loaded dies with flat impressions, hot and cold shear knives, knives per cutting sheet > 7mm, highly stressed punches, profiling rolls.

3. Experimentation

Based on the various literature survey available, electrolytic copper with density 8904 kg/m^3 is selected as a tool electrode for machining special steel WP7V. Tool electrode has circular of diameter 13.88 mm. Machining is done at various setting of current, pulse on time, pulse off time as arranged in Table 3.1. We have taken a WP7V material of 150mm length, 60 mm width and 20 mm depth. By taking the material we kept it on the magnetic chuck. Here we have taken 10 sec as cutting time that means metal cutting takes place for 10 sec and lifting time is 2.5 sec that means after cutting 10 sec the metal will lift for 2.5 sec. In this experiment EDM oil has been used as dielectric. When we are providing require amount of current the electron from electrode move with a high velocity towards the work piece and erode the work piece. By taking two input parameter current and time we have done a number of experiments on that material. As a result of machining material removal from the work piece and electrode wear values has been calculated before and after undergoing the EDM process. The volume of the hole can be calculated by calculating the area of the hole and depth of the hole. The depth of the hole is calculated by using MICRO HIGHT 350. The diameter of the hole can be calculated by using CMM (co-ordinate measuring machine) or in a PROFILE PROJECTOR. After the work piece has been machined and measured, the surface roughness measurement has been done on the Taylor Hobson Precision Subtonic 3^+ Roughness Checker. Here a sample length of 4 mm was taken; the stylus tip radius of 5 µm was used. The value of surface roughness parameter R_a for each experiment was obtained directly from the Tally-profile software integrated with the machine.

3.1 Factors & levels selected for machining of wp7v

Table 1 : Factors & levels selected for machining of WP7V

Level	Factor	
	Current,I(amp)	Time,t(min)
1	3	6
2	6	8
3	9	10
4	12	12
5	15	14

Table 2: Testing data for ANN

Serial no.	Current, I	Time(min)	MRR	R_a
1	7	9	0.0157	1.6
2	10	6	0.0849	2
3	10	8	0.17392	3
4	13	9	1.3008	2.8
5	14	7	1.5079	35

4. Methodology

4.1 methodology of ANN modeling

In the present study a multi layer feed forward ANN is trained using Error Back Propagation Training Algorithm (EBPTA) was employed for the predicting the MRR in Electric Discharge Machine.

Back propagation is a systematic method of training multi layered artificial neural networks. It build on high mathematical foundations & has very good application potentials even though it has its own limitations, it is applied to a wide range of practical problems & has successfully demonstrated its power ***(Lee et. al.)***.

The EBPTA requires a set of inputs & out puts known as training patterns for determining the MRR which is required to give the desired output.

Here is the two most important input parameters are time (in sec) & current (in amp) are used .The output parameters are Material Removing Rate (MRR).

The first step in ANN modeling development is to build an input-output database required for training for EDM experiment. In order to have the complete knowledge of EDM process over selected range of parameters a proper planning of experimentation is necessary in order to reduce the cost & time so &

experimental plan based on full factorial design (FFD) was selected using Minitab software.

4.2 Artificial neural network training

In ANN training all the inputs 7 desired out puts are normalized in the range of 0.1 to 0.9 using the expression

$$X_{norm} = 0.1 + 0.8\left(\frac{X - X_{min}}{X_{max} - X_{min}}\right)$$

Where X_{norm} = Normalized data

Same initial weights are chosen randomly between -1 to +1.bathch mode of training was used for the training network that is a set of training data is taken as input to get the output data we use *tan sigmoid* activation function was used for hidden layer and log sigmoid is used for output layer.

The ANN training is highly sensitive to the number of neurons present in the hidden layer and here we have 8 number of hidden neurons i.e., from 8 to 15.

In the present investigation we set our mean square error goal is 0.00001 and 5000 epochs for each text for a neural network that means our running program will stop if we reach up to 5000 times of iterations or we achieve the goal before 5000 of epochs.

The learning rate of the momentum coefficient were changed between 0.5 to 0.9.that's why we have to try 25 number of runs for each neural network so we have 8X25 number of runs to get our best result.

For testing the prediction ability of the model prediction error in each output node has been calculated as follows.

Absolute prediction error = |(Experimental value – ANN predicted value)|

Parametric study has been done to find out the optimal value of learning rate, momentum coefficient, number of hidden layer and number of hidden neurons in the hidden layer. The learning rate and momentum coefficient have been changed between 0.5 and 0.9. The hidden layer and number of hidden neurons in a hidden layer have been changed for each combination of learning rate and momentum coefficient. With these values, for different combination, mean square error (MSE) has been calculated with the following equation.

$$\text{MSE} = \sum_{i=1}^{N} \sum_{j=1}^{m} (T_j - O_j)^2$$

T_j is the target output of the *j*th neuron, O_j the predicted value of the *j*th neuron, *N* the total number of training pattern, and *m* is the is the number of output nodes. After examine whole combination it is shown that 2-14-1 has the least MSE error for learning rate equals to 0.9 and momentum coefficient equals to 0.5.

Out of 30 screened patterns, 25 have been used for training and 5 have been used for testing of prediction capability of the model. The maximum, minimum absolute prediction errors for this network are 0.0633, 0.0016 respectively and the mean square error is found to be 0.00007933.

4.3 Results of different architectures

Here we get the minimum result at sl no 9 experiment for *2-14-1* Neural Network structure, learning rate=*0.9* & momentum coefficient=*0.5* i.e., *0.0000793378*.

Table 3: Results of different architectures

SERIAL NO	NETWORK ARCHITECTURE	LEARNING RATE	MOMENTUM COEFFICIENT	MSE AFTER 5000 ITERATION
1	2-8-1	0.9	0.5	0.000253175
2	2-9-1	0.9	0.9	0.000338484
3	2-10-1	0.9	0.9	0.000502845
4	2-11-1	0.9	0.5	0.000337978
5	2-12-1	0.9	0.9	0.000882496
6	2-13-1	0.9	0.5	0.000302961
7	2-14-1	0.8	0.6	0.0000860536
8	2-14-1	0.8	0.5	0.0000858271
9	2-14-1	0.9	0.5	0.0000793378
10	2-14-1	0.9	0.6	0.0000795772
11	2-14-1	0.9	0.7	0.0000800171
12	2-15-1	0.9	0.5	0.000669034

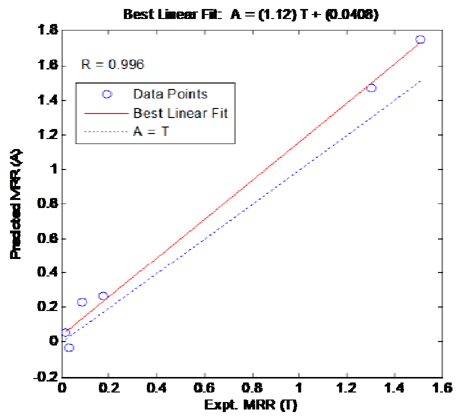

Fig 1: Comparison between neural network testing data & best linear fit

Table 4: Testing Data of Ann Model

SL NO.	MRR Actual	MRR PREDICTED BY ANN	ABS. ERROR
1	0.0157	0.0537	0.0380
2	0.0849	0.2317	0.1468
3	0.17392	0.2622	0.0883
4	1.3008	1.4685	0.1677
5	1.5079	1.7531	0.2452

5: Results and discussions
5.1 Results

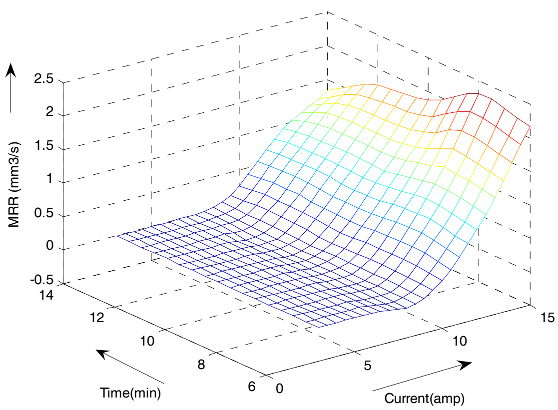

Fig 2: Effect of current and time on the MRR

5.2 Discussions

These two figures 6.1-6.2 are the three dimensional graph of our optimized Metal Removal Rate and the surface roughness value. These two graphs show the effect of current and time on metal removal rate and the surface roughness. Graph shows the gradually increase in MRR with high value of current, that means the MRR is highly sensitive with the high value of current as well as time. Now the question arises how the MRR is increased with the high value of current? When we supplied current, the dielectric breaks down and electrons are emitted from the cathode and gap is ionized. When we applied high value of current the electrons are dense and owing to form an avalanche of electrons in the spark gap where the process of ionization collision takes place. The resisting drops causing the electric spark and the spark causes a focused stream of electron to moves with a very high velocity and acceleration, and creates compression shock waves. The generation of compression shock waves develops a local rise in temperature. This temperature is sufficient to melt the metals.

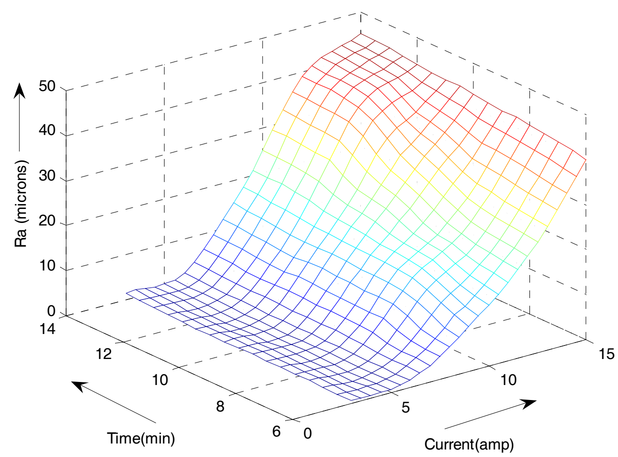

Fig 3: Effect of current and time on the surface roughness (R_a)

6. Conclusions and future scope of present work
6.1 Conclusions

The principal objective of this study was to develop an ANN model to analyze the effects of process parameters on Material removal rate (MRR) and surface roughness (R_a) during the EDM of special steel WP7V. The multilayer feed forward artificial neural network architecture; trained using back-propagation algorithm was employed for this purpose. The experiments were carried out as per full factorial design plan to create a data base for artificial neural network. Based on experimentation and investigations carried out, the following conclusions are drawn.

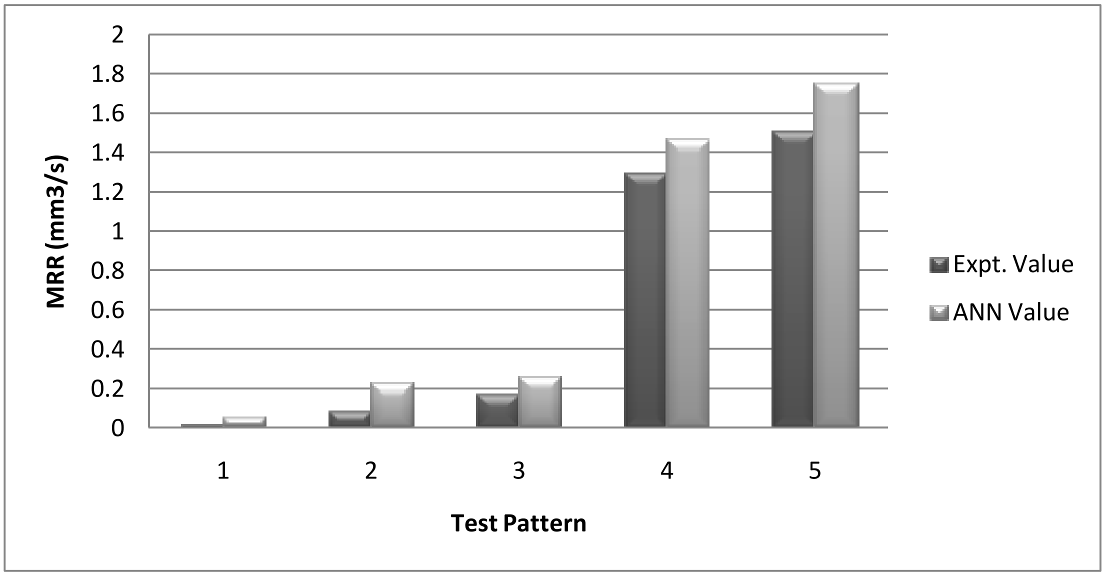

Fig 4: Graphs for testing data

- The developed ANN model shows a good correlation both for training and testing data sets, thus validating the model. The overall mean square error between the experimental and ANN predicted response parameter is found to be 0.000662 and 0.023807 respectively for training and testing data sets.
- There exists a highly non-linear relationship between the response parameters and the selected electro discharge machining process parameters.
- All the response parameters are highly sensitive to current and little sensitive to time.
- The material removal rate sharply increases with increase in current rate but little sensitive to time.
- The surface roughness parameter increases with the increase in current rate. Smaller value of time is required for the minimum surface roughness.
- By defining more number of levels in the selected ranges of the parameters and by conducting more number of experiments, it is possible to improve the prediction accuracy. However, this will increase the cost and time of experimentation.

6.2 Future scope of present work

The future scope of the present work as understood by the author is enumerated as under.

- Experiments with work-piece of different materials can be investigated.
- Experiments with different tool material can be done and comparison with the current experiments can be carried out.
- Effect of other process parameters like pulse on time, pulse off time, voltage on material removal rate and different surface roughness parameters can be investigated.
- Apart from back-propagation learning for the modeling of artificial neural network, other algorithm can be used to know if at all there is any better ANN model exists or not.
- Optimization techniques like genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), ant colony optimization (ACO) can be applied for this model optimization.

7. References

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