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Studies on the effect of Graphene in Wire Cut EDM Process using ANN and RSM

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Abstract - *The selection of optimum cutting parameters in Wire EDM is an important step for achieving the quality of machined components. The three input parameters, Pulse on time, discharge current and concentration of nano particles of graphene in dielectric fluid were varied to investigate their effects on selected output responses, like Material removal rate and Surface Roughness. Artificial Neural Network Modelling was also carried out based on feed-forward back-propagation algorithm with hidden layers. It predicts the responses by training the network with experimental data set using EasyNN plus software. Experiments were tested using Box-Bhenken method in Minitab2019 software. Runs were performed to identify the interaction effects. 3D plots were drawn for particular combination of parameters and predictability error was found by comparing ANN model results with RSM.*

Key Words: Wire EDM, Graphene nanoparticles, Response Surface Methodology, Artificial Neural Network.

1.INTRODUCTION

A Wire EDM generates spark discharges between a wire electrode and a work piece with the dielectric medium and erodes the work piece for the production of complex two- and three dimensional shapes according to a numerically controlled (NC) programmed path.Dielectric fluid acts as a flushing agent that washes away any debris created during cutting. Graphene is widely researched worldwide because of its unique properties such as zero band gap, remarkable electron mobility at room temperature, high thermal conductivity[1].

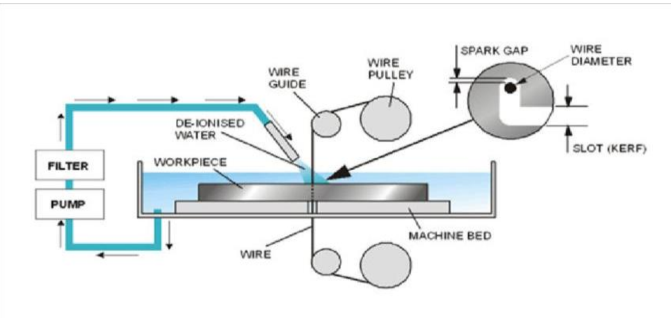

Fig -1: Schematic Diagram of Wire EDM Process

1.1 Need for Study

Wire Cut EDM machine is being extensively used in machining hard and difficult-to -machine materials of intricate shapes with very close tolerances, in the aerospace, nuclear, and automotive industries. The surface layer properties after EDM require additional finishing operations in many cases. Therefore, new methods implemented in EDM are being developed to improve surface characteristics and the material removal rate. Better quality and Performance in work using these machines, to achieve that we need to be optimizing our work and parameters of machining so that Wire cut EDM machining process optimization is essential during its operation.

1.2 Research Objectives

To find out the optimum input process parameter of Wire Cut EDM machining process with graphene incorporation using Response Surface Methodology and Artificial Neural Network and to find out the predictability error of ANN by comparing it with optimization performed by the RSM.

2. MATERIAL SELECTION

2.1 AISI D2 Steel

AISI D2 steel is air hardening Cold Work Steel with High Carbon High Chromium contents. Basically utilized as cutting tools for sheets up to 4 mm thickness, trimming dies, blanking dies for paper and plastics, shear cutting edges for sheet thicknesses up to 2 mm.

2.2 Chemical Composition Of AISI D2 Steel

Table -1: Design Chemical composition of D2 Steel

C	Si	Cr	Mo	V
1.50%	0.30%	12.00%	0.80%	0.90%

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3. DESIGN OF EXPERIMENTS

Ranges and levels of the chosen parameters (pulse-on time, discharge current, and concentration of nano particles) were considered based on trial runs[2]. In the current study, experiments were designed using MINITAB2019 software, 27 runs were designed having three factors at three levels.The considered input parameters were Pulse on-time,Discharge Current and Concentration of nanoparticles. The output responses considered were material removal rate (MRR) and surface roughness (SR)

3.2 Ranges and Levels Of Input Parameters

Table -2: Input Parameters Ranges and Levels

Process parameters	Ranges	Levels		
		Low	Medium	High
Pulse on time	60–120 μs	60	90	120
Discharge current	9–15 A	9	12	15
Conc. Of Graphene nanoparticles	0–3 g/l	0	1.5	3

3.3 RSM Optimization Software

For Response surface Methodology optimization Minitab2019 software is used Minitab is a software product that helps to analyze the data. This is designed essentially for the Six Sigma professionals. It provides a simple, effective way to input the statistical data, manipulate that data, identify trends and patterns, and then extrapolate answers to the current issues

3.4 ANN Prediction Software

For Artificial Neural Network prediction EasyNN-Plus version7.0e Software is used EasyNN-plus is a fast, simple Windows program that can build neural networks from your data with a few clicks. The neural networks make predicting, estimating and classifying easy.

4. RESPONSE SURFACE METHODOLOGY (RSM)

Response surface methodology (RSM) is a collection of statistical and mathematical practices that is used for modeling, and analysis of problems in which a response, which is under consideration, is influenced by several variables. It gives enormous information about the responses in a small number of experiments. Central composite designs are two level full factorial (2k) or fractional factorial (2k–f) designs augmented by a number of runs[G. E. P. Box and D. W. Behnken (1960)] introduced similar designs for three level factors that are widely used in response surface methods to fit second-order models to the response. The designs are referred to as Box-Behnken designs. Box-Behnken designs require factors to be run at only three levels.

4.1 Design Matrix for RSM Optimization

A well planned set of experiments, in which all parameters of interest are varied over a specified range, is a much better approach to obtain systematic data[7]. Mathematically speaking, such a complete set of experiments ought to give desired results. Matrix is designed for the range of input parameters and varied to establish their effects on output responses

Table -3: Design matrix for parameters and responses

Order	Input parameters			Output Responses	
Run order	Pulse-On time (μs)	Discharge Current (A)	Conc. of Nano Particle (g/l)	MRR	SR
1	120	12	1.5	5.2	4.57
2	90	12	3	8.53	5.12
3	60	15	0	12.22	5.37
4	60	9	0	9.62	5.39
5	60	12	0	12.22	5.98
6	120	15	0	16.02	5.56
7	60	12	1.5	8.84	4.55
8	90	9	1.5	12.15	4.11
9	90	15	1.5	8.37	5.29
10	60	9	3	11.98	4.63
11	60	15	3	12.44	5.33
12	60	15	1.5	12.22	5.37
13	90	12	0	7.63	5.94
14	90	12	1.5	10.49	5.81
15	120	15	3	13.89	5.2
16	60	9	1.5	5.32	4.22
17	120	12	3	11.9	5.14
18	90	9	3	11.3	3.98
19	90	15	3	13.58	5.57
20	60	12	3	12.65	5.28
21	120	15	1.5	15.88	5.26
22	120	12	0	12.58	4.88
23	120	9	3	12.74	5.36
24	120	9	1.5	8.02	4.58
25	90	9	0	9.62	5.39
26	90	15	0	22.61	5.53
27	120	9	0	8.82	4.99

5. INTERACTION EFFECT ANALYSIS

In statistics, an interaction is a special property of three or more variables, where two or more variables interact to affect a third variable in a non-additive manner. In other words, the two variables interact to have an effect that is more than the sum of their parts. When two or more independent variables are involved in a research design, there is more to consider than simply the "main effect" of each of the independent variables,also termed "factors".The effect of one independent variable on the dependent variable of interest may not be the same at all levels of the other independent variable. Another way to put this is that the effect of one independent variable may depend on the level of the other independent variable.

5.1 Interaction Effect On Material Removal Rate

The material removal rate is defined as the amount of material removed from the workpiece per unit time. The material removal rate can be calculated from the volume of material removal or from the weight difference before and after machining. It is a direct indicator of how efficiently you are cutting, and how profitable you are. The following graphs interprets the influence of process parameters which are pulse-on time, discharge current, and concentration of nao particles on output response material removal rate. 3D plots explain the interaction effect of two variables simultaneously on the responses

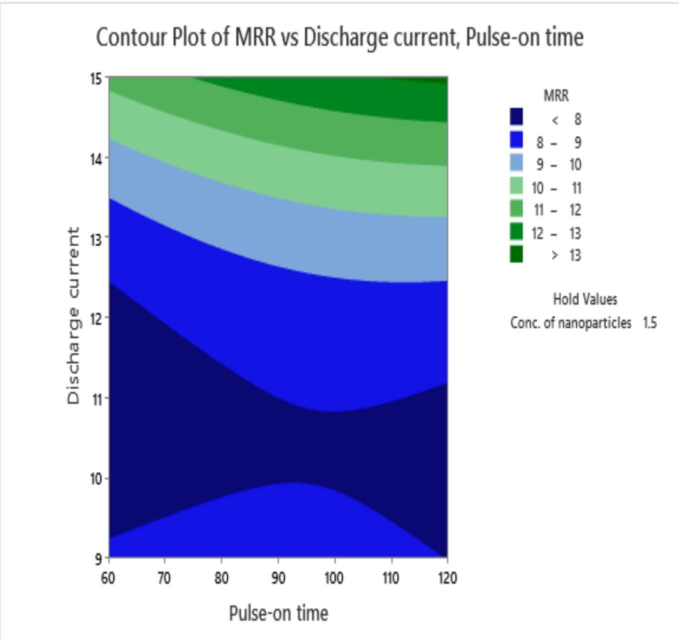


Fig -2: Contour plot of MRR Vs Discharge current, Pulse-on time

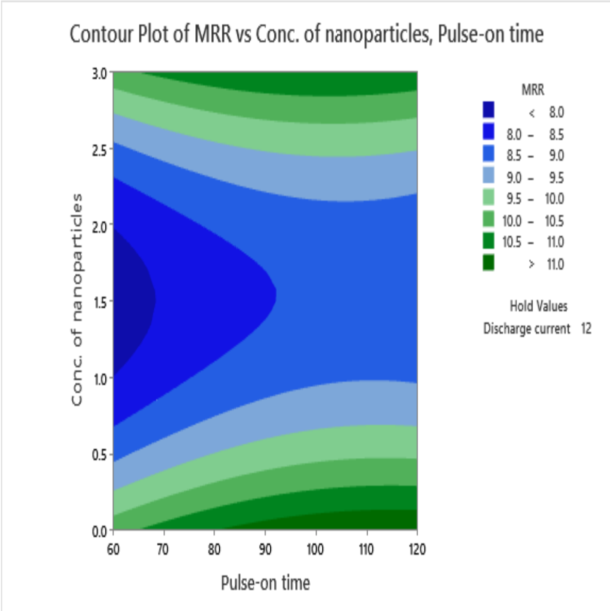


Fig -3: Contour plot of MRR Vs Conc. of nanoparticles, Pulse-on time

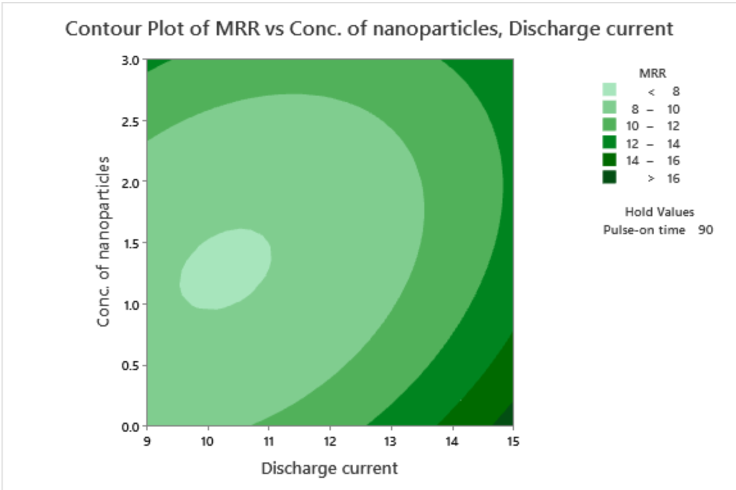


Fig -4: Contour plot of MRR Vs Conc. of nanoparticles, Discharge current

5.2 Interaction Effect on Suface Roughness

Surface roughness is defined as the shorter frequency of real surfaces relative to the troughs. It is measured using a profilometer. It is a dependable predictor of mechanical part performance, as irregularities tend to form nucleation sites for breaks or corrosion.[5] The following graphs interprets the influence of process parameters on surface roughness output response.3D plots explain the interaction effect of two variables simultaneously on the responses with the help of the contour plot graphs.

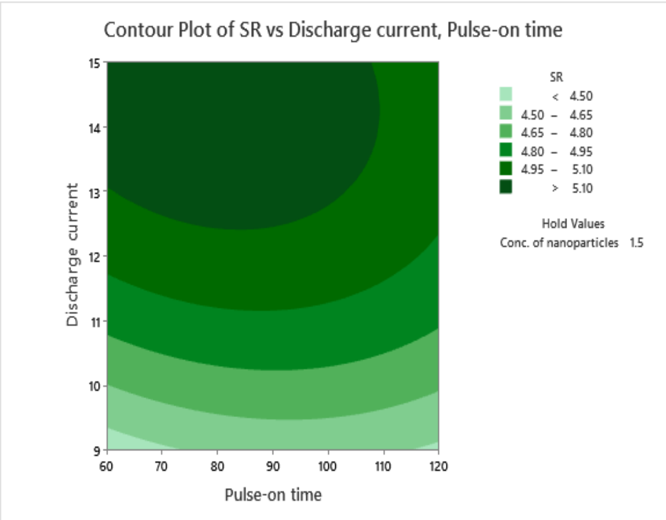


Fig -5: Contour Plot of Sr Vs Discharge Current, Pulse-On Time

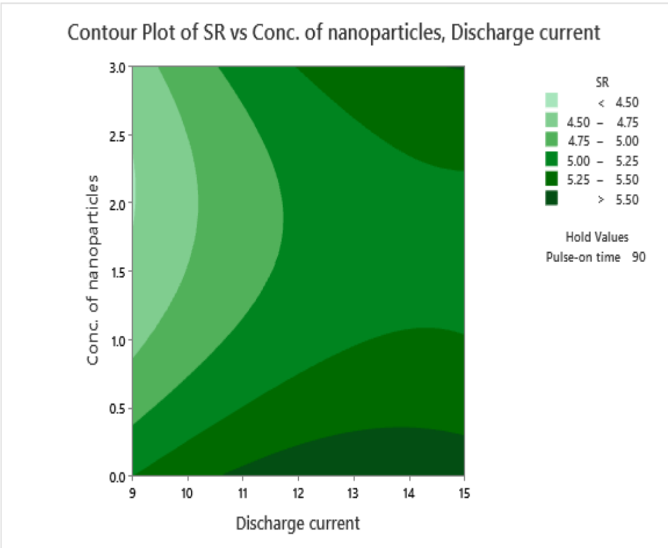


Fig -6: Contour Plot of Sr Vs Conc. of Nanoparticles, Discharge Current

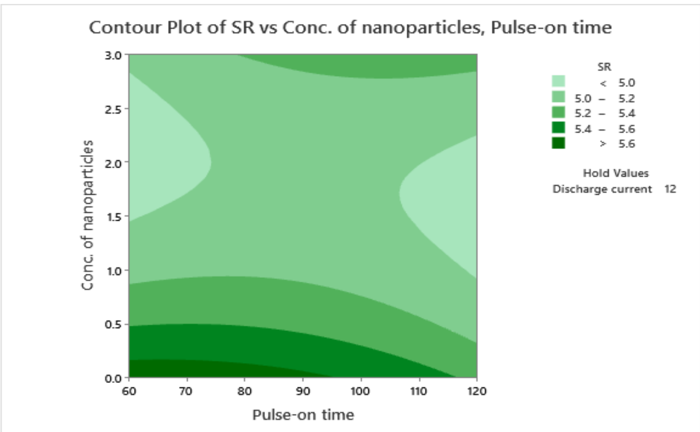


Fig -7: Contour Plot of Sr Vs Conc. of Nanoparticles, Pulse-on Time

6. REGRESSION EQUATION

Regression Equation is the mathematical expression of the relationship between a dependent that is outcome or response variable and one or more independent variables that results from conducting a regression analysis[6].

6.1 Regression Equation For Material Removal Rate

Regression Equation in Uncoded Units

MRR = 30.7 + 0.016 Pulse-on time - 4.74 Discharge current + 0.92 Conc. of nanoparticles
- 0.00037 Pulse-on time*Pulse-on time + 0.227 Discharge current*Discharge current
+ 1.170 Conc. of nanoparticles*Conc. of nanoparticles
+ 0.00579 Pulse-on time*Discharge current - 0.0035 Pulse-on time*Conc. of nanoparticles
- 0.350 Discharge current*Conc. of nanoparticles

6.2 Regression Equation for Surface Roughness

Regression Equation in Uncoded Units

SR = 0.68 + 0.0225 Pulse-on time + 0.635 Discharge current - 1.269 Conc. of nanoparticles
- 0.000112 Pulse-on time*Pulse-on time - 0.0210 Discharge current*Discharge current
+ 0.1758 Conc. of nanoparticles*Conc. of nanoparticles
- 0.00069 Pulse-on time*Discharge current + 0.00328 Pulse-on time*Conc. of nanoparticles
+ 0.0267 Discharge current*Conc. of nanoparticles

7. ARTIFICIAL NEURAL NETWORK

An artificial neural network (ANN) is the piece of a computing system designed to simulate the way the human brain analyzes and processes information. Almost any mapping between vector spaces can be approximated to arbitrary precision by feed forward ANN

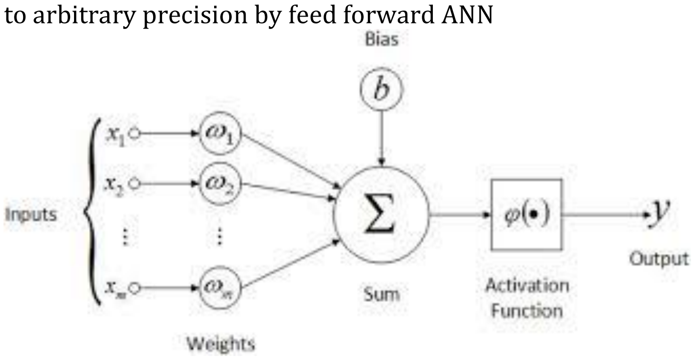


Fig -7: Layers of ANN

7.1 Steps For Growing And Learning Ann

Take a set of examples of input data and pass them through the network to obtain their prediction. Compare these predictions obtained with the values of expected labels and calculate the loss with them. Perform the back propagation in order to propagate this loss.[3] Use this propagated information to update the parameters Continue iterating in the previous steps until we consider that we have a good model

7.2 Design Matrix for ANN Prediction

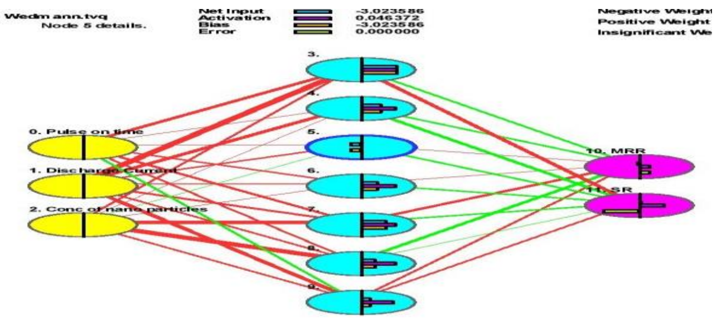
Neural network predicted the responses on time series data. The output layer collected the predictions made in the hidden layer and produced the final result[4].

Table -4: Ann Prediction Matrix

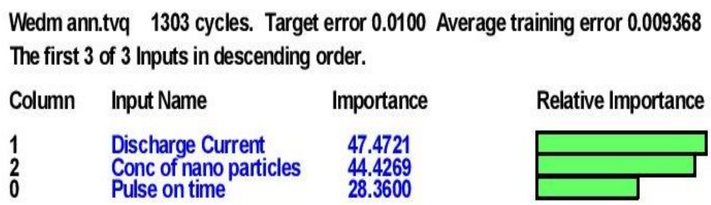
Order	Input parameters			Output Responses	
Run order	Pulse -On time (μs)	Dischrge current (A)	Conc. Of Nano particles (g/l)	MRR	SR
1	120	12	1.5	5.4101	4.5371
2	90	12	3	8.8067	5.4524
3	60	15	0	11.4957	5.9308
4	60	9	0	10.7963	5.3989
5	60	12	0	12.0868	5.8575
6	120	15	0	15.9203	5.5716
7	60	12	1.5	9.8627	4.6203
8	90	9	1.5	9.9925	4.0228
9	90	15	1.5	11.1114	5.3023
10	60	9	3	12.6580	4.6532
11	60	15	3	12.3554	5.2901
12	60	15	1.5	10.5049	5.3542
13	90	12	0	9.0951	5.9574
14	90	12	1.5	8.1342	5.5906
15	120	15	3	13.2906	5.2396
16	60	9	1.5	5.3441	4.2999
17	120	12	3	11.9539	5.1790
18	90	9	3	13.6597	4.2348
19	90	15	3	14.3070	5.2563
20	60	12	3	12.2082	5.2461
21	120	15	1.5	13.1770	5.2604
22	120	12	0	12.5190	4.9140
23	120	9	3	12.3756	5.2952
24	120	9	1.5	7.8441	4.5886
25	90	9	0	9.8288	5.1811
26	90	15	0	21.535	5.9153
27	120	9	0	8.3067	4.9486

7.3 Artificial Neural Network Structure

The Neural network structure formed for the three inpit responses for the two output responses with seven hidden layers was shown in the figure. Each input has the positive and negative weight on the output responses. Green colour and Red colour indicates the positive and negative weights respectively.



7.4 ANN Model Report



8. ERROR CALCULATION

8.1 Predictability Error

A prediction error is the failure of some expected event to occur error Analysis refers to the process of examining different set examples that your algorithm misclassified, so that we can understand the underlying causes of the errors. This can help us prioritize on which problem deserves attention and how much.

8.2 Predictability Error Percentage

$$\text{Error percentage} = \frac{\text{ANN value - RSM value}}{\text{RSM value}} \times 100$$

Table -5: Predictability Error of ANN Model

1	2	3	4	5	6	7	RUN
4.04	3.24	5.93	6.23	1.09	0.62	6.04	ERROR
8	9	10	11	12	13	14	RUN
7.16	3.27	5.66	6.56	6.04	7.2	7.15	ERROR
15	16	17	18	19	20	21	RUN
4.32	0.45	0.45	7.18	5.35	3.49	3.32	ERROR
22	23	24	25	26	27	-	RUN
5.32	5.99	2.25	6.21	6.77	5.82	-	ERROR

Average Predictability Error of ANN = 4.71%

9. RESULTS AND DISCUSSION

9.1 RSM Optimization Report for Material Removal Rate

The following pare to chart explains that the Discharge current was the only factor that significantly affects the material removal rate. Maximum material removal rate can be achieved at higher levels of discharge current and higher levels of concentration of nanoparticles. pulse on time has a least effect on MRR

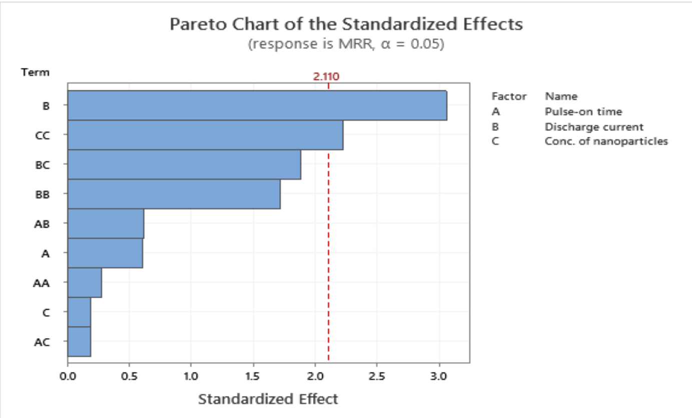


Fig -8: Pareto chart of effect on Material Removal Rate

9.2 RSM Optimization Report for Surface Roughness

The following pareto chart explains that the Discharge current was the most influential factor on Surface Roughness followed by concentration of nano particles. Pulse on time has a least effect on Surface Roughness. This graph indicates that the frequency of effect of input parameters, as well as their cumulative impact. .The length of the chart in the top position explains the most important factor which has a greater effect on the output response that is surface roughness. Discharge current influenced the surface roughness in a greater manner.

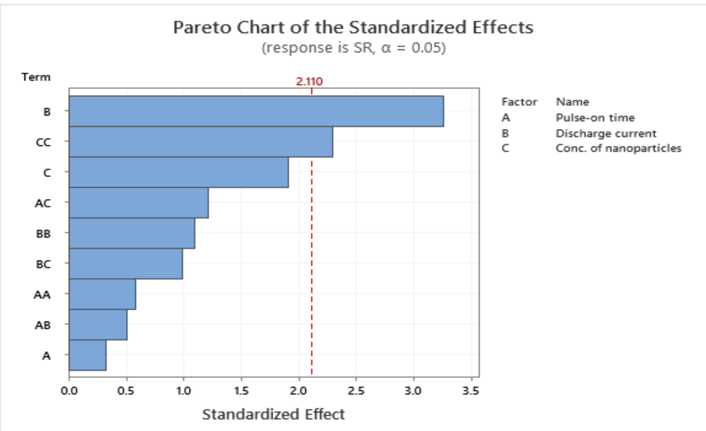


Fig -9: Pareto chart of effect on Surface Roughness

9.3 ANN Prediction Report

Among the selected input variables Discharge current has the highest relative importance on the output responses followed by concentration of nanop[articles and then Pulse on time.

Wedm ann.tvq
1303 cycles.
Target error 0.0100
Average training error 0.009368
The first 3 of 3 Inputs in descending order

Input Name	Importance	Relative Importance
1 Discharge Current	47.4721	HIGH
2 Conc of nano particles	44.4269	HIGH
3 Pulse on time	28.3600	LOW

10. CONCLUSIONS

Based on RSM optimization Model, Discharge current and concentration of nano particles are the most influencing factors affecting the material removal rate and surface roughness. It has a large effect on the responses The contour plots generated helps to identify required machining parameters that satisfy constraints of required surface finish and material removal rate for a specific industrial applications can be easily selected. Based on ANN Prediction Model, Discharge current and concentration of nano particles are relatively important input parameter for predicting the desired output responses. Average predictability error of ANN Model = 4.71%

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