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Parametric optimization in machining of Nimonic-263 alloy using RSM and particle swarm optimization

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Abstract

Machining of nickel based alloys is one of the challenging tasks in the recent past. Wire Electrical Discharge Machine (WEDM) is an advanced machine tool, extensively used to machine hard to cut materials like nickel, titanium and other super alloys. Selection of WEDM process parameters to yield the desired level of performance measures like Material removal Rate (MRR) and Surface Roughness (SR) is crucial from quality and economic view points. In the present work an attempt has been made to investigate the effect of WEDM process parameters such as pulse on time, pulse off time, peak current and servo voltage in machining of Nimonic-263 alloy. A central composite face centered design of Response Surface Methodology (RSM) has been used for experimental plan. The significance of process parameters are estimated by ANOVA analysis. Mathematical prediction models are developed for MRR and SR by RSM. Particle Swarm Optimization (PSO) algorithm has been used to optimize the performances of the process. Results of RSM and PSO technique are compared. It has been observed that, performance of the PSO is better than that of RSM. The machining data generated for the Nimonic-263 alloy will be useful for the industry.

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*Keywords:*Nimonic-263 alloy, RSM, PSO, ANOVA, WEDM

1. Introduction

Applications of nickel based alloys are increasing day by day due to their superior properties such as hardness at elevated temperatures and high corrosion resistance. Machining of nickel based alloys is one of the challenging tasks to the manufacturers in the recent past. Nimonic-263 is a nickel-chromium-cobalt-molybdenum alloy specially meant for use in high temperature and high strength applications. This material is mainly used in gas turbine hot

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section components. Wire Electrical Discharge Machine (WEDM) is one of the advanced machine tools, extensively used to machine hard to cut materials like nickel, titanium and other super alloys. Selection of WEDM process parameters to yield the desired level of performance measures like Material removal Rate (MRR) and Surface Roughness (SR) is crucial from quality and economic view points**.**

In the recent past several researchers were contributed their efforts towards developing the mathematical models for the performance measures of WEDM, and tried to optimize the same with different optimization techniques. Spedding and Wang (1997), carried out experiments based on RSM design. Mathematical models are developed using RSM and also applied a multi layered feed-forward neural network is used to model the WEDM performance. Cutting speed, surface roughness and waviness were selected as the performance measures, and the developed model is used to process performance prediction and parameter optimization. The models developed by RSM as well as ANN are compared and found both are giving accurate results. A full factorial experimental design was used by Nihat (2003), to study the variation of cutting performances with WEDM process parameters. Regression Analysis was used to develop mathematical models for cutting speed and surface roughness. Manna and Bhattacharyya (2006) carried out an experimental investigation to determine the parameter setting, Taguchi method was used to optimize WEDM parameters. Mathematical models relating to the machining performance are established using the Gauss elimination method.

Mahapatra and Patnaik (2007), attempted to determine the important machining parameters for performance measures like MRR, surface finish and kerf. Using Taguchi's parametric design significant machining parameters affecting the performance measures are identified as discharge current, pulse duration, pulse frequency, wire speed, wire tension and dielectric fluid flow rate. Mathematical models are developed by means of nonlinear regression analysis for MRR, SF, and Kerf. Finally Genetic algorithm is employed to optimize the WEDM process with Multiple-objectives. Muthu et al., (2010) demonstrated the optimization of WEDM process parameters of Incoloy800 super alloy with multiple performance characteristics such as MRR, SR and Kerf based on the Grey–Taguchi method. The variation of output responses with process parameters were mathematically modeled using non-linear regression analysis method. Optimal levels of process parameters were identified using GRA and the relatively significant parameters were determined using ANOVA.

Shandilya et al. (2012), attempted to study WEDM process performance in terms of cutting width (kerf) using RSM. The ANOVA was carried out to study the effect of process parameters on process performance. Mathematical models have also been developed for response parameter and properties of the machined surface have been examined by using SEM. RSM was used by Rao and Pawar (2009) to develop mathematical models for cutting speed and surface roughness. An artificial bee colony (ABC) algorithm was then applied to find the optimal combination of process parameters with an objective of achieving maximum machining speed for a desired value of surface finish.

In the present research RSM has been used for experimental plan as well as to model the responses with respect to process parameters. Further these models are optimized by using particle swarm optimization algorithm and these results are compared with RSM results.

Table 1. Chemical composition of Nimoni-263 alloy in percentage

Alloying element	Percentage	Alloying element	Percentage
C	0.043	Fe	0.25
Co	19.5	Ti	2.2
Mo	5.6	Al	0.48
Mn	0.43	Cu	0.002
Si	0.04	O	0.0022
S	0.005	N	0.0031
P	0.005	Ni	Bal.
Cr	20		

2. Experimental setup and procedure

WEDM of Electronica (India) made has been used to machine Nimonic-263 material with pulse on time, pulse off time, peak current and servo voltage as input parameters. Holes of 10 mm diameter are produced on 120mm×110mm×18.5 mm workpiece. The objective of the present study is to optimize the WEDM process parameters for better performance. In this study the performance measures are material removal rate and surface roughness. The levels of input parameters pulse on time, pulse off time, peak current and servo voltage are fixed based on the trial experiments and are given in Table 2. Response surface methodology-Central composite face catered design with 2 centre points has been used for experimental plan. The measured and calculated responses are given in the Table 3 after conducting the experiments as per the experimental plan. ANOVA has been applied to know the significant parameters and their contribution. ANOVA has also been applied to model the responses material removal rate and surface roughness. These models are further used to predict as well as optimization. Particle swarm optimization (PSO) has been used to optimize responses and these results are compared with RSM results.

Table 2. Levels of input parameters

Parameter	level 1	level 2	level 3
Pulse on time (T_{on}) μs	105	115	125
Pulse off time (T_{off}) μs	50	55	60
Peak current (I_p) A	10	11	12
Servo voltage (S_v) V	40	50	60

Material removal rate was calculated using the equation (1) and the surface roughness of the machined surface was measured by MarSurf M-400.

$$MRR = \frac{\pi t\left(D^2 - d^2\right)}{4T} \quad \mathrm{mm^3/min} \tag{1}$$

Here, D=diameter of the hole (mm), d=diameter of the blank (mm), t=thickness of work piece (mm) and T=Time taken for machining (min). To measure these diameters Coordinate Measuring Machine (CMM) was used.

Tale 3. Experimental plan and Responses

Run order	T_{on} (μs)	T_{off} (μs)	I_p (A)	S_v (V)	MRR (mm^3 / min)	SR (μm)
1	125	60	12	60	3.12412	2.01
2	125	60	10	60	0.359606	0.605
3	115	55	11	40	0.452898	0.525
4	115	55	11	50	0.380731	0.387
5	105	60	12	60	0.497021	0.537
6	125	55	11	50	0.327263	0.578
7	125	50	10	40	0.380919	0.484

8	115	55	12	50	2.447281	1.021
9	115	50	11	50	0.280316	0.501
10	105	50	10	40	0.446554	1.364
11	115	55	10	50	0.300545	0.514
12	105	60	10	60	0.426622	0.694
13	125	50	10	60	0.458812	0.46
14	115	55	11	50	0.310576	0.539
15	125	50	12	40	3.588263	2.027
16	105	60	10	40	0.529402	1.323
17	125	60	12	40	3.352623	2.089
18	105	55	11	50	0.396612	0.892
19	115	55	11	60	0.575236	0.76
20	115	60	11	50	0.514857	0.764
21	125	60	10	40	0.500181	1.081
22	105	50	12	40	1.768268	0.891
23	125	50	12	60	3.233984	1.85
24	105	60	12	40	0.948816	1.18
25	105	50	10	60	0.548839	0.863
26	105	50	12	60	0.771276	0.603

2.1. Particle swarm optimization:

Particle swarm optimization, PSO, was developed by Kennedy and Eberhart in 1995 and has become one of the most widely used swarm-intelligence-based algorithms due to its simplicity and flexibility (Yang, 2014). When the search space is larger, near optimal solution could be able to find by using PSO (Bharathi Raja and Baskar, 2011). PSO is a population based search technique like other evolutionary algorithms. Here particles represent population and each particle represents a candidate solution. Particles change their positions by flying around in a multi-dimensional search space until computational limitations are exceeded (Adibo, 2002). Particle swarm has includes mainly two parameters. One is velocity update and the other is position update. In each generation each particle is accelerated towards the particles previous best position and the global best position and a new velocity value for each particle is calculated based on its current velocity, the distance from its previous best position, and the distance from the global best position. The new velocity value is then used to calculate the next position of the particle in the search space. This procedure repeated number of times up to maximum iterations set, or until a minimum error is achieved.

This total procedure has been explained (Mandal, 2008) as follows. Each particle is a candidate solution and is represented by its velocity and position, denoted by *v* and *x* respectively in a search space and this i^{th} particle is represented as $x_i = (x_{i1}, x_{i2}, ...x_{id})$ in the *d* dimensional space. The best previous position of the i^{th} particle is recorded and represented as $pbest_i = (pbest_{i1}, pbest_{i2}, ...pbest_{id})$. The index of the best particle among all the particles in the group is represented by the $gbest_d$. The rate of the velocity for the particle *i* is represented as $v_i = (v_{i1}, v_{i2}, ...v_{id})$ .The modified velocity and position of each particle can be calculated using the current velocity and the distance from $pbest_i$ to $gbest_i$ and these steps are given as below.

Step 1. The initial population of particles will be generated randomly within the feasible variable ranges.
Step 2. The objective function value of each particle p_k will be calculated in the population.

Step 3. Each particle objective function value will be compared with that of its $pbest$. The particle with the best objective function value among all the $pbest$ s will be denoted as $gbest$.
Step 4. Velocity of each particle will be modified by using equation (2)

$$v_{id}^{k+1} = w \times v_{id}^{k+1} + c_1 \times rand()(pbest_i - x_{id}^{k}) + c_2 \times rand() \times (\mathrm{gbest}_i - \mathrm{x}_{id}^{k}) \quad (2)$$

Where c_1 and c_2 are the constants and are set as 2.0, k is the iteration number and w is the inertia weight and is set according to the equation (3)

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad (3)$$

Where $iter_{max}$ is the maximum number of iterations and $iter$ is the current iteration number.
Step 5. Position of each particle will be modified by using equation (4)

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \quad ; i = 1, 2, ...N_p \text{ and } d = 1, 2, ...N_g. \quad (4)$$

Where N_p and N_g represent the number of particles and number of variables in a particle respectively.
Step 6. If the new objective function value of any particle is better than that of previous value, the coordinates of that particle will be stored as it's $pbest$ and also compare the objective function values of each particle and determine $gbest$.
Step 7. If the number of iterations reaches to the maximum go to Step 8. Otherwise Step 4.
Step 8. The individual that generates the latest $gbest$ is the solution of the problem.

3. Results and analysis

ANOVA has been applied on the experimental results for both MRR and SR and are given Table 4 and Table 5 respectively.

Table 4. Results of ANOVA for MRR

Source	SS	DOF	MS	F value	P-value	Percentage Contribution
Model	29.3208	9	3.257867	44.563324	< 0.0001	96.16369159
A- T_{on}	4.492364	1	4.492364	61.449614	< 0.0001	14.73364663
B- T_{off}	0.08323	1	0.08323	1.1384719	0.3018	0.26237672
C- I_p	13.8341	1	13.8341	189.23223	< 0.0001	45.37182225
D- S_v	0.216133	1	0.216133	2.956416	0.1048	0.708853345
AC	5.718684	1	5.718684	78.224046	< 0.0001	18.75561937
BC	0.126007	1	0.126007	1.7236097	0.2077	0.413266292
CD	0.24216	1	0.24216	3.31243	0.0875	0.794214331
A^2	0.012463	1	0.012463	0.1704738	0.6852	0.040875013

C^2	2.960149	1	2.960149	40.490926	< 0.0001	9.708427311
Residual	1.169703	16	0.073106			3.836285454
Cor. Total	30.49051	25				100

From the Anova Results of MRR, it has been observed that T_{on}, I_p, interaction of T_{on} and I_p, I_p^2 are significant model terms, and are shown in the Figurs 1(a),(b) and (c). Higher the pulse-on time, higher will be the energy applied there by generating more amount of heat energy during this period and it leads to higher MRR. Peak current is the amount of power used in discharge machining. Higher the peak current, higher will be the energy applied at machining and there by increasing the MRR. The mathematical model generated for MRR was given in equation (5),in the coded form. From the ANOVA, the R-Square, adjusted R-square and predicted R-square values were found to be 96.2%, 94%and 90% respectively for the model.

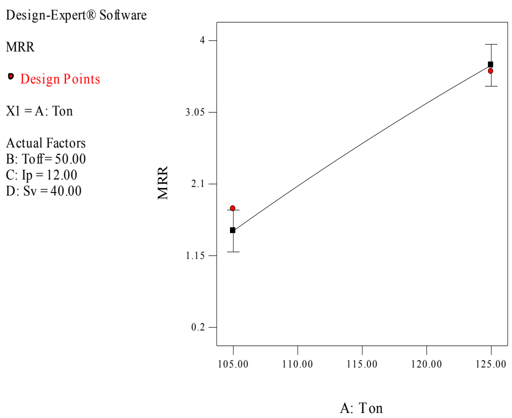

Figure 1(a) Effect of T_{on} on MRR

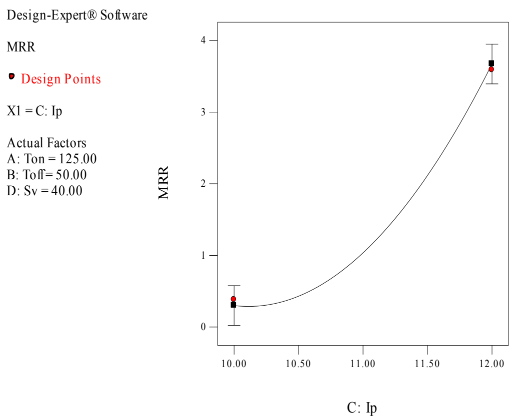

Figure 1(b) Effect of I_p on MRR

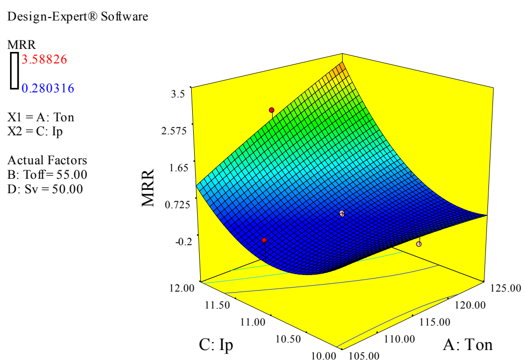

Figure 1(c) Effect of T_{on} and I_p on MRR

$$MRR = 0.42 + 0.50A - 0.068B + 0.88C - 0.11D + 0.60\,\mathrm{AC} - 0.089\,\mathrm{BC} - 0.12\,\mathrm{CD} - 0.062\,\mathrm{A}^2 + 0.95C^2 \quad (5)$$

Table 5. Results of ANOVA for SR

Source	SS	DOF	MS	F value	P-value	Percentage Contribution
Model	6.3722	11	0.579291	13.12696	< 0.0001	91.16142476
A- T_{on}	0.447143	1	0.447143	10.13243	0.0066	6.396879092
B- T_{off}	0.085422	1	0.085422	1.935701	0.1859	1.222056939
C- I_p	1.290689	1	1.290689	29.24751	< 0.0001	18.46474501
D- S_v	0.370374	1	0.370374	8.392809	0.0117	5.298490168
AB	0.056525	1	0.056525	1.28088	0.2767	0.808653139
AC	2.543228	1	2.543228	57.63053	< 0.0001	36.38371174
AD	0.106439	1	0.106439	2.411951	0.1427	1.522728554
BC	0.000473	1	0.000473	0.01072	0.919	0.006766792
CD	0.012266	1	0.012266	0.277942	0.6063	0.175478804
A^2	0.234026	1	0.234026	5.303112	0.0371	3.348002823
C^2	0.294417	1	0.294417	6.671603	0.0217	4.211963403
Residual	0.617818	14	0.04413			8.838575237
Cor Total	6.990018	25				100

From the ANOVA Results of SR, it has been observed that T_{on}, I_p, S_v and interaction effects T_{on} and I_p, T_{on}^2 and I_p^2 are significant model terms, and are shown in the Figurs 2(a),(b), (c)and (d). When the pulse-ontime increases, the number of discharges also increases. It leads to more heat energy there by increasing the machining rate and decresing the surface finish. Higher the peak current, higher will be the energy applied and it leads to higher maching rate and high surface roughness. At higher values of servo voltage, the gap between workpiece and wire becomes wider and it decreases the number of sparks, stabilizes electric discharge yielding better surface finish. The mathematical model generated for SR was given in equation (6) in the coded form.From the ANOVA, the R-Square, adjusted R-square and predicted R-square values were found to be 92%, 84.22% and 72% respectively for the model.

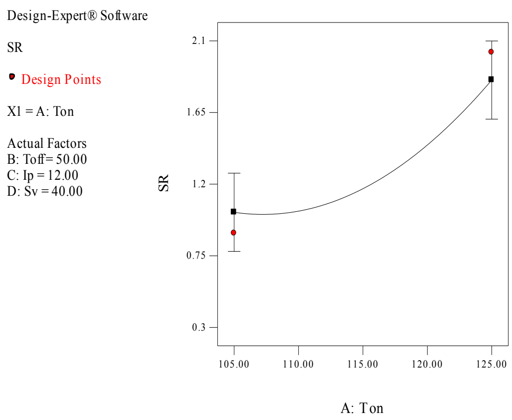

Figure 2(a) Effect of T_{on} on SR

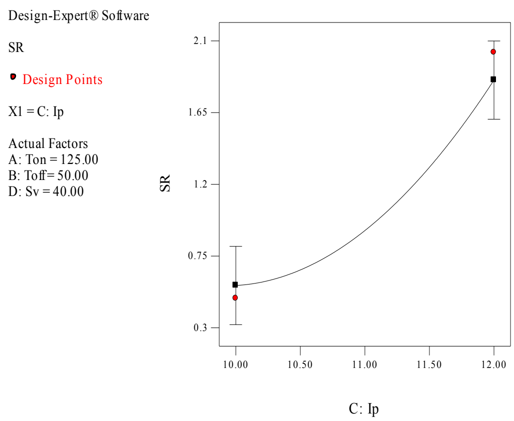

Figure 2(b) Effect of I_p on SR

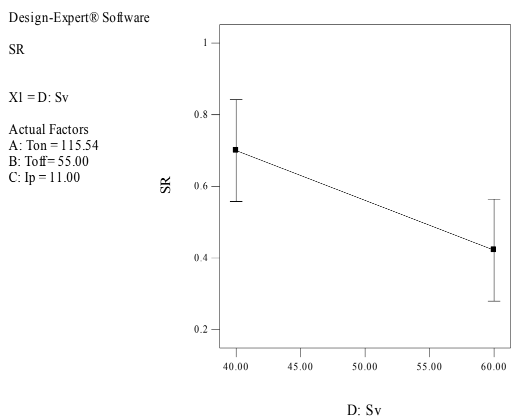

Figure 2(c) Effect of S_v on SR

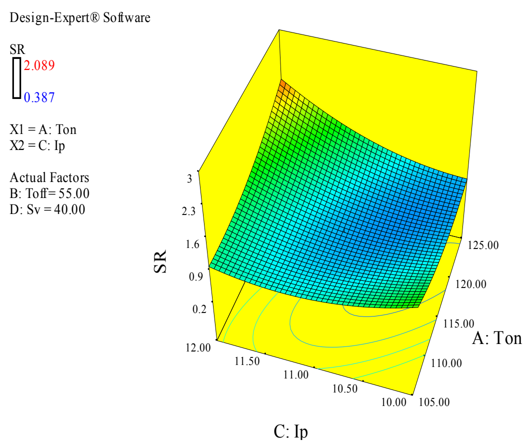

Figure 2(d) Effect of T_{on} andI_p on SR

$$SR = 0.55 + 0.16A + 0.069B + 0.27C - 0.14D + 0.059AB + 0.40AC + 0.082AD - 0.005437BC \\ + 0.028CD + 0.27A^2 + 0.30C^2 \tag{6}$$

The optimal values for MRR and SR were 3.59856 mm^3/min0.363162μmas found from RSM respectively, along with their optimal parameters are given in Table 6. Similarly the optimal values found from PSO for MRR and SR were 3.6713 mm^3/min and 0.2618μm respectively.

Table 6. The Optimal results from RSM and PSO

Response		RSM	PSO
MRR (mm^3/min)	Optimal value	3.59856	3.6713
	Optimal parameters	T_{on}:125, T_{off}:52.14, Ip:12, Sv:42	T_{on}:125, T_{off}:50, Ip:12, Sv:40
SR (µm)	Optimal value	0.363162	0.2618
	Optimal parameters	T_{on}:119, T_{off}:51, Ip:10, Sv:56	T_{on}:116, T_{off}:50, Ip:10, Sv:60

Confirmation tests have been conducted to check the effectiveness of PSO for both MRR and SR, and the results were given in Table 7.

Table 7. Confirmation Test results

Response	Predicted value from PSO	Experimental value	Deviation in percentage
MRR (mm^3/min) (T_{on}:125, T_{off}:50, I_p:12, S_v:40)	3.6713	3.614	2
SR (µm) (T_{on}:116, T_{off}:50, I_p:10, S_v:60)	0.2618	0.282	7

4. Conclusions

Response surface methodology has been used in the present study to model WEDM performance measures of material removal rate and surface roughness. Pulse on time, pulse off time, peak current and servo voltage have been considered as input parameters. The significance of process parameters have been identified by applying ANOVA analysis for both MRR and SR. For MRR it was found from the ANOVA results that, pulse on time, peak current and interaction effect of pulse on time and peak current are more influencing than other model terms. Whereas for SR it was found that pulse on time, peak current, servo voltage and interaction effect of pulse on time and Peak current are more influencing than other model terms. In the present research an attempt has been made to apply PSO to optimize the responses such as MRR and SR. The optimal response values from RSM and PSO are compared. It is found that, the results of PSO are better than that of RSM. Due to wide range of applications for Nimonic-263, the machining data generated for the first time in this work using WEDM will be useful to the industry.

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