A Combined Approach of Nature-Inspired Firefly Algorithm and Weighted Principal Component Analysis in Machining of Inconel X-750

Som Nath Pandey
M.Tech
Madan Mohan Malaviya University of Technology, Gorakhpur
Department of Mechanical Engineering
India

Jogendra Kumar
M.Tech
Madan Mohan Malaviya University of Technology, Gorakhpur
Department of Mechanical Engineering
India

Sasmit Yadav
M.Tech
Madan Mohan Malaviya University of Technology, Gorakhpur
Department of Mechanical Engineering
India

Rajesh Kumar Verma
Associate Professor
Madan Mohan Malaviya University of Technology, Gorakhpur
Department of Mechanical Engineering
India

Electrical discharge machining (EDM) is the primary unconventional machining process used for very hard conductive materials. Inconel-750 is used in various high-performance applications like aerospace, automobiles, etc. due to its improved mechanical properties. During machining, various parameters significantly affect machining performances. It is not easy for a manufacturer to make a compatible balance between parameters and responses simultaneously. In this paper, a novel hybridization module is developed for EDM of Inconel-750 using the brass tool. Taguchi based L9 orthogonal array has been used for experimentation and two optimization modules. Namely, Utility theory (UT) and Weighted Principal Component has been fruitfully coupled with a relatively new nature-inspired Firefly Algorithm(FA) to achieve the desired value of rate of material removal (MRR) and Surface roughness (SR). WPCA embedded FA performs better than Utility coupled FA modules in terms of R^2, F and P-value with model accuracy of 89.03%. The optimal settings are fund as Ip-12 amp, Ton-63μs, Toff-7μs, V-40 volts and fitness value as 0.97213. The WPCA-FA shows higher application potential and can be forwarded to the manufacturing sectors for quality monitoring and productivity concerns.

Keywords: *Inconel; Machining; Utility Theory; Firefly algorithm; Surface roughness.*

1. BACKGROUND AND RATIONALE

EDM is a machining technique widely used to machine extreme hard materials, which is almost impossible by the conventional ways of machining. This EDM process can develop critical shapes like cavities, angular and contour shapes, which is not feasible by traditional methods. Harder materials like Carbides, Monel Alloys, Inconel, Inconel alloys, etc. can be easily machined into desired shape and size [1]. In this process, tool and work material are dipped completely in a dielectric fluid, which is non-conducting in nature. There is very less gap between tool and work material, which results in sparking. The dielectric fluid does not allow the flow of current and acts as an insulator between the workpiece and the tool. The dielectric commonly consists of hydrocarbon like kerosene, oil, deionized water, etc. The dielectric helps in cooling both the electrodes and concentrates spark energy over the area between the electrodes with imparting machining [2]. As both electrodes move toward each other and distance between then becomes an order of 0.5 mm, the intensity of the electric field starts to increase and, as and when it increases ahead of the dielectric strength the breakage of the passage occurs which permits the current to readily pass between the electrodes. Due to this, strong heat is generated and thus exhibits the melting and evaporation of the small work material in the sparking zone. Dielectric goes between the zone of the tool and work material and this removes the eroded particles and also clears the gap between the electrodes and cools them[3]. Shukla et al. [4] executed the experimental trials to achieve the prime set of values that can optimize the responses using the Firefly Algorithm. Work material was decided as Aluminium metal matrix composite (MMC) and EN-31 stainless steel (SS). Moreover, the work explored Taguchi's methodology and TOPSIS theory for optimization of process parameters. It was revealed that MRR increases from 159.70 to 181.6723 gm/min whereas Ra decreased from 6.21 to 3.6767 μm and relative electrode wear ratio (REWR) decreases from 6.21 to 0.00006324%. Purohit et. al. [5] applied the Grey Relational Analysis technique for the Multi-Objective Optimization (MOO) of the EDM parameters. A set of 9 trials were conducted using the Brass electrode with M2 steel as work material. The responses considered are Material removal rate (MRR), electrode wear rate (EWR) and Overcut with a rotating tool. The observed finest setting for the optimization was 50 volts, Ton of 500 microseconds, the electrode rotation speed of 460 RPM. The outcome was heavily affected

Received: December 2019, Accepted: February 2020
Correspondence to: Dr Rajesh Kumar Verma, Faculty of Mechanical Engineering, Madan Mohan Malaviya University of Technology, Gorakhpur – 273010, India
E-mail: rkvme@mmmut.ac.in
doi:10.5937/fme2002439P

by electrode rotation speed and it was later followed by V and Ton. Prime values for the performance were MRR of 0.122 grams/min., EWR of 40.98 percent and Overcut of 0.68mm.

Majumder et. al. [6] executed Multi-objective optimization (MOO) over wire EDM input factors using the multi-objective AISI 316LN steel was considered as the work material T_{on}, T_{off}, current and wire tension were the chosen process parameters whereas the Electrode wear rate (EWR) and MRR were the output factors. Linear regression analysis (LRA) has been used to develop the model relationship between the input and the output factors and standard deviation was deployed for the transformation of multiple responses into a single function. The results reveal that the perceives particle swarm optimization (PSO) better results.

Dwivedi et. al. [7] executed investigational work for optimizing surface integrity by using a rotary tool for the machining of AISI D3 steel. Microcracks, Tool wear rate, *and* surface roughness were taken as machining performances. Excellent surface finish (SF) was obtained using a rotary tool with an overall improvement of 9-10% with reduced microcracks. The outcome of the study demonstrates that the average value of TWR obtained in the order of 25 micro-meters *and* this value is half of the stationary tools which is highly desired for an effective machining environment.

Rao et. al. [8] performed the multi-characteristic optimization while machining the Nimonic-263 alloy using the wire EDM process by using Response surface methodology (RSM) and PSO technique. MRR and SR were taken into account with Ton, T_{off}, Ip and V as the process parameters. The outcome of various analyses demonstrates that pulse on time and peak current holds the highest contribution which influencing the machining performance namely MRR and SR. The results of PSO show the high application potential than the RSM approach.

Yan-Cherng Lin et al. [9] performed the Hybrid machining using the EDM with AJM. The objective of the work was to find out the effect of the variables affecting parameters in the case of this very hybrid module with the performance parameter being the MRR, TWR, and SR. For the same, L_{18} experiments were taken into account for the SKD 61 steel and to that servo reference voltage, the polarity of the machine, current, grain size, pulse duration and pressure were chosen as the major process parameters. The most affecting parameter in the case of MRR is polarity, current and pulse duration, EWR is affected by peak current whereas SR is significantly affected mainly by the peak current, pulse duration, and air pressure. Kumar et al. [10] performed experimental work for the assessment of MRR and SR of Ti-6Al-4V (ELI) which is basically a titanium alloy. To examine the behavior of the workpiece the technique called surface morphology had been performed on the machining surface. It was concluded that the MRR has a direct dependence upon the discharge current and it rises as discharge current escalates but on the other hand had been distinctly observed that voltage and the pulse on-time do not show any prominent effect on the MRR. At greater values of I_p, T_{on} and V_g; Ra was found to be the largest whereas it was lowermost at the lowest level of input variables. Kliuev et al. [11] executed the experiments over EDM while considering the tool length and tool shape as a measure to examine the reliability of the stochastic algorithm. The number of iterations and convergence rate towards the optimal solution. The results show that 40 iterations are mandatory to reach the optimal state. It was discovered that electrode length has its effect on drilling time and TWR but very rarely affects the MRR. Pulse Duration doesn't affect the MRR whereas discharge current does and TWR is affected by current factor.

Kharwar et. al. [12] applied Grey embedded ANN-based optimization modules during the turning of GFRP composites. Machining performance considered as cutting force, surface roughness, MRR. The optimal setting is found as S-880, F-0.05, and depth of cut 0.4. The hybrid approach of GRA-ANN shows an overall improvement of overall assessment values of 8.5 % in which is highly desired for an efficient machining (drilling) environment. The proposed approach can be recommended for offline and online quality control of the machining process.

Bhaskar C. et al. [13] executed the experiments on AA6061/10% Al_2O_3 metal matrix composites (MMC) by using the Taguchi's methodology and performed the statistical assessment like ANOVA. The S/N ratio, ANOVA and F-test values discovered that current and pulse on values directly influence the MRR. Any subsequent increase in the above two factors significantly increases the MRR. The prime set of values was found to be 14 amps., pulse on value 200 μ-seconds and h of 50% gave the higher MRR. The major influencing parameter was found to be the pulse current and it prominently affects the MRR. Various pioneers scholars performed their work in EDM but very limited data is available on multi-objective optimization using nature-inspired metaheuristic algorithms. Most of the studies used the traditional method of optimization which consist of various limitation. Previous research assumes the negligible response correlation and uniform weight during aggregation of multiple conflicting responses which is not feasible in real practice. This creates error and inspection in the solution. This paper presents a novel hybridization of the WPCA embedded firefly approach to assign the response priority weight. In this paper, an attempt has been made to develop a robust hybrid optimization module by coupling of utility /WPCA into the firefly algorithm. A comparison between the modules namely Utility and WPCA is done to check the applicability of the developed method in the machining environment.

2. MATERIAL AND METHOD

2.1 Experimentation

The machining has been performed by a manual EDM setup as presented in Figure 1. The technical specification of the machines is depicted in Table 1.

Inconel X-750 has been selected as work material (Figure 2) which exists in a class of nickel-chromium precipitation-hardened grade alloy having extreme tensile strength creep-rupture properties, good formability, and excellent high-temperature oxidation-resistant features. The alloy exhibits superior mechanical properties at elevated temperatures up to 704°C. It is widely used in high-performance applications such as aircraft, automobiles, aerospace, etc. The brass electrodes are chosen as tool material which is erosion resistive in nature and highly conductive during discharge machining.

Table 1. EDM specifications

Machine Specification		
Machine Type	Manual	
Model Number	C-3822	
Process Parameter Bounds		
Parameter	Min. Value	Max. Value
Input Current (I_p)	1 ampere	20 amperes
Pulse On Value (T_{on})	1 μ-second	99 μ-seconds
Pulse Off Value (T_{off})	1 μ-second	9 μ-seconds
Voltage (V)	5 volts	60 volts

Figure 1. EDM Machine

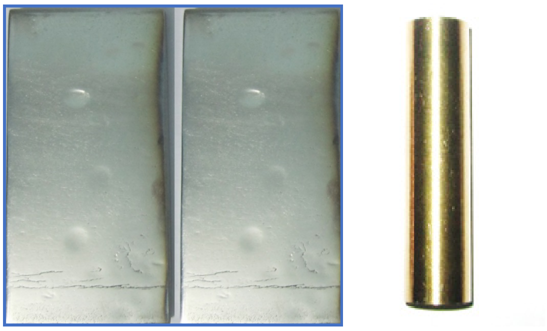

Figure 2. Inconel X-750 Sheet and Brass tool

The surface roughness was measured by roughness tester (Figure 3) made by Handy Surf Tokyo seimitsu (Japan) Model No. E-MC-S24B and rate of material removal of Inconel X-750 (density 8.276g/cm^3) computed by using expression 1.

$$MRR = \frac{W_i - W_f}{\rho \times t} \tag{1}$$

where W_i and W_f are initial and final weight respectively and ρ is density of materials and t is machining time. The domain of experiment (Table 2) is used according to Taguchi based experimental design i.e, L9 orthogonal array as shown in Table 3. The images of Machined workpiece are shown in Figure 4 and the value of experimental data from EDM of Inconel X750 EDM is depicted in Table 4.

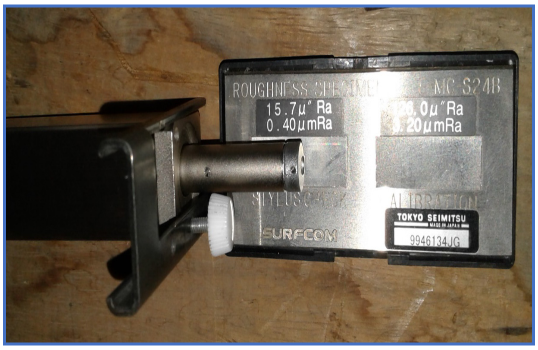

Figure 3. Surface Roughness Tester

Table 2. Domain of Experiment

Factor	Symbols	Level 1	Level 2	Level 3
Current	Ip	12	15	18
Pulse On Time	Ton	63	74	85
Pulse Off Time	Toff	7	8	9
Voltage	V	40	50	60

Table 3. L_9 Orthogonal Array

Exp. No.	Current (I_p)	Pulse On (T_{on})	Pulse Off (T_{off})	Voltage (V)
1	12	63	7	40
2	12	74	8	50
3	12	85	9	60
4	15	63	8	60
5	15	74	9	40
6	15	85	7	50
7	18	63	9	50
8	18	74	7	60
9	18	85	8	40

Figure 4. Images of machined Inconel X-750

Table 4. L_9 Evaluation of MRR and SR for Brass Tool

Exp. No.	MRR mm^3/min.	SR (μm)
1	15.20	1.86
2	27.23	4.28
3	26.22	5.44
4	25.93	3.68
5	34.96	3.46
6	40.79	3.24
7	32.41	3.68
8	47.83	4.84
9	56.15	5.34

2.2 Multi-objective Optimization

i. Utility Theory:

The utility is defined as the application feasibility or extent of usefulness of a process or product with respect to the different phases of expectation of the customer[14].

$$N\left(Q_1,Q_2,Q_3,...Qn\right) = f\left(N_1\left(Q_1\right),N_2\left(Q_2\right),N_3\left(Q_3\right)...N_n\left(Q_n\right)\right) \quad (2)$$

Here, $N_1(Q_1)$ is the utility of the i[th] attribute.

The sum of individual utilities provides the overall utility of the function if the attributes are independent.

$$N\left(Q_1,Q_2,Q_3,.Q_4...Qn\right) = \sum_{i=1}^{n} N_i\left(X_i\right) \quad (3)$$

The total utility of the function after the assignment of the weight can be expressed as:

$$N\left(Q_1,Q_2,Q_3,.Q_4...Qn\right) = \sum_{i=1}^{n} W_i N_i\left(X_i\right) \quad (4)$$

The preference number is taken on a logarithmic scale as:

$$P_i = C \times \log \frac{Q_i}{Q_l^{'}} \quad (5)$$

Here, Q_i denotes the value of any attribute i for the quality, Q'_i is just the accepted value of the quality for any property i whereas C is the constant. The value of C can be expressed with a condition $Q_i = Q'$ (here Q' is the optimal or the best value) where P_i=9; then:

$$C = \frac{9}{\log \frac{Q'}{Q_i^{'}}} \quad (6)$$

The total utility can be given as:

$$\sum_{i=1}^{n} W_i P_i \quad (7)$$

The overall utility index will be considered as the single objective function obtained by Taguchi philosophy by considering Higher the Better (HTB) quality characteristics.

ii. Weighted Principal Component Analysis:

Weighted Principal Component Analysis (WPCA) is used to identify and eradicate responses correlation and transform correlated responses into uncorrelated responses called the principal components(PCs) [15]. These PCs are accumulated further to estimate the WPCA called MPI. In this combination, it is expected that AP of each PCs is utilized as an individual response weight [16].

The steps involved in the WPCA technique are:

Normalization of data

The first stage involved normalizing the observed data between the range 0 to 1. The data are normalized to decrease variability. It is performed because the data are in several ranges and thus the unit responses are required to remove the complications and make it simple.

For Lower the Better Approach

$$Q_i^* = \frac{\min Q_i\left(k\right)}{Q_i\left(k\right)} \quad (8)$$

For Higher the Better Approach

$$Q_i^*\left(k\right) = \frac{Q_i\left(k\right)}{\max Q_i\left(k\right)} \quad (9)$$

where, $i = 1,2,3,...,n : k = 1,2,3,...n$

$Q^*_i(k)$ is the normalized value for corresponding $Q_i(k)$ experimental value.

Calculation of Correlation Coefficient

The correlation coefficient can be examined and calculated using the:

$$A_{j1} = \frac{\mathrm{cov}\left(Q_i\left(j\right),Q_i\left(1\right)\right)}{\sigma Q_i\left(j\right)\times\sigma Q_i\left(1\right)} \quad (10)$$
$$j = 1,2,3,...,n : k = 1,2,3,...,n$$

$cov(Q_i(j),Q_i(1))$ is the covariance of sequences $Q_i(j)$ and $\sigma Q_i(j)\times\sigma Q_i(1)$ is the standard deviation of sequence $i(j)$, $\sigma Q_i(j)$ is the standard deviation of sequence $Q_i(1)$.

Eigenvalue and Eigenvector

The eigenvalues and eigenvectors are evaluated from the correlation coefficient array.

$$\left(A - L_k I_m\right) S_{ik} \quad (11)$$

where L_k Eigen Values and $\sum_{k=1}^{n} L_K = n, k = 1,2,...n$

$S_{ik} = \left[a_{k1},a_{k2},...,a_{kn}\right]^T$ Eigen Vector corresponding to Eigen Value λ_k.

Calculation of Major Principal Coefficient

$$PC_{mk} = \sum_{k=1}^{n} Q_m\left(i\right) S_{ik} \quad (12)$$

where PC_{mk} is corresponding Principal Component.

Determination of MPI

The Accountability Proportion (AP) calculated by assuming the individual weight for each PC. The multi-performance index is thus calculated as:

$$MPI = AP_{pC1} \times PC1 + AP_{pC2} \times PC2 \quad (13)$$

iii. Firefly Optimization Technique

It is a metaheuristic algorithm inspired by nature principles particularly based upon the flashing behaviour of fireflies and firstly introduced in the year 2007 by Prof. Xin-She Yang of Cambridge University. Firefly Algorithm has the enormous power of globally optimizing the parameters in lesser iterations and with a large number of constraint dimensions (Figure 5). The flashing nature of fireflies are used as a signal to attract the other pastures. Both, prey and mating partner attracted by this light [17]. The intensity of light between two fireflies at distances' is depicted by inverse square. This law is given by i α $1/s^2$. moreover, the air factor also affects light intensity. The objective function of the firefly algorithm can be formulated for maximum (exploration) and minimum (exploitation).

Figure 5. Firefly Motion towards Mating/Prey Partner

The light absorption coefficient is given and defined by □. The firefly which emits more light attracts lesser light-emitting fireflies. So, firefly which have more light intensity has more attractiveness. The FA uses regression equation which is an input function and upper, lower bounds along with constraints are actually used back in the algorithm which performs optimality test. The firefly constraint is depicted in Table 5 and Pseudocode for firefly algorithm is mentioned below:

PSEUDO CODE

Objective function f(x) , V=(v^1,..................... vd)^T
Generate initial population of firefly Vi, (i=1,2……………..,n)
Light intensity Ii at Vi is determined by f(vi)
Define light absorption coefficient □
While (t< max generation)
For i=1 : n all n fireflies
For j=1 : i all n fireflies
If (Ij > Ii) , more firefly i towards j ; **end if**
Attractiveness varies with distance r via exp[-□r]
Evaluate new solutions and update light intensity
End for i
End for j
Rank the fireflies and find the best **g***
End while
Post-process results and visualization
Where,
V is the objective function of firefly
n is the number of fireflies
α is the value of randomness
β is the value of attractiveness
□ is the value of the light absorption coefficient
I is the light intensity
t is the iteration

Table 5. Constraints for Firefly Algorithm (FA)

S.No.	FA parameters	Value
1	n (Number of Fireflies)	40
2	N_Iteration	500
3	α; Alpha (Value of Randomness)	0.5
4	β; Beta min (Value of Attractiveness)	0.2
5	□; Theta (Value of Light Absorption Coefficient)	1
6	Total Number of Function Evaluation is 40×500	20000

3. RESULTS AND DISCUSSION

This paper deals with two types of multi-response optimization methods i.e, Utility Theory and WPCA method. Overall utility (U) function value is depicted in Table 6 and WPCA is a statistical tool mainly used to identify the relationship among the machining performances. Table 7 and Table 8 shows that the correlation and PCA computation respectively (correlation between MRR and SR is 0.608). The WPCA tool aggregated the conflicting responses into a single objective function i.e. Multiple performance index (MPI) during EDM of Inconel X-750 as mentioned in Table 9.

Table 6. Utility Theory

MRR	SR	PI MRR	PI SR	U OVERALL
15.20	1.86	0	9	4.5
27.23	4.28	4.014483	2.011209	3.012846
26.22	5.44	3.754095	0	1.877047
25.93	3.68	3.678271	3.27785	3.47806
34.96	3.46	5.736739	3.794805	4.765772
40.79	3.24	6.799619	4.345733	5.572676
32.41	3.68	5.215899	3.27785	4.246874
47.83	4.84	7.895383	0.980038	4.43771
56.15	5.34	9	0.155591	4.577796

Table 7. Correlation table

Variable	Value	Remarks
MRR to SR	0.608	Both are correlated

Table 8. PCA Analysis

	Φ_1	Φ_2
Eigen values	1.6083	0.3917
Eigen vector	-0.707 0.707	-0.707 -0.707
AP	0.804	0.196
CAP	0.804	1

Table 9: MPI Computation

N MRR	N SR	PC 1	PC 2	MPI
0.270741	1	1.515586	-0.89841	1.042442
0.484914	0.434579	0.798745	-0.65008	0.514775
0.466926	0.341912	0.718795	-0.57185	0.465829
0.461814	0.505435	0.885932	-0.68384	0.578256
0.622662	0.537572	0.80435	-0.82029	0.485921
0.726552	0.574074	0.767402	-0.91954	0.436761
0.577316	0.505435	0.804272	-0.76551	0.496596
0.851833	0.384298	0.489052	-0.87394	0.221905
1	0.348315	0.348315	-0.95326	0.093206

Table 10. Result of WPCA-FA module

Parameters	Current (Ip)	Pulse On (Ton)	Pulse Off (Toff)	Voltage (V)	Fitness value
Optimal setting	12 Amp	63 µs	7 µs	40 volt	0.97213

3.1 Analysis of Variance (ANOVA)

The Analysis of Variance is a statistical technique applied to know the significance and the major contributing factors towards any performance measure[18]. In this, the analysis of variance for Utility approach has been shown in Table 11. which shows the contribution of 25.97% in Ip, 0.07% in Ton, 22.70% in Toff, 28.41% in V. The maximum contribution held in this Utility approach is V and the least contribution is Ton. The model summary for the Utility approach has been shown in Table 11. In Table 12 the analysis of variance for the MPI approach has been shown in which contribution of 44.81% is there in case of Ip, 38.41% in Ton, 1.95% in Toff, 3.86% in V, and 10.97% in case of an error in this experiment. The maximum contribution held in the MPI approach is T_{on} and the least contribution is T_{off}. The model summary for the MPI approach has been shown in Table 13.

Table 11. Analysis of Variance for Utility Approach

Source	DF	Seq SS	Contribution	P-Value
Regression	4	7.42552	77.14%	0.133
Ip	1	2.49936	25.97%	0.100
Ton	1	0.00650	0.07%	0.919
Toff	1	2.18490	22.70%	0.117
V	1	2.73476	28.41%	0.090
Error	4	2.19999	22.86%	
Total	8	9.62551	100.00%	

S= 0.741618, R^2=77.14% and R^2 (adj) =54.29%

The comparison between the Utility(U) and Weighted Principal Component Analysis(WPCA) has been shown in Table 13. From this, it can be concluded that there is more error in the case of the Utility approach than in MPI approach. The value in the case of Utility and WPCA for R^2 is 77.14% and 89.03% respectively. In this case, MPI has more R^2 value than Utility. The P-Value of MPI is greater than Utility as shown in the table below. From these provided data, it is clear that MPI approach is better than Utility approach in overall respect.

Table 12. Analysis of Variance for MPI Approach

Source	DF	Seq SS	Contribution	P-Value
Regression	4	0.48590	89.03%	0.033
Ip	1	0.24456	44.81%	0.016
Ton	1	0.20963	38.41%	0.020
Toff	1	0.01065	1.95%	0.446
V	1	0.02107	3.86%	0.301
Error	4	0.05988	10.97%	
Total	8	0.54578	100.00%	

S=0.122348, R^2=89.03% and R^2 (adj) =78.06%

Now, the coupling of WPCA into the firefly algorithm is performed by using developed pseudo-codes and constraints according to Table 5. Iteration is performed until the achievement of a favorable optimal setting.

Table 13. Robustness of firefly

No. of Iterations	Value of I_p	Value of T_{on}	Value of T_{off}	Value of V	Fitness values	Results
80	12.64673	65.170906	8.32049	42.19191	0.75960	Deviating
200	13.28801	63.01348	8.66661	47.42773	0.81934	
400	12.18641	63.02189	7.89815	45.46185	0.86202	
800	12.51747	68.53173	7.72216	46.83826	0.86508	
2000	12.00006	63.00016	7.99292	43.15932	0.95532	
4000	12.00006	63.00016	7.99292	43.15932	0.95532	
8000	12	63	7	40	0.97213	Non-Deviating
12000	12	63	7	40	0.97213	
16000	12	63	7	40	0.97213	
20000	12	63	7	40	0.97213	

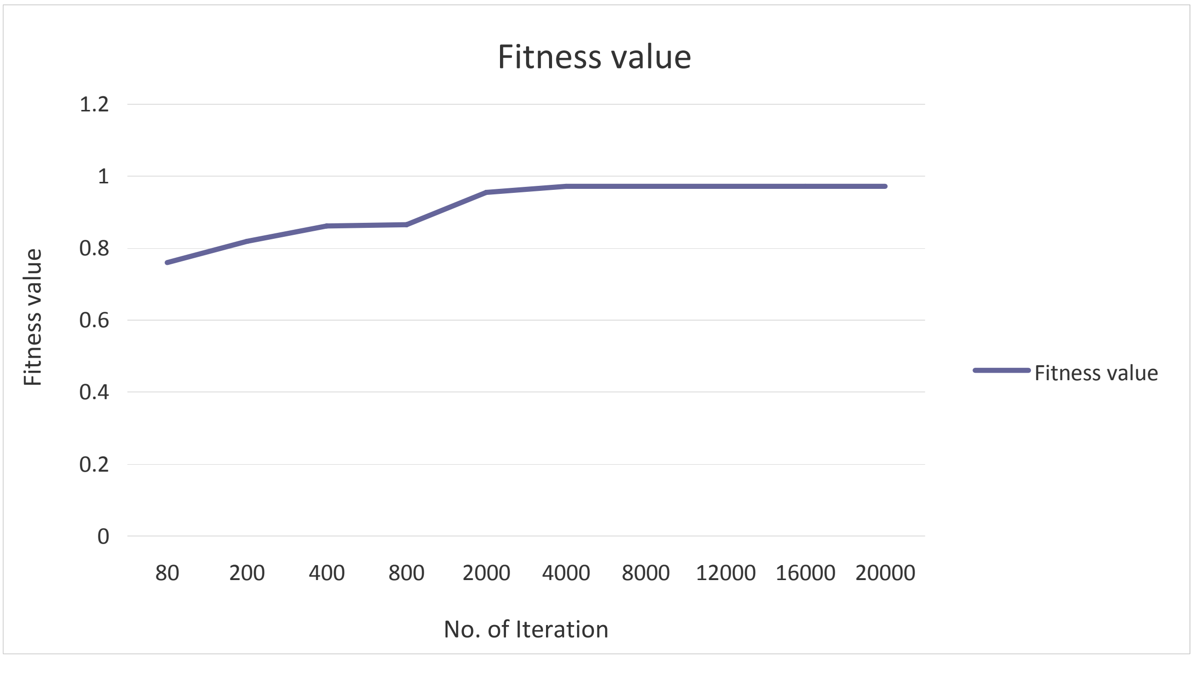

Figure 6. Convergence Plot for Firefly Algorithm

Table 14. Comparison between 'U' and 'WPCA' approaches

Tools Parameters	Brass	
	Utility	MPI
Error in Model	22.86%	10.97%
R^2	77.14%	89.03%
P-Value Closeness	MPI > Utility	
Overall Best	MPI	

Based on model adequacy of 89.03% and less average error calculation of 10.44, here hybridization of WPCA-FA is presented for the development of the robust module. A fitness function is developed to feed into the firefly algorithm as input function using equation 8.

$$MPI = -\left(3.382 - 0.0673 \times x(1) - 0.01699 \times x(2) \right. \\ \left. -0.0421 \times x(3) - 0.00593 \times x(4)\right) \tag{14}$$

3.2 Robustness of Algorithm

The above results show that algorithm fits suitably with WPCA-FA approach and robustness of the algorithm has been tested by increasing the value of the number of iterations such as 80, 200, 400, 800, 2000, 4000, 8000, 12000, 16000 and 20000 randomly for MPI regression equation (Eqn. 8). The values of the best jobs at different iterations have been found by using MATLAB 2015. For this, the MPI equation was run on the firefly algorithm, to get the value of best jobs for every respective iteration. In this, it has been found that iterations from value 8000 to 20000 are non deviating, in which values of best jobs are same which is 0.97213. Beyond this, iteration such as 80, 200, 400, 800, 2000, 4000 has deviating best job values which are not desired for favorable machining. The result obtained by WPCA-FA shows (Table 10) fitness function value of 0.97213 and optimal parametric setting as Ip-12, Ton-63, Toff-7, and V-40 at 8000 to 20000 iterations.

Table 13 shows that the algorithm shows better results from iterations 8000 to 20000, but before the iteration of 4000, i.e. from 80 to 2000 iterations, T_{on} and T_{off} value starts deviating and robustness began decreasing. The effective outcome could be seen at the value of iteration above 8000 and above as shown in the convergence plot in Fig. 6.

4. CONCLUSION

In this paper, two multi-response aggregation technique are used for conflicting machining performances of EDM X-750. WPCA performs better than the utility concept with less error in the adequate model and higher value of desired characteristics. The study shows the development of a novel hybridization approach by coupling of WPCA into a relatively advance nature-inspired metaheuristics firefly algorithm (FA).

The conclusion of the study are summarised below:

1. Both approaches have the capability to be coupled with the metaheuristic technique, specifically Firefly Algorithm but in this study, WPCA is preferred. The MPI produces better results than Utility Theory as regards the Error, Value of R^2, P-value and F-value of the factors are concerned.

2. The significance of the model has been tested by the value of the R^2. The higher value of R^2 shows the satisfactory adequacy of the developed model. The R^2 value of the WPCA-FA model (89.03%) is higher than the Utility (77.14%) model.

3. In ANOVA the maximum contribution for MPI has been held by Ip (44.81%) and then trailed by Ton (38.41%), Toff (1.95%), V(3.86%).

4. The finest setting for the conduction of experiment with the Brass Tool is 12 amperes, 63 μ-seconds, 7 μ-seconds and 40 volts for Input Current, Pulse on Time, Pulse off Time and Voltage respectively and treated as a robust module that can enhance productivity and quality of the industrial manufacturing system.

Future scope of work

Present works developed a robust hybridization approach of WPCA and relatively advanced nature-inspired FA during EDM of Inconel -750. Inconel has a wide range of high-performance applications in engineering sectors. Hence machining and machinability aspects of Inconel X-750 become potential area research for industries and academia. Inclusion of other parameters such as different dielectric mediums, different electrode materials, powder mix machining, dry EDM of Inconel X-750 can explore a better machining environment. Also, the proposed WPCA-FA approach can be customized for other conventional and nonconventional processes. It can be endorsed for online and offline quality monitoring of industrial engineering case studies of design making.

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ПРИСТУП КОМБИНАЦИЈИ ПРИРОДОМ ИНСПИРИСАНОГ АЛГОРИТМА СВИТАЦА И ПОНДЕРИСАНЕ АНАЛИЗЕ ГЛАВНИХ КОМПОНЕНАТА КОД ОБРАДЕ ЛЕГУРЕ INCONEL X-750

С.Н. Пандеј, Ј. Кумар, С. Јадав, Р.К. Верма

Електроерозивна обрада је основни неконвенционални поступак обраде који се користи код тешко обрадљивих материјала. Због побољшаних механичких својстава Inconel-750 има примену у областима где се захтевају велике перформансе, у индустрији авиона, аутомобила, итд. Током обраде различити параметри имају значајан утицај на перформансе процеса обраде. Произвођачи имају потешкоће да истовремено уравнотеже параметре и њихов одговор. У раду је приказан нови хибридни модул развијен за електроерозивну обраду легуре Inconel-750 коришћењем алата од месинга. Експерименти и два модула оптимизације су изведени применом Тагучијевог плана експеримента. Теорија корисности и пондерисана анализа главних компонената су удружени са релативно новим алгоритмом свитаца чиме је добијена циљна вредност за већу брзину скидања материјала и храпавости површине. Пондерисана анализа главних компонената са уметнутим алгоритмом свитаца даје боље резултате него теорија корисности заједно са модулима алгоритма свитаца, при чему прецизност модела износи 89,03%. Оптимална подешавања су: Ip-12 amp, Ton-63μs, Toff-7μs, V-40 волти, док је вредност прилагођености 0,97213. Значај комбинације алгоритма свитаца и пондерисане анализе главних компонената јесте у већој могућности примене и мониторингу квалитета и продуктивности од стране произвођача.