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

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 have 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 R², F and P-value with model accuracy of 89.03%. The optimal settings are found as Ip-12 amp, Ton-750 using the brass tool. Purohit et al. [5] applied a combined approach of Nature-inspired Firefly Algorithm (FA) and Grey Relational Analysis technique for the Multi-Objective Optimization (MOO) of the EDM 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 0.0006324%. 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 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].

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 them becomes an order of 0.5 mm, the intensity of the electric field starts to increase and, as and when it...
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 (EL1) 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 $V_{o}$, Ra was found to be the largest whereas it was lowermost at the lowest level of input variables.

Kliuiev 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% Al2O3 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 consists 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

| 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   |

Table 2. Domain of Experiment

| Exp. No. | Current ($I_p$) | Pulse On Time ($T_{on}$) | Pulse Off Time ($T_{off}$) | 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          |

Table 3. $L_9$ Orthogonal Array

| Exp. No. | MRR mm³/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]
The utility of the function if the attributes are independent.

\[ N(Q_1, Q_2, Q_3, \ldots Q_n) = f(N_1(Q_1), N_2(Q_2), N_3(Q_3), \ldots N_n(Q_n)) \]  
\[ N(Q_1, Q_2, Q_3, \ldots Q_n) = \sum_{i=1}^{n} N_i(X_i) \]  
\[ N(Q_1, Q_2, Q_3, \ldots Q_n) = \sum_{i=1}^{n} W_i N_i(X_i) \]  
\[ N(Q_1, Q_2, Q_3, \ldots Q_n) = \sum_{i=1}^{n} W_i P_i \]  
\[ \text{For Higher the Better Approach} \]
\[ Q_i^*(k) = \frac{Q_i(k)}{\max Q_i(k)} \] 
\[ \text{where, } i = 1, 2, 3, \ldots, n : k = 1, 2, 3, \ldots n \]
\[ Q_i^*(k) \text{ is the normalized value for corresponding } Q_i(k) \text{ experimental value.} \]

Calculation of Correlation Coefficient

The correlation coefficient can be examined and calculated using the:
\[ A_{ij} = \frac{\text{cov}(Q_i(j), Q_i(1))}{\sigma Q_i(j) \times \sigma Q_i(1)} \]  
\[ j = 1, 2, 3, \ldots, n : k = 1, 2, 3, \ldots, n \]
\[ \text{cov}(Q_i(j), Q_i(1)) \text{ is the covariance of sequences } Q_i(j) \text{ and } \sigma Q_i(j) \times \sigma Q_i(1) \text{ is the standard deviation of sequence } i(j), \]
\[ \sigma Q_i(j) \text{ is the standard deviation of sequence } Q_i(1). \]

Eigenvalue and Eigenvector

The eigenvalues and eigenvectors are evaluated from the correlation coefficient array.
\[ (A - L_k I_m) S_{ik} = 0 \]
\[ \text{where } L_k \text{ Eigen Values and } \sum_{k=1}^{n} L_K = n, k = 1, 2, \ldots n \]
\[ S_{ik} = [a_{i1}, a_{i2}, \ldots, a_{in}] \text{ Eigen Vector corresponding to Eigen Value } \lambda_k. \]

Calculation of Major Principal Coefficient

\[ PC_{mk} = \sum_{k=1}^{n} Q_m(i) S_{ik} \]  
\[ \text{where } PC_{mk} \text{ is corresponding Principal Component.} \]

Determination of MPI

The Accountability Proportion (AP) calculated by assuming the individual weight for each PC. The multi-performance index is thus calculated as:
\[ MPI = AP_{PC1} \times PC1 + AP_{PC2} \times PC2 \]  

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 \( i = 1/s^2 \). moreover, the air factor also affects light intensity. The objective function of the firefly algorithm can be formulated for maximum (exploration) and minimum (exploitation).
The light absorption coefficient is given and defined by $\alpha$. 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 $f(x)$, $V=(v_1, \ldots, v_d)^T$

Generate initial population of firefly $V_i$, $(i=1,2,\ldots,n)$

Light intensity $I_i$ at $V_i$ is determined by $f(v_i)$

Define light absorption coefficient

While ($t<\text{max generation}$)

For $i=1:n$ all n fireflies

For $j=1:i$ all n fireflies

If ($I_j > I_i$), 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 $\alpha$ is the value of randomness $\beta$ is the value of attractiveness $I$ is the value of the light absorption coefficient $t$ 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     | $\alpha$; Alpha (Value of Randomness) | 0.5  |
| 4     | $\beta$; Beta min (Value of Attractiveness) | 0.2  |
| 5     | ; Theta (Value of Light Absorption Coefficient) | 1    |
| 6     | Total Number of Function Evaluation is $40 \times 500$ | 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 | 5.218599 | 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

| Eigen values | $\Phi_1$ | $\Phi_2$ |
|--------------|---------|---------|
| 1.6083       | 0.3917  |        |

| Eigen vector | $\Phi_1$ | $\Phi_2$ |
|--------------|---------|---------|
| -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 | 0.496936 |
| 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 $\mu$s | 7 $\mu$s | 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 \( I_p \), 38.41% in \( T_{on} \), 1.95% in \( T_{off} \), 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   |
| \( I_p \) | 1  | 2.49936  | 25.97%       | 0.100   |
| \( T_{on} \) | 1  | 0.00650  | 0.07%        | 0.919   |
| \( T_{off} \) | 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%      |         |

\[ S= 0.741618, \, R^2=77.14\% \text{ and } R^2 (adj) =54.29\% \]

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   |
| \( I_p \) | 1  | 0.24456  | 44.81%       | 0.016   |
| \( T_{on} \) | 1  | 0.20963  | 38.41%       | 0.020   |
| \( T_{off} \) | 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%      |         |

\[ S=0.122348, \, R^2=89.03\% \text{ and } R^2 (adj) =78.06\% \]

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        | Non-Deviating |
| 8000              | 12                  | 63                    | 7                     | 40              | 0.97213        |           |
| 12000             | 12                  | 63                    | 7                     | 40              | 0.97213        |           |
| 16000             | 12                  | 63                    | 7                     | 40              | 0.97213        |           |
| 20000             | 12                  | 63                    | 7                     | 40              | 0.97213        |           |

\[ 80 \rightarrow 200 \rightarrow 400 \rightarrow 800 \rightarrow 2000 \rightarrow 4000 \rightarrow 8000 \rightarrow 12000 \rightarrow 16000 \rightarrow 20000 \]

**Figure 6. Convergence Plot for Firefly Algorithm**
Table 14. Comparison between ‘U’ and ‘WPCA’ approaches

| Tools Parameters | Brass | Stainless Steel | Al-4Cu-6Si | Inconel X750 |
|------------------|-------|----------------|------------|--------------|
| Error in Model   | 22.86% | 10.97%         | 22.86%     | 10.97%       |
| R²                | 77.14% | 89.03%         | 77.14%     | 89.03%       |
| P-Value Closeness| MPI > Utility | Utility > MPI | MPI > Utility | Utility > MPI |
| Overall Best     | MPI   | MPI            | MPI        | 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.

\[
MPI = -\left(3.382 - 0.0673 \times x(1) - 0.01699 \times x(2) - 0.0421 \times x(3) - 0.00593 \times x(4)\right)
\]  

\[\text{Eqn. 14}\]

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, Ton and Toff 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 R², P-value and F-value of the factors are concerned.

2. The significance of the model has been tested by the value of the R². The higher value of R² shows the satisfactory adequacy of the developed model. The R² 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 (19.5%), 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 X-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 анализы Главних Компонентоват код Обраде Легуре INCONEL X-750**

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Електроерозивна обрада је основни неконвенционални поступак обраде који се користи код тешко обрадљивих материјала. Због побољшаних механичких својства Inconel-750 има примену у областима где се захтевају велике перформансне, у индустрији авиона, аутомобила, итд. Током обраде различити параметри имају значајан утицај на перформансе процеса обраде. Произвођачи имају потешкоће да истовремено уравновеђују параметре и њихов одговор. У раду је приказан нови хибриден модул развијен за електроерозивну обраду легуре Inconel-750 коришћењем алата од месинга. Експерименти и два модула оптимизације су изведени применом Тагучиевог плана експеримента. Теорија корисности и пондерисана анализе главних компонената су удржане са релативно новим алгоритмом свитаца чиме је добијена шиљна вредност за већу брзину склипања материјала и храпљивост површине. Пондерисана анализа главних компонената са умет-нутним алгоритмом свитаца је постојала резултате неке теорије корисности заједно са модулма алгоритма свитаца, при чему прецизност модела износи 89,03%. Оптимальна подешавања су: Ip-12 a, Topp-63μs, Toff-7μs, V-40 волт, док је вредност прилагођеноста 0,97213. Значај комбинације алгоритма свитаца и пондерисане анализе главних компонената јесте у већој могућности примене и мониторирућу квалитета и продуктивности од стране произвођача.