Multi Objective Optimization of Near-Dry EDM Using PCA-TOPSIS Combined With Taguchi Philosophy

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Abstract- *Near-Dry Electrical Discharge Machining (Near-Dry EDM) is a variation of conventional EDM, which is eco friendly as compared conventional EDM since it requires very little amount of liquid as dielectric. Like all other machining processes, parameters of Near-Dry EDM also needs to optimize to give best output.*

In this paper work multiple response parameters of Near-Dry EDM are optimized simultaneously. Liquid-gas mixture (mist) is used as dielectric in Near-Dry EDM. Process parameters considered for the research are discharge current, gap voltage, air pressure, pulse on time electrode material and duty factor. The performance parameters were material removal rate (MRR), tool wear rate (TWR) and surface roughness (Ra). For design of experiment, L_{18} orthogonal array based on Taguchi method is used. For multi objective optimization PCA analysis combined with TOPSIS is used and after that Taguchi method is applied.

Keywords- Near-Dry EDM, PCA, Taguchi Method, TOPSIS

I. INTRODUCTION

Electrical Discharge Machining processes is a non conventional machining process which has ability to machine any electrically conductive material regardless of its mechanical strength due to which EDM has achieved a standing of being essential within the industry [1]. Despite of its benefits, environmental issues related to the process have been a significant disadvantage of EDM. The primary source of pollution in EDM process is the dielectric which is utilized in this process. Since there is no environment friendly substitute available at present for replacing the EDM process, totally eliminating or using different liquid dielectric medium provides a feasible solution [2]. Near-dry EDM is a modification of conventional EDM which tries to reduce problems of conventional EDM variants. The limitations of the dry and wet EDM could be eliminated by near-dry EDM, in which the mixing of a minimum quantity of the liquid with the compressed air (air-mist) or gas (gas-mist) has been used as a dielectric medium [3]. The first reference of Near-Dry EDM can be found in the report given by Tanimura et al. [4] in 1987 who investigated EDM in water mists with air, nitrogen, and argon gases. Not much study has been conducted on this process until by Kao et al. [5] in 2007 in near-dry wire EDM. It was found that near-dry EDM has the advantage in finish operation with low discharge energy considering its higher MRR than wet EDM and better surface finish quality than dry EDM [6]. Near-Dry EDM is proved beneficial for finishing operations whereas Wet and Dry EDMs were proved beneficial for roughing operation [6-7].

To get best out of a machine, its parameters need to be optimized. Tripathy et al. [8] performed an optimization to get high material removal rate (MRR) and low tool wear rate (TWR). Multi objective optimization (MOO) of input parameters of Near-Dry EDM was done by Deshmukh et al. [9] by using Response Surface Methodology (RSM) for high MRR and low TWR. Mane et al. [10] optimize input parameters to get high MRR, low TWR and low surface roughness (Ra) by using Taguchi method.

Taguchi method is a robust and effective method for parametric optimization. But Taguchi method cannot be directly employed for multi objective optimization. It needs to be combined with another technique.

In this paper Taguchi method is coupled with another hybrid MOO method which is PCA-TOPSIS. Tong et al. [11] proposed PCA combined with TOPSIS for solving various multi-response problems. PCA is used to simplify multi response problems and determine the optimization direction by using a variation mode chart and the optimal factor/level combination is determined based on the overall performance index for multiple responses obtained from TOPSIS.

II. METHODOLOGY

In this research work multi objective optimization of input parameters, which are electrode material, air pressure, discharge current, gap voltage, pulse on time and duty factor, using PCA-TOPSIS combined with Taguchi method. For this the following methodology is used based on research of Mane et al. [10].

A. Experimental Setup

The experiments were performed on a CNC die sinker EDM from Electronica. Dielectric used for machining was a mixture of kerosene and compressed air. This mixture consist of very small quantity of liquid (kerosene) mixed in compressed air so as to form a mist. A spray gun was used to spray the mixture in the inter electrode gap. The work piece material was AISI SAE D2 tool steel. Two different rotating electrodes, copper and copper-tungsten electrodes were used in the experiment. Electrodes diameter was 15mm. Polarity of electrode was kept as negative and that of workpiece is kept was positive. Each experiment was performed for 20 minutes. The responses selected for the experiment were material removal rate (MRR), tool wear rate (TWR) and surface roughness (Ra) [10].

B. Selection of process parameters and their levels

The process parameters selected based on literature survey were electrode material, air pressure, gap voltage, discharge current, pulse on time and duty factor. The process parameters and their levels are given in Table 1. For the experiment 3 levels of each parameter were selected [10].

Table-1: Process parameters under study and their levels.

Factor	Levels		
	Level 1	Level 2	Level 3
(A) Electrode material	Copper-Tungsten (CuW)	Copper (Cu)	--------
(B) Air pressure (kg/cm^2)	4	5	6
(C) Discharge Current(Amps)	8	12	16
(D) Gap voltage (volts)	40	60	80
(E) Pulse on time (µs)	100	150	200
(F) Duty factor (%)	7	9	11

(Table 1 source: Mane, S.G. and Hargude, N.V., "Parametric Optimization of Near Dry Electrical Discharge Machining Process for AISI SAE D-2 Tool steel" [10])

C. Design of Experiment

DoE chosen for this investigation is Taguchi's Orthogonal Array. The smallest mixed 2-level and 3-level array, L_{18} orthogonal array, meets the requirements of experiment [10].

Table-2: L_{18} Orthogonal Array

Exp. No.	*Cu/CuW*	P_a	*Ip*	*V*	*Ton*	T
1	CuW	4	8	40	100	7
2	CuW	4	12	60	150	9
3	CuW	4	16	80	200	11
4	CuW	5	8	40	150	9
5	CuW	5	12	60	200	11
6	CuW	5	16	80	100	7
7	CuW	6	8	60	100	11
8	CuW	6	12	80	150	7
9	CuW	6	16	40	200	9
10	Cu	4	8	80	200	9
11	Cu	4	12	40	100	11
12	Cu	4	16	60	150	7
13	Cu	5	8	60	200	7
14	Cu	5	12	80	100	9
15	Cu	5	16	40	150	11
16	Cu	6	8	80	150	11
17	Cu	6	12	40	200	7
18	Cu	6	16	60	100	9

(Table 2 source: Mane, S.G. and Hargude, N.V., "Parametric Optimization of Near Dry Electrical Discharge Machining Process for AISI SAE D-2 Tool steel" [10])

D. PCA-TOPSIS Combined with Taguchi Method

PCA is initially performed on the SN values obtained from each response to integrate the dimension of multiple responses to a smaller number of uncorrelated components. The variation mode charts for components obtained from PCA are then used to investigate the variation pattern of various integrated responses. Then, TOPSIS is used to determine the optimal factor/level combination for multiple responses [11]. Finally Taguchi method is employed to get optimized values.
Following steps are involved for optimizing multi response problems using PCA-TOPSIS [11-12]:

Step-1: Let there are *m* number of experiments for which there are *n* number of responses for each experiment.
Before performing PCA analysis, *S/N* ratio is calculated for each response depending on the type of response desired, using the criteria given below:

For nominal the best (NTB) by using, S/N= $-10 \log \frac{\bar{y}}{s_y^2}$

For smaller the better (STB) by using, S/N= $-10 \log \frac{1}{n}\sum y^2$

For larger the better (LTB) by using, S/N= $-10 \log \frac{1}{n}\sum \frac{1}{y^2}$,

Step-2: *S* / *N* ratio of each response variable are normalized using the following equation:

$x_{ij} = \frac{SN_{ij} - \overline{SN_j}}{s_{SN_j}}$

Where,

x_{ij} are the normalized variables,

SN_{ij} denotes the *S/N* ratio of the j^{th} response in the i^{th} experimental run,

$\overline{SN_j}$ denotes mean for j^{th} response,

S_{SN_j} denotes standard deviation for j^{th} response.

Step-3: Checking for correlation between each pair of quality characteristics by calculating variance-covariance through the normalized values:

Let $Q_i = \{x_0(i),\ x_1(i),\ ....,\ x_m(i)\}$, where i = 1, 2, 3,....., n

It is the normalized series of the i^{th} quality characteristic. The correlation coefficient among two quality characteristics is evaluated by the following equation:

$R_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma Q_j * \sigma Q_k}$

Where,

j = 1, 2, 3,....., n

k = 1, 2, 3,....., n

$k \neq j$

$Cov(Q_j, Q_k)$ is the covariance of Q_j and Q_k of response variable *j* and *k*.

σQ_j and σQ_k are the standard deviation of response variable *j* and *k*.

Step-4: Eigen values, Eigen vectors and principal component scores are obtained by conducting PCA analysis on normalized S/N ratios of response variables.

Procedure to conduct PCA analysis:

i. Solve the characteristic equation, $|\boldsymbol{R} - \lambda \boldsymbol{I}| = 0$

Where,

R = Correlation matrix of order $n \times n$

I = Identity matrix of order $n \times n$

λ = Eigen Values ($\lambda_1, \lambda_2, \lambda_3, \dots\dots, \lambda_k$),

$\sum_{k=1}^{n} \lambda_k = n$; k = 1, 2, 3,....., n

ii. Once the Eigen values λ's are determined proportion of variance explained by each PC (Principal Component) and cumulative variance can also be calculated.

iii. From the Eigen values, the Eigen vector for each Eigen value (λ) can be computed by solving,

$(\boldsymbol{R} - \lambda \boldsymbol{I})\mathbf{V} = 0$, subjected to $V^T V = 1$

Where,

V = Eigen vector of order $p \times 1$ for λ_k

$$\boldsymbol{V} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ \vdots \\ v_k \end{bmatrix}$$

iv. Calculate the principal component scores of the comparative sequence and normalized reference sequence utilizing the equation shown below:

$y_i\ (l) = \sum_{j=1}^{n} x_{ij} * v_{jk}$,

Where,

i = 1, 2, 3,......., m,

k = 1, 2, 3,......., n,

l = 1, 2, 3, ..., n.

i.e., principal component score will be

$y_i\ (1) = x_{i1}v_{11} + x_{i2}v_{21} + ... + x_{in}v_{n1}$

$y_i\ (2) = x_{i1}v_{12} + x_{i2}v_{22} + ... + x_{in}v_{n2}$

....

.... (Eq. 3.12)

$y_i\ (l) = x_{i1}v_{1l} + x_{i2}v_{2l} + ...$

Here, y_i (l) is the principal component score of the l^{th} element in the i^{th} series. x_{ij} is the normalized value of the j^{th} element in the i^{th} sequence, and v_{kj} is the j^{th} element of the Eigen vector v_k.

Step-5: Determine the number of principal components to be retained. The number of principal components retained should account for 100% variation in the original values.

For extracting PC's there different methods they are listed below:

- Cumulative percentage of total variance
- Kaiser's rule (Eigen-value criteria)
- Average root method
- Broken stick method
- Scree plot
- Bartlett's Hypothesis test

Step-6: Determine the optimization direction or type i.e., whether it is maximizing or minimizing, for the selected principal components by developing the variation mode charts.

The variation mode chart of l^{th} (l= 1,2,3,…,q and $q \leq p$) principal component (y_l) is the plot of the upper and lower variation extent limits, $VEL_1(y_l)$ and $VEL_2(y_l)$, respectively, with respect to n response variables. The values of $VEL_1(y_l)$ and $VEL_2(y_l)$ are computed using the following equations:

$VEL_1(y_l) = (3a_{11}\sqrt{\lambda_1}, 3a_{21}\sqrt{\lambda_1},\dots\dots\dots, 3a_{p1}\sqrt{\lambda_1})$

$VEL_2(y_l) = (-3a_{11}\sqrt{\lambda_1}, -3a_{21}\sqrt{\lambda_1},\dots\dots\dots, -3a_{p1}\sqrt{\lambda_1})$

Where λ_1 is the Eigen value of the l^{th} *(l= 1,2,3,…,q and q ≤ p)* principal component [11]. The variation mode chart helps to determine the optimization direction of each selected principal component with respect to the integrated response. For example, positive values of $VEL_1(y_l)$ for all the variables imply that the S/N ratios of each response can be enhanced simultaneously, and therefore, the principal component y_1 will be considered as the LTB type with respect to the integrated response. A principal component can also be STB type. It may be noted that this knowledge is necessary for the determination of the ideal and negative ideal solutions as described in step 9. Here '*l* ' should be equal to ' *n*' as we should not consider Eigen values that are greater than 1 only [11-12].

Step-7: Evaluate a normalized matrix, for all the retained principal components. The normalized matrix for i^{th} trial and l^{th} principal component score is evaluated using formula given below.

$$x^{*}_{il} = \frac{y_{il}}{\sqrt{\sum_{i=1}^{m} y_{il}^{2}}}$$

Where,

x^{*}_{il} represents the normalized value of the l^{th} principal component score corresponding to the i^{th} trial.

Step-8: Obtain the weighted matrix. The weighted performance measure for the l^{th} attribute corresponding to the i^{th} trial (W_{il}) can be derived as follows:

$$W_{il} = w_l \, x^{*}_{il}$$

Where, w_l represents the weight of attribute x^{*}_{il}. In PCA-TOPSIS, weight (w_l) is taken as the Eigen value corresponding to process parameter.

Step 9: Determine the ideal and the negative-ideal solutions.

The ideal value set, W^{+} and the negative-ideal value set, W^{-} are determined as follows:

W^{+} = {(max W_{il} | $l \in L$) or (min W_{il} | $l \in L'$), i = 1, 2, ….., m}

= $W_1^{+}, W_2^{+}, \ldots, W_n^{+}$

W^{-} = {(min W_{il} | $l \in L$) or (max W_{il} | $l \in L'$), i = 1, 2, ….., m}

= $W_1^{-}, W_2^{-}, \ldots, W_n^{-}$

Where,

L = {l = 1, 2, ….., n | W_{il}, a larger response is desired }

L' = {l = 1, 2, ….., n | W_{il} , a smaller response is desired }

Step-10: Calculate the separation measures.

The separation of each alternative from the ideal solution (S_i^{+}) is given as follows:

$$S_i^{+} = \sqrt{\sum_{l=1}^{n}(W_{il} - W_q^{+})^2}$$

The separation of each alternative from the ideal solution (S_i^{-}) is denoted as below:

$$S_i^{-} = \sqrt{\sum_{l=1}^{n}(W_{il} - W_q^{-})^2}$$

Step-11: Calculate the relative closeness of various alternatives to the ideal solution, which is considered as the C_j. Ideal solution is a point which is best of everything & Negative ideal solution is point where all the worst exists.

The *C* for the i^{th} trial can be computed using the following equation:

$$C_j = \frac{S_i^{-}}{S_i^{+} + S_i^{-}}$$

- If i^{th} alternative is at the Ideal solution, then S_i^{+} = 0

C_j = 1 =100%

- If i^{th} alternative coincides with Negative Ideal solution, then S_i^{-} = 0

C_j = 0

The relative closeness of the alternative shows the closeness to the ideal solution, and value is between 0 and 1. If the value is closer to '1' then the alternative is closer to the ideal solution.

Step-12: C_j for each run has been termed as Multi-Performance Characteristic Index (MPCI) which has been optimized by Taguchi method.

III. RESULT AND DISCUSSION

Response variables obtained according to setting of parameters for each run are measured and shown in Table-3.

Table-3: Experimental data

Exp. No.	*MRR* (*mm³/min*)	*TWR* (*mm³/min*)	*Ra*
1	1.218815	0.027027	3.22
2	2.891112	0.036486	3.314
3	8.050936	0.043919	4.447
4	1.383836	0.028378	2.908
5	2.584459	0.041892	2.77
6	12.96778	0.047297	3.934
7	8.316008	0.02027	3.179
8	11.16164	0.055574	3.909
9	10.16112	0.042905	4.138
10	7.445426	0.089286	4.42
11	1.663202	0.083705	3.948
12	10.08966	0.128348	4.928
13	10.66788	0.089286	4.419
14	8.77079	0.200893	3.447
15	12.9158	0.15067	3.818
16	7.87422	0.122768	4.527
17	10.50546	0.172991	3.722
18	9.881757	0.061384	4.922

(Table 3 source: Mane, S.G. and Hargude, N.V., "Parametric Optimization of Near Dry Electrical Discharge Machining Process for AISI SAE D-2 Tool steel" [10])

PCA analysis is performed on normalized values of S/N ratios of response variables using MINITAB 15. PCA result obtained is given in Table-4 and Table-5.

Table-4: PCA result: Eigen Values and Eigen Vectors

Variable	PC1	PC2	PC3
Eigen Value	2.034972	0.572584	0.392444
Eigen Vectors			
	PC1	PC2	PC3
MRR	-0.59537	-0.37508	0.710531
TWR	0.540632	-0.84121	0.008942
Ra	0.594353	0.389459	0.703609

Table-5: PCA components obtained from PCA analysis.

Exp. No.	PC1	PC2
1	2.491101	0.067351
2	1.515084	-0.02868
3	-0.40384	-0.94114
4	2.710219	0.299044
5	2.106939	0.599827
6	-0.39193	-0.79421
7	1.345097	-1.15329
8	-0.38728	-0.51055
9	-0.30874	-0.91551
10	-0.88891	-0.01362
11	0.65957	0.859649
12	-1.77733	0.047665
13	-1.15386	-0.18051
14	-0.79638	1.475168
15	-1.20649	0.708106
16	-1.26592	0.300027
17	-1.07578	1.032678
18	-1.17154	-0.852

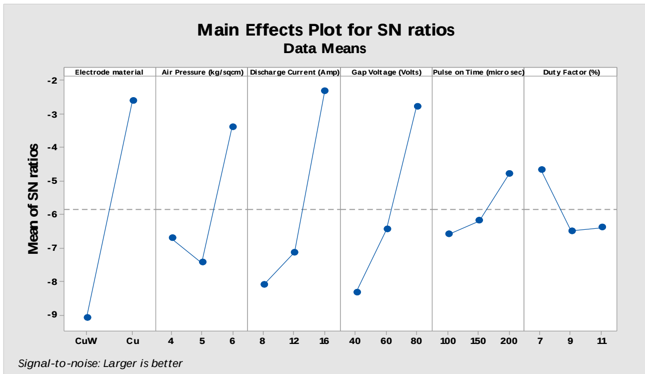
The separation measures of each alternative from the ideal solutions have been computed and then closeness coefficient is computed which is treated as overall performance index to perform Taguchi analysis.

Table-6: Computed values of separation measures, closeness coefficient and corresponding S/N ratios.

Exp. No.	S^-	S^+	C_i	S/N Ratio
1	1.493699	0.269262	0.152733	-16.3213
2	1.157666	0.497144	0.300423	-10.4453
3	0.476797	1.165103	0.709607	-2.97965
4	1.575328	0.215848	0.120506	-18.3798
5	1.381868	0.263388	0.16009	-15.9127
6	0.483832	1.151268	0.704096	-3.04736
7	1.080306	0.67511	0.384587	-8.30011
8	0.495188	1.13195	0.695669	-3.15194
9	0.509976	1.132918	0.689587	-3.22822
10	0.371791	1.274862	0.774214	-2.22278
11	0.920509	0.718426	0.43835	-7.16359
12	0.220406	1.574563	0.877209	-1.13794
13	0.280007	1.371001	0.830402	-1.61423
14	0.589817	1.213225	0.672877	-3.44129
15	0.394596	1.362407	0.775415	-2.20931
16	0.320074	1.392479	0.813101	-1.79711
17	0.468893	1.312406	0.736769	-2.65337
18	0.216763	1.409299	0.866695	-1.24268

Main effect plot for S/N ratio (using Larger-the-better setting) is obtained from MINITAB 15, from which optimal setting can be obtained. The larger values in Main effect plot of S/N ratio shows the best value of input parameters.

Fig.-1: Main Effect Plot for S/N ratio



The optimal setting obtained from Main effect plot corresponding to the highest value of S/N ratio is illustrated in Table-7.

Table-7: Obtained Optimal Setting

Factor	CuW/Cu	Pa	Ip	V	Ton	τ
Level	Cu	6 kg/cm^2	16 amp	80 V	200 μ-sec	7%

Table-8: Predicted result for obtained optimized result.

MRR (mm³/min)	*TWR (mm³/min)*	*Ra*
23.563	0.17210	5.89

IV. CONCLUSION AND FUTURE SCOPE

For the process to be efficient, high MRR (Material Removal Rate), good surface roughness (low Ra), low tool wear rate (TWR) are desired; which can be obtained by manipulating the input parameters like air pressure, discharge current, gap voltage, pulse on time, duty factor, electrode material etc. In this study, MRR, Ra, TWR of AISI SAE D2 tool steel was experimentally investigated, to find the optimized parameters using PCA-TOPSIS combined with Taguchi's robust optimization philosophy. Finally, the optimum input factors (process control parameters) and their corresponding levels were found out using S/N ratio concept.

The predicted values of response parameters obtained from the optimized values of input parameters show that optimization is achieved by the proposed method. Optimized values give high MRR, relatively low TWR and considerable surface roughness.

Future Scope:

i. There are various combinations of electrode materials and liquid gas mixtures as dielectric mediums that can be used.
ii. Different combinations of machining parameters like gap size, frequency etc can be used to perform experiments.
iii. Different conditions like machine tool vibration, cryogenic effect on tool etc. can be adopted
iv. Different multi objective optimization techniques can be applied like grey relational analysis, genetic algorithm, evolutionary algorithms and combined methods like grey-fuzzy method combined with Taguchi method.
v. Theoretical modelling and process simulation in near dry EDM can be done. Present literature is insufficient on this regard.

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