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Optimization of Performance Parameters for OHNS Die Steel using Dimensional Analysis Integrated with Desirability Function

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ABSTRACT

Wire electrical discharge machining (WEDM) of oil hardening die steel materials is a complicated machining process. Hence, to determine the best set of process parameters is an important step in the wire EDM process. In the present work, multi-response optimization of machining parameters was done by using a technique called desirability function analysis coupled with the dimensional analysis(DA) approach. The experimentations were carried out as per Taguchi's L_{27} orthogonal array for (Oil Hardening Non-Shrinking Die Steel) the OHNS die steel material. Parameters of the WEDM process, such as pulse on time, pulse off time, input current, wire feed rate, and the servo voltage, were optimized by a multi-response optimization technique to optimize the responses such as material removal rate and surface roughness. Based on desirability analysis, the set of most favorable levels of parameters has been identified. The significant contribution of parameters is determined by dimensional analysis. From the experimental results, it has been observed that the DA approach is in good agreement with the measured responses. The correlation up to 99% has been achieved between the developed model and the measured responses by using dimensional analysis approach. Thus, the presented methodology can be used in the future for the critical analysis of any engineering process.

1. Introduction

Wire-electrical discharge machining (WEDM) is a non-traditional machining process that is used to cut the materials with an electrode that follows a definite pathway to shape complex and complicated products. M.R.Phate & V.H.Tatwawadi [1,2] used an approach of dimensional analysis to formulate the model for the dry machining of ferrous and nonferrous materials. Ilhan Asilturk and Mehmet Cunkas [3] used multiple regressions and the artificial neural network for the turning process. They analyzed the impact of cutting speed, feed, and depth of cut on surface roughness. Gaitinde et al. [4] used an artificial neural network technique to analyze the performance of conventional and wiper ceramic inserts in hard turning. An acceptable and efficient result was obtained by these techniques. I.M.Jamadar and D.P.Vakharia [5] used a DA approach and ANN based on back-propagation neural network (BPNN) to analyze the vibration responses due to artificially spalled

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bearing components to quantify the level of structural damages to these components. Acceptable results were obtained by the DA method. Ravindranadh Bobbili et al. [6] evaluated the significance machine variables such as pulse-on time, flushing pressure, input power, thermal diffusivity, and latent heat of vaporization on responses such as material removal rate and the surface roughness. Buckingham's pi theorem was used for the model formulation of the material such as aluminum alloy 7017 and rolled homogeneous armor. Murahari Kolli and Adepu Kumar [7] used the Taguchi method to analyze the impact of dielectric fluid on the discharge of WEDM of titanium alloy. The various responses considered are Material Removal Rate (MRR), Surface Roughness (SR), Tool wear rate (TWR), and Recast Layer Thickness (RLT). Pujari Srinivasa Rao et al. [8] investigated the residual stresses developed in the machining of Aluminium alloy by Taguchi method.

J.R.Mevada (2013) [9] investigated two responses, i.e., MRR and Surface roughness. This investigation was carried out to find the best optimal level for a higher material removal rate at lower surface roughness for Inconel 600 material. The experiments were conducted by the varying pulse on times, pulse off times, and peak currents. Yu Huang et al. [10] studied the effect of various process parameters on surface roughness, material removal rate, and average gap voltage in the WEDM of high hardness tool steel YG15. Regression models were used to obtain the optimum cutting parameter combination. Pulse-on time, cutting feed rate, and water pressure were more important than other factors in MRR. Tzeng et al. [12] proposed a valuable process parameter optimization approach that integrates Taguchi's parameter design method, response surface methodology (RSM), a back-propagation neural network (BPNN), and a genetic algorithm (GA) on engineering optimization concepts to determine the best parameter settings of the WEDM process in consideration of multiple responses. Material removal rate and work-piece surface finish on process parameters during the manufacturing of pure tungsten profiles by wire electrical discharge machining (WEDM). Mangesh et al. [14] used the approach based on the dimensional analysis for the turning of ferrous and nonferrous materials. Al 6063, brass, Steel EN1A, EN8, and SS 304 were used for the experimentation. Surface roughness model was developed for the ferrous and nonferrous materials by using the DA approach. A random plan of experimentation was used for the data collection. Good agreement between experimental and calculated surface roughnesses was observed in the presented work. R.S.Kadu et al. [15] used the dimensional analysis approach for analyzing the performance of boring machining operation. The factors such as cutting speed, depth of cut, insert material, and cooling environment along with the length and diameter of the tool were considered as influencing parameters. The material used for the experimentation was cast iron in boring machining operation. The principle of max-min was used for optimizing the performance parameters such as surface roughness and the cutting time. Kumar et al. [16] used Tungsten powder during the EDM of Die material. He investigated the performance of EDM process parameters for the optimized use. Sanjeev et al. [17] used the EDM process for the surface modification using tungsten powder-mixed dielectric fluid. OHNS die steel was used for the experimentation. Mangesh Phate and Pratik Gaikwad [20] used the biodynamic model approach for analyzing the biodynamic responses. There are so many modeling techniques used by the worldwide authors; however, the most suitable dimensional analysis (DA) technique is implemented effectively in the presented work. Jha et al. [20] used the Taguchi method, and Vaysi et al. [22] used the fuzzy FMEA tool for the optimization of the process.

2. Material and Method

2-1. Material

The experiments were conducted using EZEECUT NXG –Wire EDM with 320 X 400mm axis travel and 360 X 600 maximum work piece diameters. Brass wire with wire diameters of 0.2 mm was used with an accuracy of 0.1 mm. The Electric Discharge Machine typically consists of a machine, a power unit, and a spark unit. Wire moves through the work piece from upper and lower wire paths. Oil Hardening Non-Shrinking Die Steel (OHNS) is a chemical composition and is shown in Table 1. A work piece with dimensions of 200 X 75 X 10 mm was used as a work piece material while brass wire was used as the tool electrode materials. A picture of experimental setup is shown in Figure 1. The various inputs and performance parameters are shown in Table 2.

2-2. Formulation of governing equation using dimensional analysis (DA) approach

This study was carried out for the performance analysis of the WEDM of OHNS steel. The various performance indicators, such as surface roughness, were measured by the MITUTOYO SJ-201P roughness tester. This is the most important parameter in the WEDM process. The second and the most important wire EDM machining characteristic, i.e., material removal rate (MRR) calculated using the material removed w.r.t the span of actual machining.

Tab. 1. Chemical composition of work piece material

Elems.	C	Mn	Cr	Si	P	W	V
Weight (%)	0.85-0.95	1.0-1.3	0.4-0.6	0.2-0.4	0.03 max	0.4-0.6	0.20 max

The main aim of this segment is to structure a generalized dimension model for various responses mentioned above for the wire EDM of OHNS machining [11,13]. Dimensional analysis (DA) is a very easy and strong technique that can be used in the model formulation for any complex engineering system. The DA approach is used for the system where the number of variables is huge, and correlating such high number of variables is a challenging task.

For the purpose of DA-based model formulation, let us assume that there is a relationship between the response variables, i.e., dependent variables, and the governing parameters, i.e., independent variables. [11,18] In other words, let N be the total number of variables (such as Pulse on time, pulse off time, wire feed rate, servo voltage, input current, density of material, wire tension, dielectric fluid flow, coefficient of thermal expansion, surface roughness, and material removal rate) that can be assured as a relation between ($N-N_1$) dimensionless groups (pi terms) of variables, where N_1 is the number of basic dimensions, i.e., M, L, and T; hence, $N_1 = 3$, [13,19,23-25]. The wire EDM parameters, such as pulse-on time (PON), work piece density (ρ), and the servo voltage (V), were selected as repeating parameters. The other parameters were selected to establish the DA model. The primary dimensions of selected parameters are given in Table 2.

Suppose that the following function f designates the dependency of wire EDM process, i.e., response variable with input factors as Eq. (1,2),

$$\text{Response variables} = f\,(\text{Independent variables}) \quad (1)$$

In Eq. 1, f represents the relationship between dependent and the independent variables, i.e.,

$$\text{Response variable} = f\left(I_1, I_2, I_3, I_4, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots I_N\right) \quad (2)$$

where I_1, I_2, I_3,I_4.................................I_N are the number of input parameters that can influence the WEDM process.

Tab. 2. The primary dimensions of the parameters in WEDM

S.N	Parameters	Symbols	Primary dimension	Nature
1	Pulse on time	PON	$M^0 L^0 T^1$	Independent
2	Pulse off time	POFF	$M^0 L^0 T^1$	Independent
3	Wire feed rate	WFR	$M^0 L^1 T^{-1}$	
4	Input current	CR	$M^0 L^0 T^0$	Independent
5	Servo voltage	SV	$M^1 L^2 T^{-3}$	
6	Work piece density	ρ	$M^1 L^{-3} T^0$	Independent
7	Wire tension	WT	$M^1 L^1 T^{-2}$	Independent
8	Dielectric flu pressure	DQ	$M^0 L^3 T^{-1}$	Independent
9	Coefficient thermal expansion	α	$M^0 L^0 T^0$	Independent
10	Surface roughness	RA	$M^0 L^1 T^0$	Dependent
11	Material removal rate	MRR	$M^0 L^3 T^{-1}$	Dependent

Eq.(2) can be written as Eq. (3)

$$f\,(PON, POFF, WFR, CR, SV, \rho, WT, DQ, , RA, KRF, MRR) = 0 \quad (3)$$

According to theories of engineering experimentation by H. Schenck Jr. [11]. Most systems require at least three primaries; however, the investigator is free to choose any reasonable set he wishes, the only requirement being that his variables must be expressible in his system. There is really nothing base or fundamental about the primary dimensions. In this research, all the variables are expressed in mass (M), length (L), and time (T); hence, M, L, & T are chosen as primary dimensions. The process variables, their symbols, and dimensions are listed in Table 2.

The basic equation, which correlates all input parameters with the response variables, is as follows [11,14].
The dimensional matrix of repeating variables can be written as a 3 x 3 square matrix [11] as follows: (Because there are only three primary dimensions)

$$[P] = \begin{array}{c} \begin{bmatrix} P11 & P12 & P13 \\ P21 & P22 & P23 \\ P31 & P32 & P33 \end{bmatrix} \end{array} \begin{array}{c} M \\ L \\ T \end{array}$$

All the variables other than the repeating variables can be written as a dimensional matrix of non-repeating variables. This matrix is of 3 x N order, where N is the number of non- repeating variables.

$$[Q] = \begin{bmatrix} Q11 & Q12 & \ldots\ldots\ldots\ldots\ldots..Q1N \\ Q21 & Q22 & \ldots\ldots\ldots\ldots\ldots..Q2N \\ Q31 & Q32 & \ldots\ldots\ldots\ldots\ldots..Q3N \end{bmatrix} \begin{array}{c} M \\ L \\ T \end{array}$$

According to the matrix method of dimensional analysis [11], the Nth **dimensionless group** can be formulated as Eq. (4)

$$\frac{Q_N}{P_1{}^{a1N} P_2{}^{a2N} P_3{}^{a3N}} = M^0 L^0 T^0 = (\Pi_N) \quad (4)$$

Thus, the basic pi terms can be formulated for all non-repeating variables by using Eq. (4). The following pi terms can be formulated as follows:

$\pi_1 = (PON)^a\,(\rho)^b\,(SV)^c\,POFF$
[Pi term related to the pulse off time POFF] (4a)

$\pi_2 = (PON)^a\,(S\rho)^b\,(SV)^c\,CR$
[Pi term related to the input current CR] (4b)

$\pi_3 = (PON)^a\,(\rho)^b\,(SV)^c\,WFR$
[Pi term related to the wire feed rate WFR] (4c)

$\pi_4 = (PON)^a\,(\rho)^b\,(SV)^c\,WT$
[Pi term related to the wire tension WT] (4e)

$\pi_5 = (PON)^a\,(\rho)^b\,(SV)^c\,DQ$
[Pi term related to dielectric fluid flow DQ] (4f)

$\pi_6 = (PON)^a\,(\rho)^b\,(SV)^c\,\alpha$
[Pi term related to Coefficient of thermal expansion α] (4g)

$\pi_7 = (PON)^a\,(\rho)^b\,(SV)^c\,RA$
[Pi term related to surface roughness Ra] (4h)

$\pi_8 = (PON)^a\,(\rho)^b\,(SV)^c\,MRR$
[Pi term related to the material removal rate] (4i)

$\Pi_1, \Pi_2, \Pi_3, \Pi_4, \Pi_5$, and Π_6 can be expressed as a function of Π_7, Π_8, and Π_9 as in Eqs. 5-7.

$$\pi_7 = f(\pi_1, \pi_2, \pi_3, \pi_4, \pi_5, \pi_6) \quad (5)$$
$$\pi_8 = f(\pi_1, \pi_2, \pi_3, \pi_4, \pi_5, \pi_6) \quad (6)$$
$$\pi_9 = f(\pi_1, \pi_2, \pi_3, \pi_4, \pi_5, \pi_6) \quad (7)$$

By comparing the indices of basic pi terms on both sides, the following expressions are derived. Equation (4) is deduced as in (6-8).
In the above Eqs. (5a-5j), unknowns can be calculated by representing them as a system of linear algebraic equations as in Eqs.(6-8)[5],

$$P_{11}\,a_{1n} + P_{12}\,a_{2n} + P_{13}\,a_{3n} = Q_{1n} \quad (6)$$
$$P_{21}\,a_{1n} + P_{22}\,a_{2n} + Pa_{3n} = Q_{2n} \quad (7)$$
$$P_{31}\,a_{1n} + P_{32}\,a_{2n} + P_{33}\,a_{3n} = Q_{3n} \quad (8)$$

In matrix form, this system can be rewritten as in Eq. (9):

$$\begin{bmatrix} P11 & P12 & P13 \\ P21 & P22 & P23 \\ P31 & P32 & P33 \end{bmatrix} \begin{bmatrix} a_{1n} \\ a_{2n} \\ a_{3n} \end{bmatrix} = \begin{bmatrix} Q_{1n} \\ Q_{2n} \\ Q_{3n} \end{bmatrix} \quad (9)$$

It can be written in the matrix form as in Eq. (10):

$$[P]\,[A] = [Q] \quad (10)$$

The solution of Eq. (10) can be obtain as in Eq. (11):

$$[A] = [P]^{-1}\,[Q] \quad (11)$$

By repeating the procedure for all non-repeating variables, i.e. Nine, a set of basic dimensionless terms is obtained and listed in Table 2 [13]. The number of pi terms, i.e., dimensionless groups, is equal to that of non-repeating variables, i.e., nine pi terms can be formulated.
Hence, the relationship in Eq. (12) can be formulated as follows:

$$\pi_D = f\big(\pi_1, \pi_2, \pi_3, \pi_4, \pi_5, \pi_6\big)$$
i.e., $\pi_D = \varphi \times \pi_1{}^{A1} \times \pi_2{}^{B1} \times \pi_3{}^{C1} \times \pi_4{}^{D1} \times \pi_5{}^{E1} \times \pi_6{}^{F1}$ (12)

where Π_D is the pi term related to the response variables. Eq. (13) represents the governing equation that is used as a DA model for predicting the various responses of WEDM process. The response given by Eq. (13) depends on six basic pi terms instead of all of the original 9 variables involved in Eq. (4). Experimental data are assigned to the number of pi terms. For the solution of Eq. (13), let us take log on both sides of Eq. (13). We obtain

$$\ln(\pi_D) = \ln(\varphi) + A1 + B1 * \ln(\pi_2) + C1 * \ln(\pi_3) + D1 * \ln(\pi_4) + E1 * \ln(\pi_5) + F1 * \ln(\pi_6) \quad (13)$$

Simplified by assuming

$$Z = \ln(\pi D) \ , X_1 = \ln(\pi_1) \ , X_2 = \ln(\pi_2) \ , X_3 = \ln(\pi_3) \ , X_4 = \ln(\pi_4)$$
$$X_5 = \ln(\pi_5) \ , X_6 = \ln(\pi_6) \ \& \ K_0 = \ln(\varphi)$$

Hence, the linear form of Eq. (13) can be written as Eq. (14)

$$Z = K_0 + A1 * X_1 + B1 * X_2 + C1 * X_3 + D1 * X_4 + E1 * X_5 + F1 * X_6 \quad (14)$$

If 'n' experiments are to be executed, then the response of any 'm^{th}' experiment can be obtained as follows:

$$Z_m = K_0 + A1 * X_{m1} + B1 * X_2 + C1 * X_{m3} + D1 * X_{m4} + E1 * X_{m5} + F1 * X_{m6}$$

Now, we can sum up the results of all 'n' experiments as in Eq. (15)

$$\sum_{m=1}^{n} Z_m = n * K_0 + A1 * \sum_{m=1}^{n} X_{m1} + B1 * \sum_{m=1}^{n} X_{m2} + C1 * \sum_{m=1}^{n} X_{m3} + D1 * \sum_{m=1}^{n} X_{m4} + E1 * \sum_{m=1}^{n} X_{m5} + F1 * \sum_{m=1}^{n} X_{m6} \quad (15)$$

2-3. Experimental setup :

The experiments were conducted using EZEECUT NXG –WEDM with 320 X 400mm axis travel and 360 X 600 maximum work piece diameters. Brass wire with wire diameters from 0.2 to 0.25mm was used with an accuracy of 0.1 mm. The experimental setup of the WEDM process is shown in Figure 2. The various parameters are correlated as in the input/output process and are shown in Fig. 3. The various input factors and their selected levels are presented in Table 3. Twenty-seven different experiments were conducted at random according to Box-Behnken design with 5 factors. The pulse on time, pulse off time, wire feed rate, servo voltage, and the input current are considered as design variables in order to determine the optimum value of the material removal rate and surface roughness in the WEDM process on OHNS steel. The experiments were conducted by Taguchi's L_{27} array. Three replicates were used, and the average value of the response variables is noted in **Annexure 1**. The DA models were formulated in the MATLAB. The methodology adopted for the present work is shown in Fig. 1. Fig. 3 shows the methodology adopted for the dimensional analysis. The data were collected by using L_{27} plan of experimentation. The dimensional model was formulated by Matlab.

Tab. 3. Various input parameters and their selected levels

S.N	Parameters	Symbols	Levels		
			Low	Medium	High
1	Pulse on time	PON (Micro-sec)	25	35	45
2	Pulse off time	POFF (Micro-sec)	4	6	8
3	Wire feed rate	WFR (m/min)	2	3	4
4	Input current	CR (Amp)	40	70	99
5	Servo Voltage	SV (Volt)	90	100	110

The level of various process parameters is presented in Table 2, while the experimental results are shown in Table 3.

$$RA = K_1 \frac{PON^{\frac{3}{5}} * SV^{\frac{1}{5}}}{\rho^{\frac{1}{5}}} \left(\frac{POFF}{PON}\right)^{A1} (CR)^{B1} \left(\frac{PON^{\frac{2}{5}} * \rho^{\frac{1}{5}} * WFR}{SV^{\frac{1}{5}}}\right)^{C1} \left(\frac{\rho^{\frac{3}{5}} * DQ}{PON^{\frac{4}{5}} * SV^{\frac{3}{5}}}\right)^{D1} \left(\frac{WT}{PON^{\frac{2}{5}} * SV^{\frac{4}{5}} * \rho^{\frac{1}{5}}}\right)^{E1} \propto^{F1} \quad (16)$$

$$MRR = K_3 \frac{PON^{\frac{4}{5}} * SV^{\frac{3}{5}}}{\rho^{\frac{3}{5}}} \left(\frac{POFF}{PON}\right)^{A2} (CR)^{B2} \left(\frac{PON^{\frac{2}{5}} * \rho^{\frac{1}{5}} * WFR}{SV^{\frac{1}{5}}}\right)^{C2} \left(\frac{\rho^{\frac{3}{5}} * DQ}{PON^{\frac{4}{5}} * SV^{\frac{3}{5}}}\right)^{D2} \left(\frac{WT}{PON^{\frac{2}{5}} * SV^{\frac{4}{5}} * \rho^{\frac{1}{5}}}\right)^{E2} \propto^{F2} \quad (17)$$

Eqs. (16,17) represent dimensional equations for surface roughness and MRR, respectively, where K_1, K_2, and K_3 are the exponential constants for RA and MRR models. A_1, B_1, C_1, D_1, E_1 & F_1 are the power indices for the surface roughness model. A_2, B_2, C_2, D_2, E_2 & F_2 are the power indices for the MRR model. The values of all the above constants are given in Table 4. The indices can be calculated by using Matlab [20].

3. Multi-Response Optimization Using Desirability Function

3-1. Desirability function approach (DFA) :

The desirability function approach (DFA) is a very efficient approach that assigns a "score" to a set of output functions or response variables and selects the best set of input parameters that maximizes the score. It is based on the thought that the "superiority" of any product of the process that has several response characteristics. The method finds the operating situation that provides the "most attractive or favorable" outputs. The DFA consists of the following steps:

Step 1: Calculate the individual desirability index (d_i) for the corresponding responses using the formula proposed by the Derringer and Suich [1980]. There are three forms of the desirability functions according to the response characteristics. The desirability function for "Nominal or target is best": If a response is of the "nominal is best" kind, then its individual desirability function is as follows:

Tab. 4. Constants and indices for the various DA models

S.N	Constant/ Indices	RA Model	MRR Model
1	Exponential constant(K)	0.0011853	0.00026
2	Power indices for PFF(A)	0.0499	0.1272
3	Power indices for the CR(B)	0.0523	0.1907
4	Power indices for the WFR (C)	-0.0502	0.1016
5	Power indices for the DQ (D)	1.051	0.6303
6	Power indices for the WT (E)	-0.1762	0.1741
7	Power indices for the α (F)	3.3011	3.7518
8	Mean absolute percentage error (MAPE)	0.98944	0.95365
9	Mean absolute percentage error (MAPE)	0.07314	0.07395
10	Mean absolute percentage error (MAPE)	0.89951	2.23111

$$D_i Z_i = \begin{cases} 0, & \text{if } Z_i\,(x) < LO_i \\ \left(\frac{Z_i\,(x) - LO_i}{TR_i - LO_i}\right)^S & \text{if } LO_i < Z_i\,(x) < TR_i \\ \left(\frac{Z_i\,(x) - UP_i}{TR_i - UP_i}\right)^T & \text{if } TR_i < Y_i\,(x) < UP_i \\ 0, & \text{if } Z_i\,(x) < UP_i \end{cases} \quad (18)$$

Exponents S and ***T*** determine how important it is to hit the target value. Desirability function for maximizing a response or larger is best if a response is to be maximized instead. The individual desirability is defined as follows:

$$D_i Z_i = \begin{cases} 0, & \text{if } Z_i\,(x) < LO_i \\ \left(\frac{Z_i\,(x) - LO_i}{TR_i - LO_i}\right)^S & \text{if } LO_i < Z_i\,(x) < TR_i \\ 0, & \text{if } Z_i\,(x) > TR_i \end{cases} \quad (19)$$

With $\mathbf{TR_i}$ in this case interpreted as a large enough value for the response, the desirability function for minimizing a response or smaller is the best. We could use

$$D_i Z_i = \begin{cases} 1, & \text{if } Z_i\,(x) < TR_i \\ \left(\frac{Z_i\,(x) - UP_i}{TR_i - UP_i}\right)^S & \text{if } TR_i < Z_i\,(x) < UP_i \\ 0, & \text{if } Z_i\,(x) > UP_i \end{cases} \quad (20)$$

$\mathbf{TR_i}$ denotes a small enough value for the response.

In this study, "larger is the better" for material removal rate, and "the smaller the better" for the surface roughness characteristic is applied to determine the individual desirability values for Material removal rate and the surface roughness, delamination factor, and machining force since all responses are to be minimized.

Step 2: For each response variable Z_i **(x)**, a desirability function $\mathbf{D_i}$ $\mathbf{(Z_i)}$ allocates statistics between 0 and 1 to the probable values of Z_i, with $\mathbf{D_i(Z_i) = 0}$ representing a totally disagreeable value of $\mathbf{Z_i}$ and $\mathbf{D_i}$ $\mathbf{(Z_i) = 1}$ representing a completely advantageous or perfect response value. The individual desirabilities are then united using the geometric mean, producing the overall desirability $\mathbf{D_o}$ as shown in Equation (27).

$$D_o = \sqrt[W]{{D_1}^{w1} \times {D_2}^{w2} \times {D_3}^{w3} \times ------D_Z^{wz}} \quad (21)$$

where **w** denotes the weight of an individual response variable, while W is the total of weights assigned. Let $\mathbf{LO_i}$, $\mathbf{UP_i}$, and $\mathbf{TR_i}$ be the lower, upper, and target values, respectively, that are desired for response $\mathbf{Z_i}$, with $\mathbf{LO_i} \leq \mathbf{TR_i} \leq \mathbf{UP_i}$.
Step 3: Finally, the combination whose overall desirability (Do) is highest is selected as an optimized parameter.

3-2. Optimization by using DFA:
Optimal combinations of parameters are determined based on the assumed weight of surface roughness and the material removal rate, respectively. Both surface roughness and the material removal rate play a vital and identical role in machining performance; hence, it is given equal weight. Based on the assumed weight, the composite desirability values are also calculated and tabulated in **Annexure 2.** From the above analysis, it has been observed that the highest value for the composite desirability score is 0.888996 corresponding to the observation No 19. Hence, the optimal or the best set of process parameters lies at pulse on time 45 micro sec, pulse off time 4 micro sec, current 4 amp, wire feed rate 70 mm/min, and the voltage 90 volts.

4. Results and Discussion
In this section, the results obtained from the dimensional analysis (DA) are discussed: An empirical model for surface roughness [18-20] and the material removal rate has been developed with process variables of pulse-on time, input current, pulse off time, voltage, and other related properties of OHNS material. Figs. 4-7 illustrate the effect of various input parameters of the responses. From Fig. 4, it is observed that the minimum surface roughness is obtained when the parameter of pulse on time is 35 micro- sec, while the maximum material removal rate and the kef width can be obtained with the PON being 45 micro-sec. The minimum surface roughness is obtained when the input current (CR) is 35 amp and the maximum material removal rate and the kef width can be obtained with the PON being an amp. The minimum surface roughness is obtained when the wire feed rate (WFR) is 70 mm/min, and the maximum material removal rate and the kef width can be obtained with the wire feed rate being 99 mm/min. The minimum surface roughness is obtained when the pulse off time is 6 micro sec with the maximum material removal rate. Similarly, the minimum surface roughness is obtained when the servo voltage is 100 volt and the maximum material removal rate can be obtained with the SV 90 volt.
The experiments were conducted to observe the various performance indicators of WEDM. The observations indicated that when pulse on time (PON) increases from 25 to 35 micro-secs, surface roughness and MRR increase by 13.10% and 3.89069%, respectively. A surface roughness by 1.867% is notified about an increase in MRR by 2.45303 % when the pulse on time further changes from 35 to 45 micro-sec. A reduction in surface roughness by 64.503% and MRR by 83.84 % is notified when pulse off time increases from 4 to 6 micro-secs. When pulse off time is further increased from 6 micro-secs to 8 micro-secs, surface roughness and MRR increase by 4.44548 % and 21.088%, respectively.
When input current (CR) is changed from 2 to 3 amp, surface roughness increases by 2.4286% with a reduction in MRR by 3.0117 %. A reduction in MRR by 16.525% with an increase in surface roughness by 2.42865 is observed when input current (CR) is changed from 3 to 4 amp. When wire feed rate (WFR) is changed from 40-70 mm/min, surface roughness increases by 2.1719% with a reduction in MRR by 0.6891%. A reduction in surface roughness by 8.864 % with an increase in MRR by 10.4677 % is observed. When servo voltage (SV) is changed from 90 to 110 volts, a reduction in surface roughness by 5.6087 % and MRR by 2.2133% is observed. An increase in surface roughness by 0.98% and MRR by 4.41128% is observed during the experimentation. In analyzing the data, the-smaller-the-better concept of normalization is used while surface roughness is considered, since these two performance parameters have to be minimized. However, the-higher-the-better concept is used for MRR since this performance parameter should be maximized. From Fig. 8, it is observed that the average error achieved in these models is below 2%. This indicates good agreement between the two datasets.

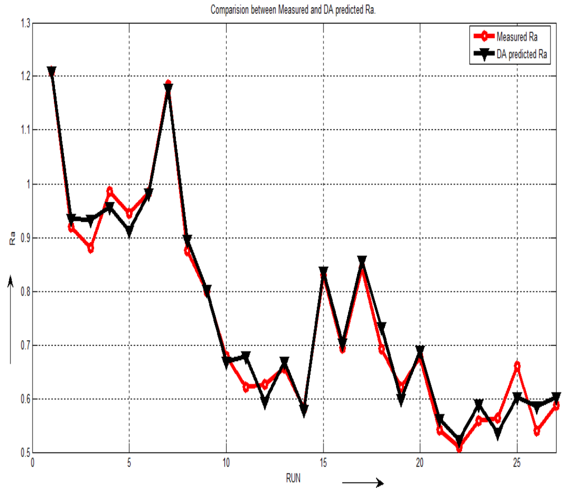

Fig. 1. Comparison between measured and DA predicted Ra for WEDM.

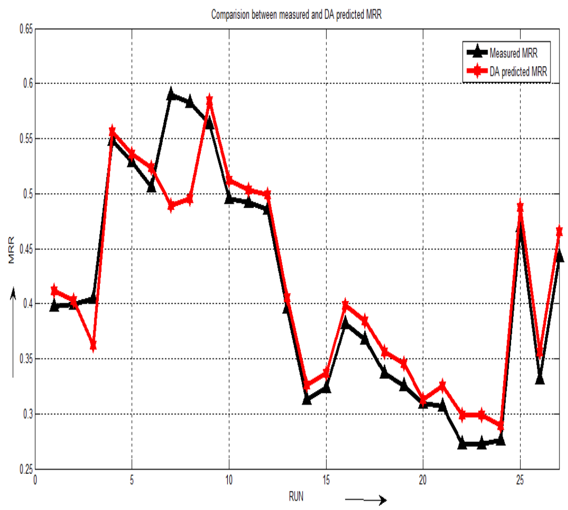

Fig. 2. Comparison between measured and DA predicted MRR for WEDM.

Figs. 1 & 2 show that the measured and calculated responses based on the DA approach are very close and show the good agreement. By observing the formulated DA model (Eqs. 24-26), the indices of the surface roughness and MRR DA model, i.e., Table 3, we can conclude that the power indices of the pi term Π_6 (Pi term related to Coefficient of thermal expansion) & Π_4 (pi term related to the dielectric fluid flow) of the DA model (Ra) are very high. Hence, the coefficient of thermal expansion and the dielectric fluid flow are the most influencing parameters that can affect directly surface roughness and the MRR in the WEDM of OHNS steel. Similarly, the parameters such as pulse off time, wire feed rate, and the input current have moderate effect on the response variables. The minimum surface roughness is obtained for the 3-2-1-3-1 level of the input parameters. For the maximum surface roughness, MRR can be obtained for the 3-3-2-1-3 levels of the input parameters.

After formulating the model successfully to predict Ra and MRR in WEDM of OHNS materials by DA, the formulated models were compared with the experimental or measured data. The results obtained were compared by some statistical tools such as root mean square error (RMSE), mean absolute percentage error (MAPE), and the correlation coefficient (R^2), as given by the following Eq. (22) [1].

$$\left.\begin{aligned} \mathrm{RMSE} &= \sqrt{\frac{\sum_{i=1}^{n}(Y_i - Y_{Ci})^2}{N}} \\ \mathrm{MAPE} &= \frac{\sum_{i=1}^{n}\left|\frac{Y_i - Y_{Ci}}{Yi}\right|}{N} X100 \\ \boldsymbol{R^2} &= \mathbf{1} - \left(\frac{\sum_{i=1}^{n}(Y_i - Y_{Ci})^2}{\sum_{i=1}^{n}(Y_{Ci})^2}\right) \end{aligned}\right\} \quad (22)$$

where 'N' is the number of runs or data set. Y_i is the experimental result, and Y_{ci} is the calculated results of the various models. The correlation (R^2) for the surface roughness DA model and the MRR DA model is 0.98944 and 0.95365, respectively. The root mean square (RMSE) of the error for the surface roughness DA model and the MRR DA model is 0.07314 and 0.07395, respectively. The mean absolute percentage error (MAPE) of the surface roughness DA model is 0.89951, and that of the MRR DA model is 2.23111. Figs. 9-11 show the comparison between the experimental and predicted results for the various responses.

5. Conclusion

In this study, the application of Buckingham's pi theorem (Dimensional analysis) for formulating the model for the surface roughness and the material removal rate of OHNS die steel in WEDM was studied. The dependence of the response and the governing variables were discussed. The conclusions are presented as follows:

- Empirical models were developed using Buckingham pi theorem for the performance variables such as Ra and MRR to establish the relationship between the variables such as pulse off time, pulse on time, wire feed rate, servo voltage, input current, work piece density, and the coefficient of thermal expansion. Results obtained by the formulated DA model are very close to the experiment results.

- The rise of pulse-on time from 25 micro-secs to 45 micro-secs causes deterioration in surface roughness and improvement in the MRR.
- Thus, the dimensionless pi terms have provided the the idea of the collective effect of the parameters related to that pi term. The DA approach helps the end user handle the huge number of variables involved in the analysis. The DA models developed for different combinations of parameters can be successfully utilized for the system analysis.

Overall, the good agreement between the theoretical model formulations based on the dimensional analysis theory and the experimental data powerfully supported the validation of the theoretical formulations. Finally, it is of significance to note here that the dimensional analysis tool applied in the current study is given as a general procedure of human energy analysis in which the formulation of non-dimensional numbers, i.e., pi terms, will also facilitate the correlation of the various parameters. The presented method of dimensional analysis is a very easy and efficient technique to formulate the model for any engineering system. Thus, DA approach can be used efficiently in other streams or applications in engineering.

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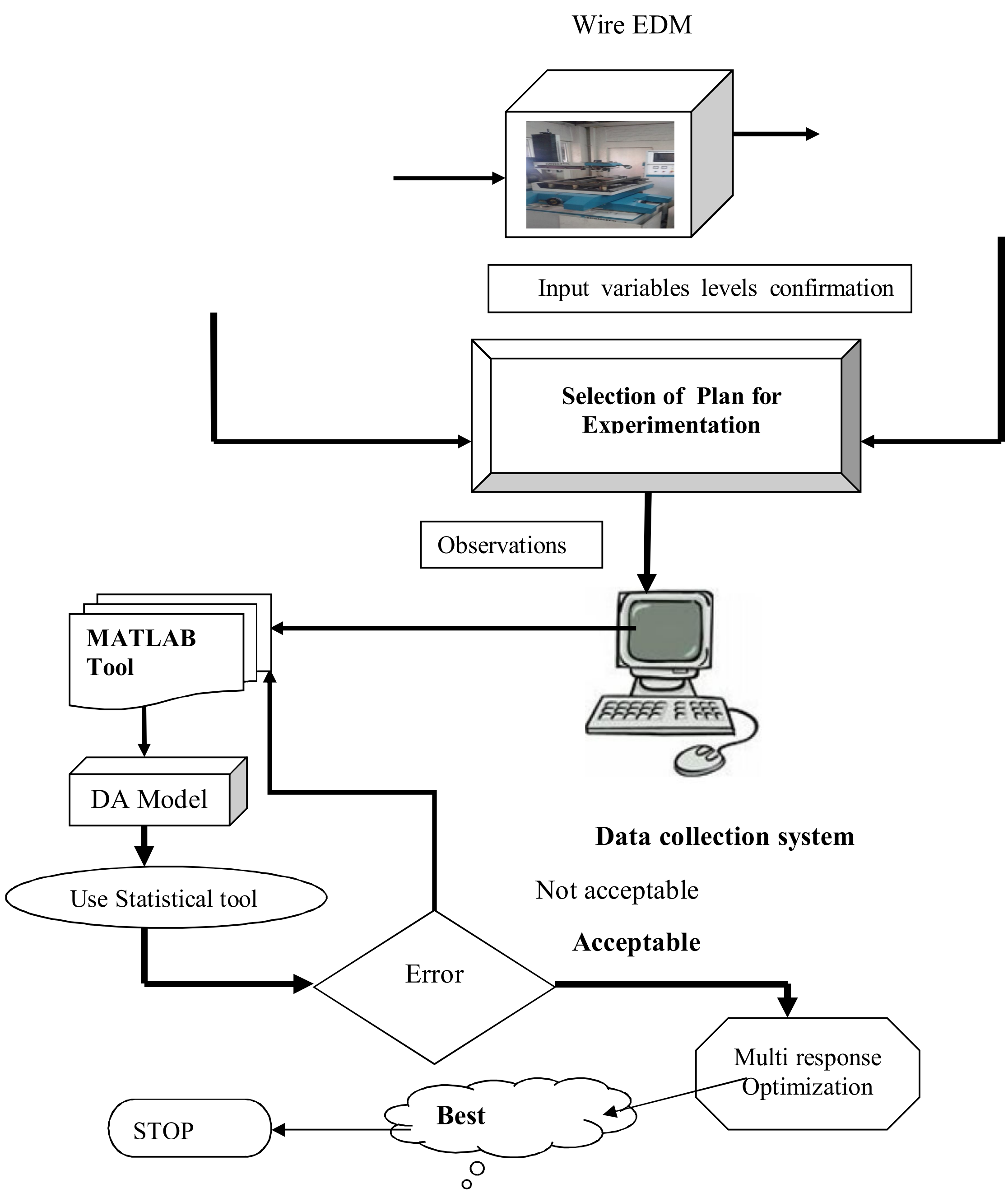

Fig. 3. Methodology adopted for WEDM analysis using the DA approach.

Annextures 1. Observation table

RUN	WEDM Variables					WEDM Responses	
	PON	POFF	CR	WFR	VT	RA	MRR
1	1	1	1	1	1	1.414	1.8285
2	1	1	1	1	2	1.200	2.4045
3	1	1	1	1	3	1.104	1.1455
4	1	2	2	2	1	1.411	1.9875
5	1	2	2	2	2	1.321	1.2535
6	1	2	2	2	3	1.578	1.6295
7	1	3	3	3	1	1.294	1.6535
8	1	3	3	3	2	1.001	1.6355
9	1	3	3	3	3	0.923	1.7925
10	2	1	2	3	1	0.825	2.0755
11	2	1	2	3	2	0.986	2.0305
12	2	1	2	3	3	1.023	1.5945
13	2	2	3	1	1	1.125	2.1295
14	2	2	3	1	2	1.352	1.1635
15	2	2	3	1	3	1.731	1.8855
16	2	3	1	2	1	0.895	1.5905
17	2	3	1	2	2	1.712	1.8355
18	2	3	1	2	3	0.958	2.1645
19	3	1	3	2	1	0.865	2.5545
20	3	1	3	2	2	1.403	2.4385
21	3	1	3	2	3	1.586	1.2365
22	3	2	1	3	1	1.239	2.0235
23	3	2	1	3	2	1.632	2.6605
24	3	2	1	3	3	1.736	1.2365
25	3	3	2	1	1	1.199	2.6905
26	3	3	2	1	2	1.512	1.3255
27	3	3	2	1	3	1.892	2.8615

Annexture 2. Overall desirability calculation.

RUN	WEDM Variables					WEDM Responses		Individual Desiribility		Composite Desirability
	PON	POFF	CR	WFR	VT	RA	MRR	RA	MRR	
1	1	1	1	1	1	1.414	1.8285	0.448	0.398019	0.422263408
2	1	1	1	1	2	1.200	2.4045	0.649	0.733683	0.689802971
3	1	1	1	1	3	1.104	1.1455	0.739	0	0
4	1	2	2	2	1	1.411	1.9875	0.451	0.490676	0.470313811
5	1	2	2	2	2	1.321	1.2535	0.535	0.062937	0.1835224
6	1	2	2	2	3	1.578	1.6295	0.294	0.282051	0.288102252
7	1	3	3	3	1	1.294	1.6535	0.56	0.296037	0.407325498
8	1	3	3	3	2	1.001	1.6355	0.835	0.285548	0.488310475
9	1	3	3	3	3	0.923	1.7925	0.908	0.37704	0.585158041
10	2	1	2	3	1	0.825	2.0755	1	0.541958	0.736177996

11	2	1	2	3	2	0.986	2.0305	0.849	0.515734	0.661751421
12	2	1	2	3	3	1.023	1.5945	0.814	0.261655	0.461628068
13	2	2	3	1	1	1.125	2.1295	0.719	0.573427	0.642028607
14	2	2	3	1	2	1.352	1.1635	0.506	0.01049	0.072860522
15	2	2	3	1	3	1.731	1.8855	0.151	0.431235	0.255086777
16	2	3	1	2	1	0.895	1.5905	0.934	0.259324	0.492251143
17	2	3	1	2	2	1.712	1.8355	0.169	0.402098	0.260447352
18	2	3	1	2	3	0.958	2.1645	0.875	0.593823	0.720974125
19	3	1	3	2	1	0.865	2.5545	0.963	0.821096	0.888996123
20	3	1	3	2	2	1.403	2.4385	0.458	0.753497	0.587642017
21	3	1	3	2	3	1.586	1.2365	0.287	0.05303	0.123322
22	3	2	1	3	1	1.239	2.0235	0.612	0.511655	0.559581048
23	3	2	1	3	2	1.632	2.6605	0.244	0.882867	0.463822849
24	3	2	1	3	3	1.736	1.2365	0.146	0.05303	0.088052592
25	3	3	2	1	1	1.199	2.6905	0.649	0.90035	0.764698094
26	3	3	2	1	2	1.512	1.3255	0.356	0.104895	0.193280126
27	3	3	2	1	3	1.892	2.8615	0	1	0

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