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Estimation and Comparison of Machining Performances in WEDM for HCHCr Material using MRA and GMDH

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***Abstract:* -- Wire Electrical Discharge Machining (WEDM) is a specialized thermo electrical machining process capable of accurately machining parts with varying hardness or complex shapes. Present study outlines the estimation of machining performances in the wire electric discharge machining of HCHCr material using Multiple Regression Analysis (MRA) and Group Method of Data Handling (GMDH) technique. HCHCr material was machined using different process parameters based on Taguchi's L27 standard orthogonal array. Parameters such as pulse-on time, pulse-off time, current and bed speed were varied. The response variables measured for the analysis are dimensional error, surface roughness and volumetric material removal rate. Machining performances have been compared using sophisticated mathematical models viz., MRA and GMDH. Different GMDH models can be obtained by varying the percentage of data in the training set and the best model can be selected from these, viz., 50%, 62.5% & 75%. The best model is selected from the said percentages of data. Three different criterion functions, viz., Root Mean Square (Regularity or RMS) criterion, Unbiased criterion and Combined criterion were considered for estimation. Estimation and comparison of machining performances were carried out using MRA and GMDH techniques. Estimates from MRA and GMDH were compared and it was observed that GMDH gives better results than MRA.**

Index Terms— WEDM, Machining performances, Comparison, MRA and GMDH..

I.INTRODUCTION

WEDM is a widely accepted non-traditional material removal process used to manufacture components with intricate shapes and profiles irrespective of hardness. WEDM has evolved as a simple means of making tools and dies to the best alternative of producing micro-scale parts with the highest degree of dimensional accuracy and surface finish. Molybdenum wire is used in limited applications which require very high tensile strength to provide a reasonable load carrying capacity in small diameter wire. The effect of process parameters on the machining performances was investigated experimentally in WEDM. An attempt has been made to estimate the machining performances using MRA, and GMDH techniques. HCHCr was machined using different process parameters based on Taguchi's L27 standard orthogonal array. Input process parameters viz., as pulse-on time, pulse-off time, current and bed speed were considered. The response variables measured for the analysis are Dimensional Error (DE), Surface Roughness (SR) and Volumetric Material Removal Rate (VMRR).

Some of the researchers have attempted to apply six most popular population-based non-traditional optimization algorithms for two WEDM processes. Selection of optimal values of different process parameters, such as pulse duration, pulse frequency, duty factor, peak current, dielectric flow rate, wire speed, wire tension, effective wire offset. The major performance measures of WEDM process generally include MRR, cutting width (kerf), SR and dimensional shift. It was found that although all these six algorithms have high potential in achieving the optimal parameter settings, but the biogeography-based algorithm out performs the others with respect to optimization performance, quick convergence and dispersion of the optimal solutions from their mean [1]. The optimization techniques and the comparison of the latest five year research from 2007 to 2011 that used evolutionary optimization techniques to optimize machining process parameter of both traditional and modern machining. Five techniques are considered, namely Genetic Algorithm (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) algorithm. Literature found that GA was widely applied by researchers to optimize the machining process parameters. Multi-pass turning was the largest machining operation that deals with GA optimization. In terms of machining performance, SR was mostly studied with GA, SA, PSO, ACO and ABC evolutionary techniques [2]. Neural Network (NN) model were used for the Increased Explosive Electrical Discharge Grinding (IEEDG) process. GA was then applied to the trained NN model to determine

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the optimal process parameter values, in which Gray Relation Analysis (GRA) is conducted to determine the weights of the two performance characteristics. The integrated NN–GRA–GA system was successful in determining the optimal process parameter when obtaining the overall better performance is considered [3]. An ANFIS model for the prediction of the White Layer Thickness (WLT) and the average SR achieved as a function of the process parameters. Pulse duration, open circuit voltage, dielectric flushing pressure and wire feed rate were taken as model's input features. The model's predictions were compared with experimental results for verifying the approach. As a result, this approach can greatly improve the process responses such as SR and WLT in the WEDM process [4]. The effect of temperature field and thermal stress on material removal of insulating ceramics Si3N4 during the machining process by reciprocating traveling WEDM was simulated and analyzed. The influences of peak current, pulse duration and the movement/speed of wire electrode to discharge craters were studied. The simulation shows that the conductive layer on insulating ceramics makes a larger effect on thermal transmission in the radius direction of discharge crater than in depth direction [5].

Regression Analysis (RA) and GRA for evaluating the performance of the various tool materials at two different duty cycles were studied. Their objective is to maximize the MRR and to minimize the roundness, SR, TWR, Weight Wear Ratio (WWR) and taper angle during EDM of hot pressed ZrB2. Mathematical models are proposed for the modeling and analysis of the effects of pulse on time and tool materials on the performance characteristics in the EDM using RA. The performance of the tool are rated using entropy based GRA and best suited value of pulse on time also found out. Interaction of pulse on time with various tool materials was investigated by using analysis of variance [6]. Thermo-electrical model were used for predicting the MRR of different materials. Better simulation results were achieved when considering the material properties as temperature-dependent. In addition, the latent heats of fusion and vaporization showed to have a significant influence on simulation results [7]. A maintenance-schedule and fault-diagnosis system that integrates an ANN and an Expert System (ES) were developed. In WEDM, some faults such as wire breaking and unsatisfactory accuracy may occur due to improper operations or inappropriate machine maintenance. Suggestions to eliminate faults are proposed sequentially according to the inferred priority once a fault is taking place. Moreover, it can provide explanations [8]. A binary relational analysis and ES base module for maintenance and fault diagnosis of CNC WEDM were proposed. In this study, 15 inputs were considered to observe eight probable causes with the help of the forward and backward propagation algorithms. To detect the fault and remedial action, application of backward propagation is recommended. The developed system can help the operators, trainees, and manufacturing engineers in achieving trouble free machining through quick detection of faults and proper maintenance of machines in actual practice [9]. The RSM and ANN based mathematical modeling for average cutting speed of SiCp/6061 Al MMC during WEDM was described. Four WEDM parameters viz., Servo Voltage (SV), pulse-on time, pulse-off time and Wire Feed Rate (WF) were chosen as machining process parameters. The performance of the developed ANN models were compared with the RSM mathematical models of average cutting speed. The comparison clearly indicates that the ANN models provide more accurate prediction compared to the RSM models [10].

II.EXPERIMENTAL WORK

The experiments were performed on CONCORD DK7720C four axes CNC WED machine. It allows the operator to choose input parameters according to the material and height of the work piece. The WED machine has several special features. Unlike other WED machines, it uses the reusable wire technology. i.e., wire can't be thrown out once used; instead it is reused adopting the re-looping wire technology. The experimental set-up for the data acquisition is illustrated in the Fig. 1. But in this WED machine only one pass is used.

Fig. 1. Experimental set-up

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The gap between wire and work piece is 0.02 mm and is constantly maintained by a computer controlled positioning system. Molybdenum wire having diameter of 0.18 mm was used as an electrode. The control factors were chosen based on review of literature and experts are as listed in Table 1. Each time the experiment was performed, an optimized set of input parameters was chosen. In this study, four machining parameters were used as control factors and each parameter was designed to have three levels denoted I, II and III.

Table 1 Machining settings used in experiments

Control Factors		Level		
		I	II	III
A	Pulse-on	20	24	28
B	Pulse-off	4	6	8
C	Current	4	5	6
D	Bed Speed	30	35	40

Multiple Regression Analysis (MRA)

The objective of multiple regression analysis is to construct a model that explains as much as possible, the variability in a dependent variable, using several independent variables. The model fit is usually a linear model, though some timer non-linear models such as log-linear models are also constructed. When the model constructed is a linear model, the population regression equation is

$$Y_i = \alpha + \beta_1 X_{1i} + \ldots\ldots\ldots\ldots + \beta_m X_{mi} + e_i \qquad (1)$$

Where Y_i is the dependent variable and X_{1i} ………… X_{mi} are the independent variables for i^{th} data point and e_i is the error term. Error term is assumed to have zero mean. This error term is the combined effect of variables that are not considered explicitly in the equation, but have an effect on the dependent variable. The co-efficients α, β_1,……………β_m are not known and estimates of these values, designated as a, b_1…….b_m have to be determined from the sampled data. For this least squares estimation is used, which consists of minimizing.

$$SS = \sum_{i=1}^{n} e_i^{\,2} = \sum_{i=1}^{n} \left(Y_i - a - b_i X_{1i} \ldots\ldots\ldots\ldots - b_m X_{mi}\right)^2 \qquad (2)$$

With respect to each of the co-efficients a, b_1…..b_m. This will give k+1 equations from which a, b_1…..b_m. can be obtained. These least squared estimates are the best linear unbiased estimates and hence gives the best linear unbiased estimate of the dependent variable.

$$Y = a + b_1X_1 + b_2X_2 + \ldots\ldots\ldots\ldots + b_mX_m \qquad (3)$$

The obtained regression model for estimating surface roughness for HCHCr material is,

$$R_a = 5.7e\text{-}2 \times A + 7.3e\text{-}2 \times B + 9.3e\text{-}2 \times C - 5.11e\text{-}3 \times D + 4.8e\text{-}1 \qquad (4)$$

The obtained regression model for estimating material removal rate for HCHCr material is,

$$VMRR = 5.2e\text{-}1 \times A + 3.6e\text{-}1 \times B + 6.0e\text{-}1 \times C - 2.6e\text{-}2 \times D - 8.39 \qquad (5)$$

The obtained regression model for estimating accuracy for HCHCr material is,

$$Accuracy = 6.1e\text{-}1 \times A + 1.36 \times B + 4.4e\text{-}1 \times C - 1.4e\text{-}1 \times D - 11.3 \qquad (6)$$

Group Method of Data Handling

GMDH is a family of inductive algorithms for computer-based mathematical modeling of multi-parametric datasets that features fully automatic structural and parametric optimization of models. GMDH is used in such fields as data mining, knowledge discovery, prediction complex systems modeling, optimization and pattern recognition. GMDH algorithms are characterized by inductive procedure that performs sorting-out of gradually complicated polynomial models and selecting the best solution by means of the so-called external criterion.

A GMDH model with multiple inputs and one output is a subset of components of the base function (7).

$$Y(x_1, \ldots\ldots, x_n) = a_0 + \sum_{i=1}^{m} a_i f_i \qquad (7)$$

Where *f* are elementary functions dependent on different sets of inputs, *a* is coefficients and m is the number of the base function components. In order to find the best solution GMDH algorithm consider various component subsets of the base function (7) called partial models. Coefficients of these models estimated by the least squares method. GMDH algorithm gradually increase the number of partial model components and find a model structure with optimal complexity indicated by the minimum value of an external criterion. This process is called self-organization of models. The most popular base function used in GMDH is the gradually complicated Kolmogorov-Gabor polynomial (8).

$$Y(x_1, \ldots\ldots, x_n) = a_0 + \sum_{i=n}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \ldots\ldots \qquad (8)$$

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GMDH is also known as polynomial neural networks and statistical learning networks thanks to implementation of the corresponding algorithms in several commercial software products.

III. RESULTS AND DISCUSSIONS

Prediction of response variables of HCHCr material

The prediction of responses was carried out using MRA and GMDH, for various training sets of data is used in MRA and 50%, 62.5% and 75% of data is used in GMDH. The three criterion functions, viz., regularity, unbiased and combined were tried out for machining performances. An attempt was made to identify the best criterion and best percentage of data in the training set to estimate machining performances. An attempt was also made to identify the level at which better estimation was obtained. Identification of the best criterion, best percentage of data and the optimal level of estimation was according to the value of Standard Error (SE) of estimation. The results of GMDH for different machining conditions are presented and discussed. When the training is completed, it is necessary to check the network performance and determine if any changes need to be made to the training process, network architecture or the data sets.

Table 2. L_{27} orthogonal array

Run	Pulse-on (µs)	Pulse-off (µs)	Current (Amps)	Bed speed (µm/s)
1	20	4	4	30
2	20	4	5	35
3	20	4	6	40
4	20	6	4	35
5	20	6	5	40
6	20	6	6	30
7	20	8	4	40
8	20	8	5	30
9	20	8	6	35
10	24	4	4	35
11	24	4	5	40
12	24	4	6	30
13	24	6	4	40
14	24	6	5	30
15	24	6	6	35
16	24	8	4	30
17	24	8	5	35
18	24	8	6	40
19	28	4	4	40
20	28	4	5	30
21	28	4	6	35
22	28	6	4	30
23	28	6	5	35
24	28	6	6	40
25	28	8	4	35
26	28	8	5	40
27	28	8	6	30

Fig. 2 shows that prediction of measured and responses was carried out using MRA. From the Fig. 2 it is clearly observed predicted DE, Ra and VMRR were correlating well measured one.

Table 3. Machining performances using L_{27} orthogonal array

Run	Surface Roughness (µm)	VMRR (mm^3/min)	Accuracy (µm)
1	2.10	4.97	3
2	2.11	5.15	4
3	2.22	6.11	3
4	2.23	5.52	5
5	2.29	5.79	5
6	2.42	7.13	7
7	2.38	6.13	6
8	2.46	6.99	8
9	2.54	7.58	8
10	2.48	7.16	8
11	2.53	7.95	6
12	2.66	8.89	8
13	2.55	8.22	10
14	2.69	8.56	12
15	2.73	8.99	10
16	2.79	9.01	12
17	2.81	9.59	13
18	2.88	9.96	13
19	2.52	9.12	6
20	2.63	9.83	6
21	2.72	9.93	8
22	2.64	10.00	11
23	2.79	10.25	12
24	2.83	10.67	9
25	2.75	10.22	13
26	2.86	10.96	12
27	3.13	11.90	16

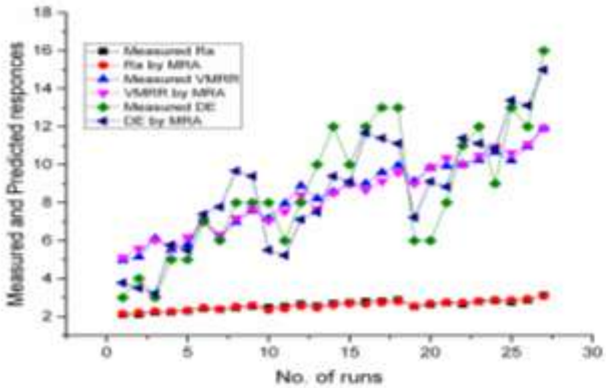

Fig. 2. Measured and predicted responses by MRA

Fig. 3 shows GMDH estimates of Ra from various criterions for 75% of data in training set. Referring to the Fig. 3, it was observed that the Ra estimate obtained by regularity criterion correlates well with the measured Ra. Since the estimate by this criterion closely matches with the measured Ra with lesser SE of estimate than the unbiased and combined criterions. Estimate from unbiased and combined criterions gave poor results.

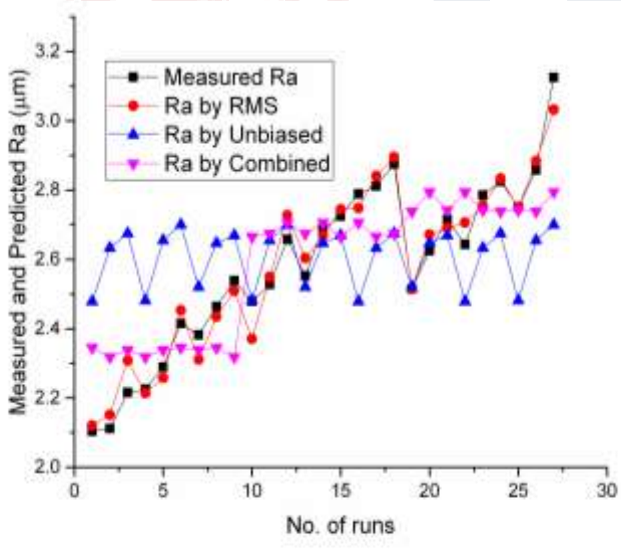

Fig. 3. Measured and predicted Ra at criterions

Fig. 4 shows GMDH estimates of Ra from regularity criteria, for various percentages of data in the training set. It was observed from the Fig. 4, that with the increase in the percentage of data in the training set, the estimation power of regularity criterion also increases. Least error and best fit was obtained when 75% of data is used in the training set. The least SE is 0.0091 for 75% of data in training set at level 1. Further GMDH estimation will be carried out for DE and VMRR of HCHCr material.

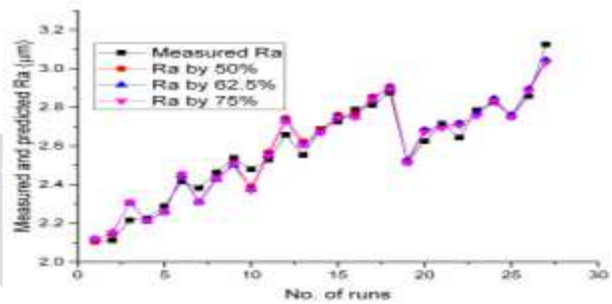

Fig. 4. Measured and predicted Ra at various percentage of data by GMDH

From Fig. 5, it is clearly shows that, the results from the GMDH, least error of estimation and best-fit was found for 75% of data in training set under RMS criteria for DE and VMRR.

It is observed from the Fig. 6 predicted surface roughness of 75% of the data set by GMDH exhibits better correlation with the measured surface roughness when compared to the MRA.

It is clearly observed from the Fig. 7 predicted VMRR of 75% of the data set by GMDH exhibits better correlation with the measured VMRR when compared to the MRA.

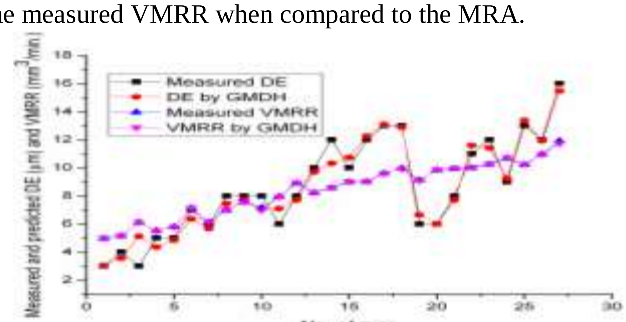

Fig. 5. Measured and predicted DE & VMRR by GMDH

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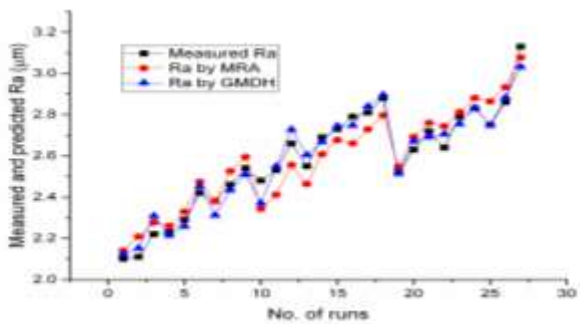

Fig. 6. Comparison of measured and predicted Ra using MRA and GMDH

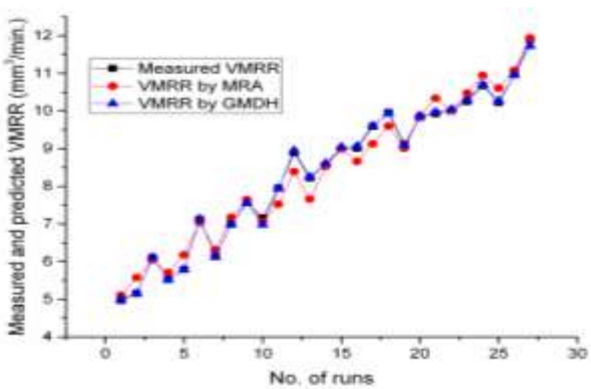

Fig. 7. Comparison of measured and predicted VMRR using MRA and GMDH

Fig. 8 shows that, predicted DE of 75% of the data set by GMDH exhibits better correlation with the measured DE when compared to the MRA.

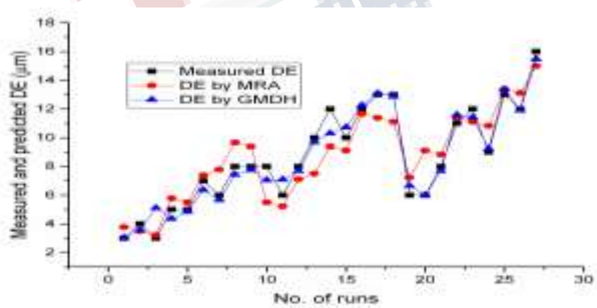

Fig. 8. Comparison of measured and predicted DE using MRA and GMDH

IV. CONCLUSION

This paper has presented an investigation on the estimation and prediction of machining parameters on accuracy, surface roughness and VMRR in WEDM operations. It was found that, each control factors are affecting the response variables to different extent. MRA is used to estimate the machining response variable viz., surface roughness, VMRR, and accuracy. Three different criterion functions of GMDH viz., regularity (RMS), unbiased and combined criterions have been tried for estimation of machining performances HCHCr.

The results from the GMDH show that the regularity criteria function provides good estimation than the other function. Different models of GMDH were built by varying the number of data in the training set to 50%, 62.5% and 75% of the total data. It was found that the least error of estimation and best-fit was found for 75% of data in training set at level 1 under RMS or regularity criteria for surface roughness, VMRR and accuracy. Comparison of the two theoretical methods for estimation of machining performances, it was found that, GMDH technique has an edge over MRA method.

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