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Estimation of Machining Performances using MRA and GMDH in Wire EDM of Al2024 based Hybrid MMC

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Abstract

Present study outlines the estimation of machining performances in the wire electric discharge machining of hybrid composite alloy using Multiple Regression Analysis (MRA) and Group Method of Data Handling (GMDH) technique. Al2024-5%TiC-5% flyash hybrid metal matrix composite synthesized by stir casting route was machined using different process parameters based on Taguchi's L_{27} 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 (DE), Surface Roughness (SR), Volumetric Material Removal Rate (VMRR) and Electrode Wear (EW). Machining performances have been compared using sophisticated mathematical models viz., MRA and GMDH. The GMDH algorithm is designed to learn the process by training the algorithm with the experimental data. 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.

Keywords: WEDM; VMR; SR; DE; MRA and GMDH.

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1. Introduction

Wire cut Electrical Discharge Machining (WEDM) is a special form of EDM process in which electrode is a continuously moving conductive wire. The material removal is by controlled erosion through a series of repetitive sparks between workpiece and wire electrode. During the machining process there is no direct contact between the workpiece and the wire electrode. WEDM is a specialized thermo electrical machining process capable of accurately machining parts with varying hardness or complex shapes. The model and optimize of complex electric discharge machining process using soft computing techniques was discussed. Artificial Neural Network (ANN) with back propagation algorithm is used to model the process. VICTOR-1 die-sink EDM machine is used for experiment. C40 steel work piece and Copper wire is used. Machining parameters such as pulse-on time, pulse-off time and discharge current are considered to evaluate material removal rate and tool wear. A multi-objective optimization method, non-dominating sorting genetic algorithm-II is used to optimize the process. A pareto-optimal set of 100 solutions are obtained [1]. The selection of WEDM process parameters, such as pulse duration, pulse frequency, duty factor, peak current, dielectric flow rate, wire speed, wire tension, effective wire offset is utmost importance for enhanced process performance were discussed. The responses measured are surface roughness, kerf width and dimensional shift. Genetic Algorithm (GA), particle swarm optimization, sheep flock algorithm, ant colony optimization, artificial bee colony and biogeography-based optimization for single and multi-objective optimization of WEDM process are done. Thus, Biogeography-based optimization algorithm can be used as a global optimization tool [2]. The variations of cutting velocity and surface finish on WEDM process were analyzed. Experiment is done based on orthogonal array of Taguchi's method. Experimental factors are pulse-on time, pulse-off time, arc off time, servo voltage, feed rate, wire tension and dielectric pressure. Back-Propagation Neural Network (BPNN) and Simulated Annealing Algorithm (SAA) is proposed to determine an optimal parameter setting of wire EDM process. The results of proposed algorithm and confirmation experiments are show that the BPNN/SAA method is effective tool for optimization of WEDM process parameters. Through ANOVA, pulse-on time is most significant factor for the WEDM process [3].

An optimization of process parameters using Taguchi technique with grey relational analysis was carried out. The experimentation is carried using standard L_{27} orthogonal array. The multi-response optimization of the process parameters viz., Metal Removal Rate (MRR), Tool Wear Rate (TWR), Taper (T), Radial Overcut (ROC), and Surface Roughness (SR) on electric discharge machining (EDM) of Al–10%SiCP as cast metal matrix composites using Orthogonal Array (OA) with Grey relational analysis is reported. The experimental result for the optimal setting shows that there is considerable improvement in the process. The application of this technique converts the multi response variable to a single response Grey relational grade and, therefore, simplifies the optimization procedure [4]. The intelligent modeling and multi-characteristics optimization of dry WEDM process while machining of Al–SiC metal matrix composite were carried out. Experiments were designed and conducted based on L_{27} Taguchi's orthogonal array to study the effect of pulse on time, pulse off time, gap voltage, discharge current, wire tension and wire feed on Cutting Velocity (CV) and SR. Analysis of variances (ANOVA) has been performed to identify significant factors. In order to correlate relationship between process inputs and responses, an Adaptive Neuro-Fuzzy Inference System (ANFIS) has been employed to predict the process characteristics based on experimental observations. The ANFIS model could predict the cutting velocity and surface roughness as well due to low values of RMSE in testing. The optimal results which are obtained through ANFIS-ABC have been verified by confirmatory experiment to show the efficiency of proposed method [5]. They have compared the machining performances of WEDM in Stavax material using Multiple Regression Analysis (MRA) and Group Method of Data Handling (GMDH). Experimentation was performed as per L_{16} orthogonal array. Each experiment is performed under cutting conditions like pulse on time, pulse off time, current and bed speed. Voltage and flush rate are kept constant. Surface roughness, accuracy, volumetric material removal rate and electrode wear are measured. The result from the GMDH shows that the regularity criterion function provides good estimation rather than unbiased and combined criterion. Set of data are trained in 50%, 62.5% and 75% training set. Predicted response variables of 62.5% and 75% of data are correlated well with measured variables. From the result, GMDH technique gave better prediction than MRA [6].

2. Experimental details

The experiments were performed on CONCORD DK7720C four axes CNC WED machine. The basic parts of the WED machine consist of a wire electrode, a work table, a servo control system, a power supply and dielectric supply system. The CONCORD DK7720C 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. The WEDM process generally consists of several stages, a rough cut phase, a rough cut with finishing stage, and a finishing stage. But in this WED machine only one pass is used.

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 and fixed parameters selected are as listed in Table 1. The control factors were chosen based on review of literature and experts. 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 four levels denoted I, II and III as shown in Table 1.

Fig. 1. Experimental Set-up

Table 1. Machining settings used in experiments

Control Factors/Level		Level		
		I	II	III
A	Pulse –on	20	24	28
B	Pulse-off	5	6	7
C	Current	4	5	6
D	Bed speed	30	35	40

3. Results and Discussions

3.1. Multiple Regression Analysis

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, $ß_1$,……………$ß_m$ 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.

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

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.

$$Y = a + b_1X_1 + b_2X_2 + \ldots\ldots\ldots\ldots + b_mX_m \tag{3}$$

The obtained regression model for estimating surface roughness for Al2024 material is,

$$R_a = 6.98e\text{-}2 \text{ x } A + 7.28e\text{-}2 \text{ x } B + 2.71e\text{-}1 \text{ x } C + 3.93e\text{-}2 \text{ x } D - 1.13 \tag{4}$$

The obtained regression model for estimating material removal rate for Al2024 material is,

$$VMRR= 3.90e\text{-}2 \text{ x } A - 4.38e\text{-}1 \text{ x } B + 3.98e\text{-}1 \text{ x } C + 1.97e\text{-}1 \text{ x } D + 3.04 \tag{5}$$

The obtained regression model for estimating accuracy for Al2024 material is,

$$Accuracy = - 1.67e\text{-}1 \text{ x } A - 1.22 \text{ x } B + 2.28 \text{ x } C + 2.67e\text{-}1 \text{ x } D + 2.43 \tag{6}$$

3.2. Group Method of Data Handling

Group method of data handling (GMDH) is a family of inductive algorithms for computer-based mathematical modelling 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 modelling, 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)*.

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

Where f are elementary functions dependent on different sets of inputs, a are 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 *(8)* 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)*.

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

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

In the present study outlines the estimation of process parameters in machining Al2024 alloy material. The experiments were performed based on L_{27} orthogonal array. Experiments were done for various Pulse on, Pulse off, Current and Bed speed. Surface roughness, accuracy and VMRR were measured. Process Parameters are optimized with consideration of multiple performance characteristics, such as workpiece Surface roughness, Accuracy and VMRR. The verification experiments are conducted using the optimized process parameters and compared with the results obtained from the initial set of readings. The parameters are predicted using mathematical models viz., MRA, GMDH. Comparison of measured values with predicted values with standard error is done to know the behavior.

The Table 2 gives the consideration of the various cutting condition and involving of input parameter like Pulse-on time, Pulse-off time Current and Bed speed. Output parameter like Surface roughness, Accuracy and VMRR had been tabulated with the data obtained during experiments conducted on Al2024 alloy. The verification experiments are conducted using the optimized process parameters and compared with the results obtained from the initial set of readings.

The Table 2 gives the consideration of the various cutting condition and involving of input parameter had been tabulated with the data obtained during experiments conducted on Al2024MMC material.

Table 2. L_{27} orthogonal array for surface roughness, accuracy, and VMRR in machining Al2024 alloy

Run	Pulse-On (µsec)	Pulse-Off (µsec)	Current (amps)	Bed Speed (µm/sec)	Ra (µm)	Accuracy (µm)	VMRR (mm^3/min)
1	20	5	4	30	3.06	10	9.61
2	20	5	5	35	3.25	13	10.98
3	20	5	6	40	3.53	17	12.52
4	20	6	4	35	2.83	11	9.46
5	20	6	5	40	3.26	12	11.60
6	20	6	6	30	3.11	14	10.35
7	20	7	4	40	3.31	10	10.53
8	20	7	5	30	3.21	9	9.15
9	20	7	6	35	3.86	15	9.74
10	24	5	4	35	3.95	12	9.02
11	24	5	5	40	4.13	15	10.80
12	24	5	6	30	4.11	14	9.00
13	24	6	4	40	3.81	10	10.43
14	24	6	5	30	3.57	10	9.22
15	24	6	6	35	4.37	15	9.50
16	24	7	4	30	3.63	8	8.12
17	24	7	5	35	4.11	10	9.11
18	24	7	6	40	4.89	15	10.25
19	28	5	4	40	3.89	12	11.76
20	28	5	5	30	3.37	10	10.29
21	28	5	6	35	4.52	15	11.60
22	28	6	4	30	3.15	8	9.21
23	28	6	5	35	3.47	10	10.60
24	28	6	6	40	3.94	15	12.49
25	28	7	4	35	3.92	8	9.60
26	28	7	5	40	4.09	11	11.74
27	28	7	6	30	4.10	10	9.46

3.3. Estimation of Performances by MRA

Multiple regression analysis method is used for the estimation of surface roughness, accuracy and VMRR. The objective of MRA 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 sometimes non linear models such as log-linear models are also constructed. Pulse-on time, pulse-off time, current and bed speed are considered as independent variables to estimate surface roughness, accuracy and VMRR. The variations of the measured and estimated surface roughness, accuracy and VMRR with time have been presented in the form of graphs for further discussion and comparison.

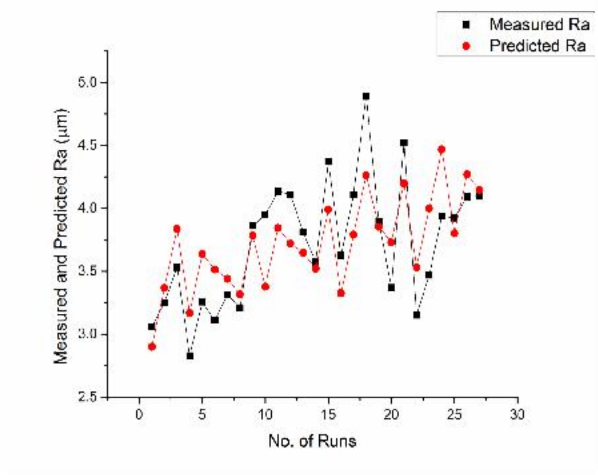

Fig 2. Measured and predicted surface roughness

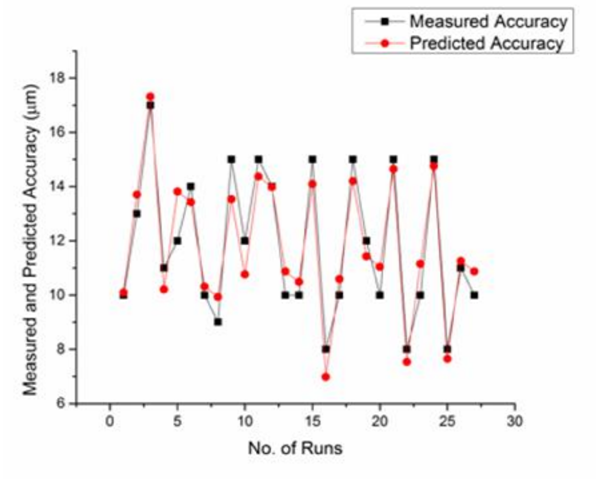

Fig 3. Measured and predicted accuracy

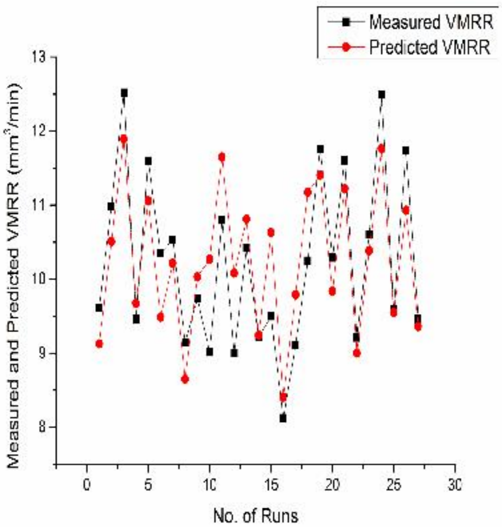

Fig 4. Measured and predicted value of VMRR (mm^3/min)

Fig 2 shows the multiple regression estimates the surface roughness, accuracy and VMRR for various pulse-on (20, 24 and 28µsec), pulse-off (5, 6 and7µsec), current (4, 5 and 6Amps) and bed speed (30, 35 and 40µm/sec). Roughness increases corresponding to the number of experiments. The MRA helps in the estimation of surface roughness, accuracy and VMRR corresponding to the measured one. The measured value of surface roughness, accuracy and VMRR are closely correlates with the estimated value of multiple regression analysis. From the Fig 2 and Fig 4, it is observed that the measured value at lower and higher cutting condition correlates well with the estimated value.

3.4. Estimation of Performances by GMDH

The prediction of responses was carried out using GMDH, for various training sets of 50%, 62.5% and 75% of data. There are three criteria's, viz., regularity, unbiased and combined criteria's is used in GMDH. 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.

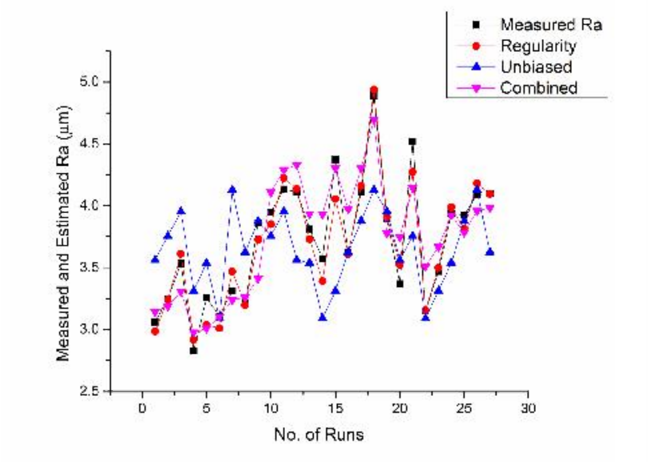

Fig 5. GMDH estimates of surface roughness for various criterions

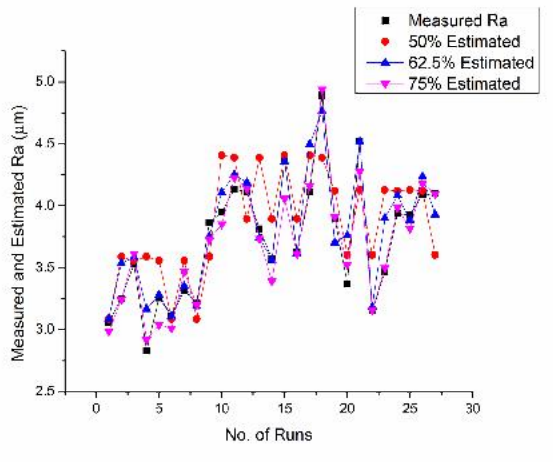

Fig 6. GMDH estimates of surface roughness for various percentages of data

Fig 5 and Fig 6 shows the comparison of experimental and GMDH estimates of roughness from three criterions, for 75% of data in training set. It is observed that a regularity criterion was correlated to the measured value. The least standard error was 0.0231 from the regularity criteria of 75% training set of data's when compare to other criterions and other two percentage of data in training set.

3.5. Comparative Study of MRA and GMDH

MRA and GMDH were used to estimate surface roughness, accuracy, VMRR in machining of Al2024 alloy. Both methods were found to estimate surface roughness, accuracy, VMRR well as discussed in the above sections. From the standpoint of identifying a better method among the two, the results from both the methods were compared. In GMDH, regularity criterion gave better estimation than the other criteria with 75% of data in training set. Hence, it was considered for the comparison.

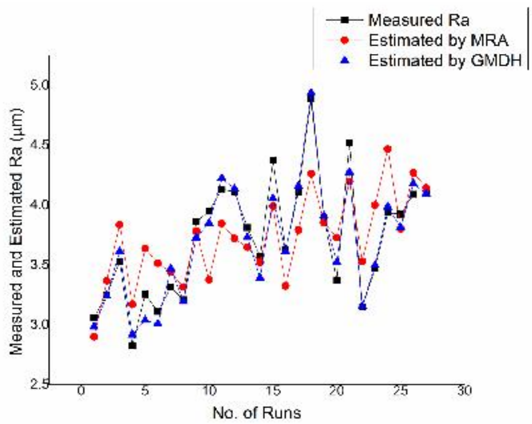

Fig 7. Comparison of MRA and GMDH estimates of surface roughness

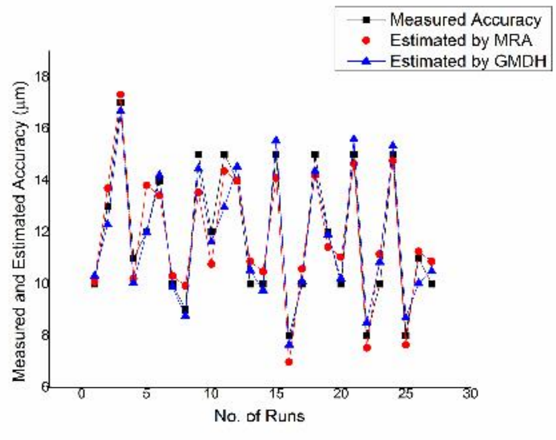

Fig 8. Comparison of MRA and GMDH estimates of accuracy

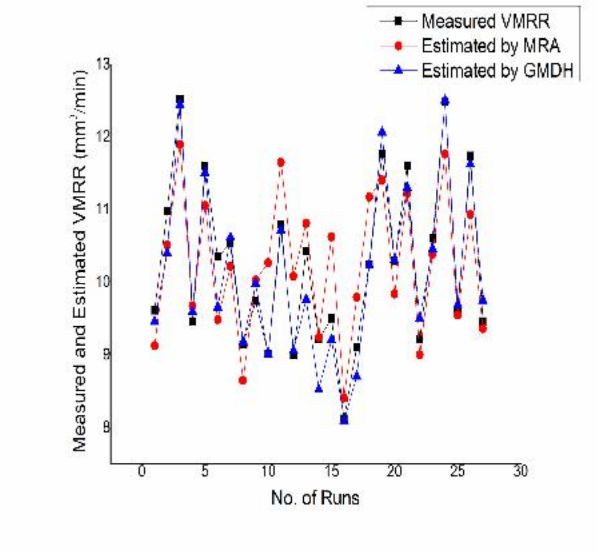

Fig 9. Comparison of MRA and GMDH estimates of VMRR

From Fig 7, Fig 8 and Fig 9 observed that the 75% training set of data of regularity criteria in group method data handling is well correlating with the measured surface roughness than the multiple regression analysis. The standard error will be 0.0231 from 75% of training set of group method data handling. This is because GMDH is a self-organizing method of modelling, which fits a high degree polynomial using a multi-layered network like structure.

4. Conclusions

Based on the results of theoretical and experimental analysis following conclusion were drawn

- Pulse on, pulse off, current and bed speed were considered as independent variable affecting the response variables to different extent.
- Machining at low pulse-off (5µsec) and low current (4amps) can minimize dimensional error.
- Maximum Material removal can be achieved with high bed speed (40µm/sec) and high pulse-on (28µsec).
- Multiple regression analysis method can be considered for reliable estimation of surface roughness, accuracy, VMRR based on the on the parameters like pulse-on, pulse-off, current and bed speed.
- The estimation capability of the multiple regression analysis method was better at lower cutting conditions than at higher cutting conditions, due to the lesser value of measured parameters at those conditions. This implies that the data handling capability of this estimation method is less.
- Three different criterion functions of GMDH viz., regularity, unbaised and combined criterions have been tried for surface roughness, accuracy and VMRR estimation.
- 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 the training set. The regularity criterion function provides good estimation than the other two functions.
- In GMDH, measured parameters correlates well with surface roughness, accuracy and VMRR. The estimation capability of the GMDH was better at higher cutting conditions than at lower cutting conditions, as the standard errors at higher conditions are very less. This implies that the data handling capability of this estimation method is high.

Comparison of the two theoretical methods for estimation of surface roughness, accuracy and VMRR, it was found that regularity criterion function of GMDH had an edge over MRA method.

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