APPLICATION OF DESIRABILITY BASED HYBRID ANFIS MODEL FOR OPTIMIZATION OF ELECTRO DISCHARGE MACHINING OF HASTEALLOY C-276

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Abstract: *Hastealloy C-276 is a difficult to machine superalloy and comprehensively employed in various engineering fields such as nuclear applications, aerospace and gas turbines. Hastealloy C-276 having better strength and poor thermal conductivity makes them difficult to machine materials which results in reduced life of the cutting tool and poor machinability by conventional methods of material removal. Advanced metal removal methods have evolved to accomplish those kind of needs and appealed to be an opposite alternative approach to traditional machining. Electro Discharge Machining (EDM) is considered as one of the nontraditional metal removal process which is especially adopted for machining of hard to machine materials. In this present investigation Spark Erosion Machining has been employed for machining of Haste Alloy C-276 with copper electrode by using Taguchi's experimental design approach. Applied current (A), pulse on time (T_{ON}) and pulse off time (T_{OFF}) were considered as the input process variables and the performance of spark erosion machining has been assessed by considering the performance measures such as material removal rate, surface roughness, overcut, form and orientation tolerance errors. The significance of process variables were analyzed by Analysis of Variance (ANOVA). Multi objective optimization has been performed by desirability function analysis to obtain better machining performance. In addition DFA based Adaptive Neuro Fuzzy Inference System (ANFIS) have been evolved to optimize the desired performance characteristics.*

Keywords: *EDM, Haste Alloy, Taguchi's Design, Desirability Function Analysis, ANFIS*

1. INTRODUCTION

Nickel based Superalloys are superior heat resistant and the properties of the materials are remains unaffected during high temperature applications (Cai et al. 2014). The exceptional material properties of Superalloys such as improved strength, hardness and lower thermal diffusivity makes them as difficult to machine materials which results in poor performance in machining and more tool wear by traditional machining processes. Therefore there is a need to find a solution for machining of these super alloys which are electrically conductive with an aid of advanced material removal processes. Spark Erosion Machining which also called Electro Discharge Machining (EDM) is one of the contemporary machining process widely used for machining the various engineering components that are used in automobiles, aerospace and biomedical industries. A continuous repeated electrical discharges between the electrode and the work material, results in removal of material from the work material in the presence of dielectric fluid [(Wu, 2007; Salman et al. (2014); Kuppan et al. (2015); Qu et al. (2014)]. The tool (electrode) moves towards the workpiece until the distance among the tool and workpiece is close enough to ionize the dielectric fluid with the help of supplied voltage. Tool and the workpiece are separated by the short duration discharges in the dielectric gap. The material removal takes place because of the erosive action. The removal of material happens with irrespective of the hardness of the material. The schematic of EDM approach is presented in Fig.1 (Ho & Newman, 2003).

An exploration on EDM drilling of nickel alloy detailed the importance of peak current and the supplied current is the important process parameter for attaining the improved rate of material removal (Luis et al. 2005). The plan of experiment is most important for determining the importance of the process parameters. Taguchi's experimental design approach is an influential approach for planning the experiments and to resolve the single aspect optimization problems. The machining performance and influence of process variables are detailed by various researchers on EDM process [(Kuppan et al. (2008); Dhanabalan et al. (2013); Bharti et al. (2010)]. Apposite selection of process variables combination for ascertaining the better machining performance is yet an intricate one. Most commonly all of the engineering based applications are not only single objective, sometimes it belongs multi-objective category. If the process has multi factors, then the application of the optimum combination of control factors, while an improvement of one response may influences the another remaining responses. Consequently for determining the solution for multi aspect optimization problems, it is appropriate to convert all the desired multi aspects into a corresponding single aspect function. This converted equivalent objective function is the representation of all the quality characteristics of the product which is to be optimized. Among the available multi criteria decision making methods, desirability function analysis is an effective and efficient approach for solving various multi aspects optimization problems (Derringer and Suich, 1980). It does not requires the complicated mathematical theory and thus the proposed method was adopted by various researchers. Baraskar et al. (2009) evolved empirical relations for correlating the roughness of machined portion and rate of material removal for selected input variables such as discharge current, pulse on and off time with the help of response surface methodology approach for the spark erosion machining process. DFA method also has been adopted to identify the best possible combination of process parameters for obtaining the better multi performance machining characteristics. Regardless of various benefits, the output variables have some uncertainty and unclear data in DFA approach. To overcome such kind of limitations, MCDM based hybrid optimization method have been employed for EDM process (Sengottuvel et al. 2013). The use of MCDM based fuzzy method will significantly enhances the machining performance. The Grey fuzzy approach has momentous influence on the enhancement of machining performance and accuracy of outcomes (Ahilan et al. 2009; Lin et al. 2000; Pandey and Panda 2014; Suresh et al. 2014). The evolution of artificial tools for intelligent decision making to envisage the desired performance measure makes momentous development in the various manufacturing domain. Innumerable tools were established for decision making in spark erosion machining process (Pradhan and Biswas 2010). ANFIS is an intelligent tool which is having the advantages of both neuro and fuzzy models and it is evolved by coalescing the ability to accomplish a robust tool which makes upgrading in the evolved model and results in minimum error. Furthermore it is an intelligent decision making tool for multi aspects optimization (Jang et al. 1997; Teimouri et al. 2015; Caydas et al. 2009) and it can be further enhanced by using DFA based ANFIS.

The form and orientation tolerance errors of machined surface plays a significant role in mechanical design and quality control of a geometrical product. The effective measurement and efficient evaluation of these tolerances as performance measure needs attention. It is observed from the literature, that there are lack of investigation performed on multi-aspects optimization of process variables using DFA based ANFIS approach by considering the output measures namely rate of material removal (MRR), machine portion roughness (SR), dimensional deviation (Overcut), circularity error and perpendicularity error for EDM process. Taguchi based DFA approach is adopted for determining the individual desirability values and calculated individual desirability values have been used as input values to develop the ANFIS model. In this

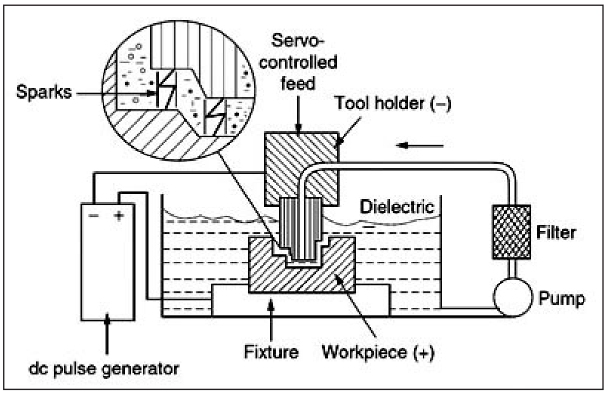

Fig 1. Schematic of Electrical Discharge Machine

present article, an attempt has been taken to develop the multi aspects optimization model using DFA based ANFIS method to predict the multi performance characteristics.

2. MATERIALS AND METHODS

Hastealloy C-276 was used as work material in the present investigation and it is clamped inside of the machining chamber. Hastealloy C-276 belongs to a category of difficult to machine super alloy and comprehensively used in numerous engineering applications. Because of its outstanding properties, the selected work material have broader applications specially in digesters and bleach plants in paper industries, heat exchangers, sulfuric acid reactors, and chemical environments. Copper is the electrode tool material for machining of selected work material.

In conventional experimental design approach, there are need of more experimental runs to be conducted with desired process parameters and their levels. These types of difficulties may be solved by adopting Taguchi's design approach. Taguchi suggested a unique design which is called as Orthogonal Array (OA) for performing the experimental runs and to investigate the process variables with minimum number of experimental runs. Applied Current (Amps), pulse on time (µs) and pulse off time (µs) were deemed as input process variables and rate of material removal (MRR), roughness of the machined surface, dimensional deviation (overcut), form and orientation tolerance errors were deemed as performance measures. As per the considered parameters and levels, an L_{27} OA have been picked for spark erosion drilling of Hastealloy C-276. The selected input process variables and their levels with range of values are detailed in Table 1.

The experimental runs were done on spark erosion machine (Model EMS 5030) for producing through holes. Copper is the material for tool electrode for machining of selected work material. Weight loss approach is selected to evaluate the removal rate of material. Roughness of the machined surface is assessed by Mitutoyo surface roughness tester (SJ 410 model). The dimensional deviation (overcut), errors of form and orientation tolerance are evaluated by Co-ordinate Measuring Machine (Model 216-142). In spark erosion machine, maximum MRR and minimum roughness of machined surface and minimum dimensional deviation (overcut), minimum form and orientation tolerances are the indicators of better machining performance.The experimental runs were performed as per L_{27} OA and the experimental observations are depicted in Table 2.

Table 1: Input Process Parameters and Levels

Symbols	Process Variables	Levels		
		1	2	3
A	Current (A)	5	10	15
B	Pulse on Time (µs)	30	60	90
C	Pulse off time (µs)	3	6	9

2.1 Desirability Function Analysis (DFA)

Desirability Function Analysis (DFA) has been considered as one of the most comprehensively adopted approach for the determining the multi performance index. DFA changes the multi objective problems into single objective problems. As a result, the optimization of intricate multi objective problem would be made into optimization of a single aspect problem which is called as composite desirability (Derringer and Suich 1980).

Step 1: Individual desirability index (d_i) for the each responses has to be determined.

For the maximum-the-better, the desirability function can be expressed as in Equation. (1) the value of $\hat{Y}$ is likely to be the maximum-the-better. When the '$\hat{Y}$' surpasses a particular criteria value, which can be observed as the requirement, the desirability value equals to 1; if the '$\hat{Y}$' is less than a specific criteria value, which is undesirable, the desirability value equals to 0.

$$d_i = \begin{cases} 0, & \hat{y} \le y_{min} \\ \left(\frac{\hat{y}-y_{min}}{y_{max}-y_{min}}\right)^r, & y_{min} \le \hat{y} \le y_{max}, \quad r \ge 0 \\ 1, & \hat{y} \ge y_{max} \end{cases} \tag{1}$$

where the 'y_{min}' represents the lower tolerance limit of '$\hat{Y}$', the 'y_{max}' represents the upper tolerance limit of $\hat{Y}$ and r refers to the weight.

For the minimum-the-better, the desirability function can be expressed as in Equation (2). The value of '$\hat{Y}$' is likely to be the minimum-the-better while '$\hat{Y}$' is less than a particular criterion value, the desirability value will be equal to 1; if the '$\hat{Y}$' exceeds a particular criterion value, the desirability value will be equal to 0.

$$d_i = \begin{cases} 1, & \hat{y} \leq y_{min} \\ \left(\frac{\hat{y}-y_{max}}{y_{min}-y_{max}}\right)^r, & y_{min} \leq \hat{y} \leq y_{max}, \quad r \geq 0 \\ 0, & \hat{y} \geq y_{max} \end{cases} \quad (2)$$

where the y_{min} represents the lower tolerance limit of 'Ŷ', the 'y_{max}' represents the upper tolerance limit of 'Ŷ' and r refers to the weight.

Step 2: The index of individual desirability for entire responses can be amalgamated to form a single value called composite desirability (d_G) using Equation. (3).

$$d_G = \sqrt[w]{(d_1^{w_1} * d_2^{w_2} \ldots\ldots\ldots\ldots * d_i^{w_i})} \quad (3)$$

where 'd_i' is the individual desirability of the property 'Y_i', 'w_i' refers to the weight of the property "Y_i" in the composite desirability, and 'w' is the summation of the individual weights.

Table 2: Experimental Observations for Spark Erosion Machining of Haste Alloy

Order	Material Removal Rate (g/min)	Surface Roughness (Microns)	Overcut (mm)	Circularity error (mm)	Perpendicularity error (mm)
1	0.0435	0.30	0.8842	0.3487	0.6440
2	0.0443	0.32	0.9029	0.3634	0.6821
3	0.0459	0.32	0.9280	0.3753	0.7444
4	0.0481	0.32	0.9404	0.3927	0.7546
5	0.0490	0.32	0.9427	0.4033	0.7590
6	0.0512	0.33	0.9449	0.4148	0.7961
7	0.0519	0.34	1.1043	0.4248	0.9427
8	0.0523	0.34	1.1956	0.4252	0.9948
9	0.0526	0.35	1.3080	0.5163	0.8050
10	0.0534	0.35	0.5389	0.2359	0.3740
11	0.0540	0.36	0.5878	0.2413	0.3928
12	0.0546	0.40	0.7334	0.2489	0.4039
13	0.0563	0.40	0.7695	0.2744	0.4252
14	0.0574	0.40	0.7829	0.2802	0.4354
15	0.0581	0.40	0.8089	0.2817	0.4895
16	0.0620	0.41	0.8398	0.2838	0.5104
17	0.0636	0.41	0.8402	0.2961	0.5163
18	0.0645	0.42	0.8681	0.3182	0.5922
19	0.0651	0.45	0.1611	0.0795	0.0230
20	0.0655	0.49	0.1884	0.1266	0.0457
21	0.0662	0.50	0.2597	0.1579	0.1468
22	0.0674	0.50	0.3311	0.1693	0.1935
23	0.0678	0.50	0.3647	0.1909	0.2433
24	0.0685	0.50	0.4549	0.1914	0.2628
25	0.0749	0.52	0.4617	0.1994	0.2917
26	0.0783	0.54	0.5029	0.2055	0.3150
27	0.0812	0.56	0.5368	0.2143	0.3490

Step 3: At last, the optimum process parameter and its level of combinations should be ascertained. The higher the composite desirability value implies better product quality. Thus, on the basis of the composite desirability (d_G), the parameter effect and the optimum level for each parameter are estimated.

2.2 Development of DFA based ANFIS Model

The proposed ANFIS model is evolved with input five neurons and a single output neuron with corresponding membership functions of Sugeno type FIS. The input data given to the ANFIS model for spark erosion drilling of Haste Alloy C276 is individual desirability values of material removal rate, surface roughness, overcut, form and orientation tolerance errors. The developed ANFIS model is to envisage the composite desirability (multi performance machining index) in EDM of Haste alloy C-276. A model with more precision which relates the EDM parameters and the desired performance measures characteristic can be attained. The ANFIS Graphic User Interface (GUI) in MATLAB has been adopted to train the developed ANFIS model. The evolved ANFIS model with input of five neurons (individual desirability) and a single output parameter (composite desirability) is trained and the details of training are depicted in Table 3. The ANFIS model is developed with 'trimf' membership function contains 243 rules that are made as per the given input data set. Fig 2 illustrates the ANFIS editor. The developed ANFIS model has been further utilized for prediction of composite desirability (multi performance index). The ANFIS rule viewer for prediction of composite desirability is shown in Fig. 3.

Table 3: Training Parameters for the ANFIS Model

No. of membership function at each input level	3 3 3 3 3
Type of Membership function for Input	trimf
Type of membership function for output	Constant
Method of optimization	Backpropagation
Error tolerance	0
No. of epochs	500

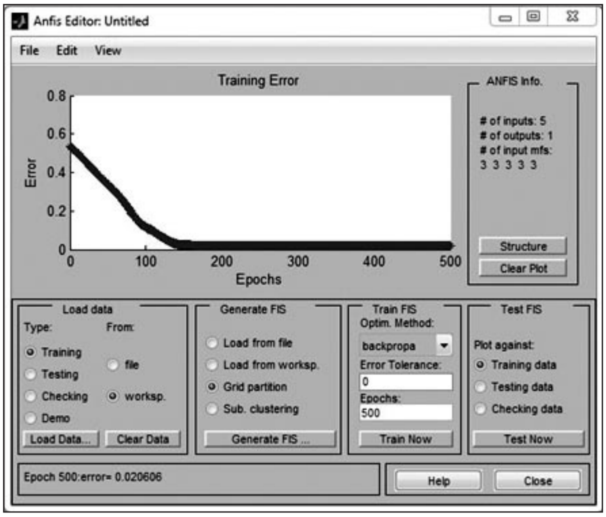

Fig 2. ANFIS Editor

3. RESULTS AND DISCUSSION

The individual desirability values and composite desirability values for spark erosion machining of Haste alloy C276 are estimated and presented. The calculated individual desirability values are further used for developing the ANFIS model. Multi aspects optimization using DFA and development of ANFIS model were presented in this section.

3.1 Multi-response Optimization Using DFA

For every response, the individual desirability index (d_i) was calculated depends upon the required quality features. As the objective of material removal rate is of maximum the better type, whereas the remaining responses belongs to minimization type, accordingly the maximum-the-better type Eq.(1) and the minimum-the-better-type Eq. (2) were chosen. After calculating individual desirability index for each response,

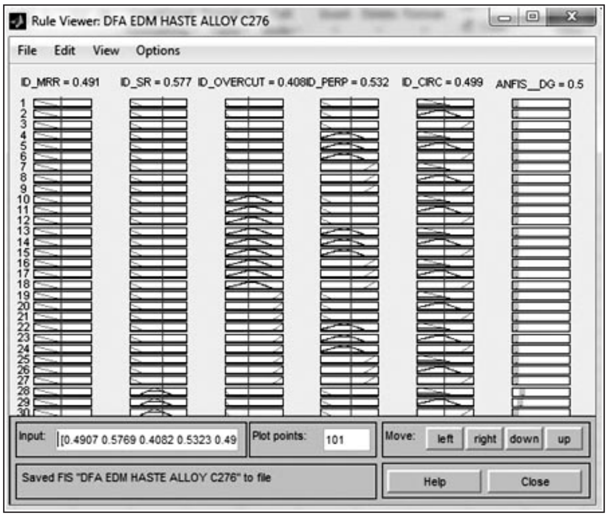

Fig 3. Rule Viewer

Table 4: Individual Desirability and Composite Desirability

Exp No.	Individual desirability index (d_i)					Composite desirability (d_G)
	Material Removal Rate (g/min)	Surface Roughness (Microns)	Overcut (mm)	Circularity error (mm)	Perpendicularity error (mm)	
1	0.0000	1.0000	0.3695	0.3837	0.3610	0.4228
2	0.0212	0.9231	0.3532	0.3500	0.3218	0.3939
3	0.0637	0.9231	0.3313	0.3228	0.2577	0.3797
4	0.1220	0.9231	0.3205	0.2830	0.2472	0.3791
5	0.1459	0.9231	0.3185	0.2587	0.2426	0.3778
6	0.2042	0.8846	0.3166	0.2324	0.2045	0.3685
7	0.2228	0.8462	0.1776	0.2095	0.0536	0.3019
8	0.2334	0.8462	0.0980	0.2086	0.0000	0.2772
9	0.2414	0.8077	0.0000	0.0000	0.1953	0.2489
10	0.2626	0.8077	0.6706	0.6419	0.6388	0.6043
11	0.2785	0.7692	0.6280	0.6296	0.6195	0.5849
12	0.2944	0.6154	0.5010	0.6122	0.6080	0.5262
13	0.3395	0.6154	0.4695	0.5538	0.5861	0.5129
14	0.3687	0.6154	0.4578	0.5405	0.5756	0.5116
15	0.3873	0.6154	0.4352	0.5371	0.5200	0.4990
16	0.4907	0.5769	0.4082	0.5323	0.4985	0.5013
17	0.5332	0.5769	0.4079	0.5041	0.4924	0.5029
18	0.5570	0.5385	0.3836	0.4535	0.4143	0.4694
19	0.5729	0.4231	1.0000	1.0000	1.0000	0.7992
20	0.5836	0.2692	0.9762	0.8922	0.9766	0.7396
21	0.6021	0.2308	0.9140	0.8205	0.8726	0.6880
22	0.6340	0.2308	0.8518	0.7944	0.8246	0.6671
23	0.6446	0.2308	0.8225	0.7450	0.7733	0.6432
24	0.6631	0.2308	0.7438	0.7438	0.7532	0.6270
25	0.8329	0.1538	0.7379	0.7255	0.7235	0.6347
26	0.9231	0.0769	0.7020	0.7115	0.6995	0.6226
27	1.0000	0.0000	0.6724	0.6914	0.6645	0.6057

composite desirability values were calculated with the help of Eq. (3) by considering equal weightage for all the responses and presented in Table 4. It is observed from the results of desirability function analysis, that the 19th experimental run possess the maximum composite desirability value which means that the trial has the better multi aspect machining performance among the all conducted 27 set of experimental runs. The maximum 'd_G' value denotes that the corresponding combination of process variables is close to most promising optimum parameter setting for attaining improved multi aspects machining performance.

Effect of process variables on composite desirability: The response analysis for composite desirability during spark erosion machining of haste alloy C-276 is illustrated graphically in Fig 4. It is depicted from the illustration that the composite desirability is improved with increase of applied current and the same is decreased with increase of pulse on time and pulse off time. The response analysis for composite desirability has been done and it is presented in Table 5. From the analysis the possible combination of process variable for attaining better multi aspect EDM machining were identified as $A_3B_1C_1$.

Table 5: Response Table for Composite Desirability

Levels	Means			S/N Ratio		
	C	P_{ON}	P_{OFF}	C	P_{ON}	P_{OFF}
1	0.3500	**0.5710**	**0.5359**	-9.2400	**-5.1560**	**-5.765**
2	0.5236	0.5096	0.5171	-5.6450	-6.0680	-6.079
3	**0.6697**	0.4627	0.4903	**-3.5150**	-7.1760	-6.556
Delta	0.3197	0.1082	0.0457	5.7240	2.0200	0.791
Rank	1	2	3	1	2	3
C – Current (A), P_{ON} – Pulse On Time (µs), P_{OFF} – Pulse Off Time (µs)						

Table 6: Results of the ANOVA for Composite Desirability (d_G)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Current (A)	2	0.461076	0.461076	0.230538	369.56	0.0000
Pulse On (µs)	2	0.053021	0.053021	0.026511	42.5	0.0000
Pulse Off (µs)	2	0.009475	0.009475	0.004738	7.59	0.0040
Error	20	0.012476	0.012476	0.000624	---	---
Total	26	0.536049	---	---	---	---

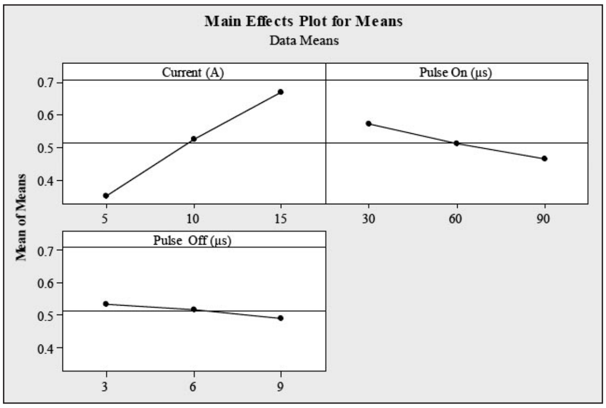

Fig 4. Effect of Process Variables on Composite Desirability

3.2 ANOVA for Composite Desirability

The significance of individual process parameters on the multi performance index (composite desirability) has been determined and depicted in Table 6. It is perceived from the analysis that the applied current (Percentage contribution, *P* = 86.01%) is the most significant machining parameter which influences the multiple performance characteristics for EDM of hastealloy C276 followed by pulse on time (*P* = 9.89%) and pulse off time (P = 1.77%).

After developing the ANFIS model, it is further used by giving input parameters using ANFIS rule viewer for the prediction of composite desirability (multi performance index). While changing the input values, the corresponding output is automatically obtained from the fuzzy logic system. The developed ANFIS model has been employed for predicting the composite desirability (multi performance index) at various input conditions.

Table 7: Validation Results of Proposed ANFIS Model

S. No	Composite Desirability		Absolute Percentage Error
	Calculated	Predicted	
1	0.4228	0.4170	1.372
2	0.3939	0.3990	1.295
3	0.3797	0.3760	0.974
4	0.3685	0.3670	0.407
5	0.3019	0.3020	0.033
6	0.2772	0.2770	0.072
7	0.6347	0.6380	0.520
8	0.6226	0.6210	0.257
9	0.6057	0.6068	0.182

3.3 Validation of Developed ANFIS Model

Once the evolved model is trained, then it is validated and the outcomes are depicted in Table 7. The results envisaged by evolved model were compared with the experimental outcomes and it is exposed that the developed model has a close relationship between the actual and the envisaged outcomes. The absolute percentage error attained between the actual and predicted values of composite desirability exhibits that the evolved model was precise for prediction of preferred performance measures. The graphical representation of comparison among the values of actual composite desirability and ANFIS predicted composite desirability were shown in Fig. 5.

3.4 Influence of Individual Desirability Values on ANFIS-d_G:

The influence of individual desirability values of various performance measures on ANFIS predicted composite desirability were shown in Fig. 6. The effect of individual desirability values of MRR and overcut on ANFIS predicted composite desirability values were presented. It is conspicuous from the illustration that the ANFIS predicted composite desirability value was higher while the individual desirability values of MRR and overcut are at higher level. It was observed from the illustration that the effect of individual desirability values of MRR and surface roughness on ANFIS predicted composite desirability. It is conspicuous from the illustration that the ANFIS-predicted composite desirability was maximum during lower individual desirability values of surface roughness and higher individual desirability values of MRR.

It is witnessed from the illustration that the effect of individual desirability values of overcut and circularity, surface roughness, perpendicularity on ANFIS predicted composite desirability. It is conspicuous from the illustrations that the ANFIS predicted composite desirability is maximum during the lower individual desirability values of MRR and intermediate individual desirability values of overcut, circularity, perpendicularity.

3.5 Performance Analysis of Developed ANFIS Model

Numerical deviation between the actual and predicted values from the developed ANFIS model is known as error. The mean absolute percentage error of developed model is tested by calculating the prediction error using the following equation (4):

$$\text{Mean Absolute Percentage Error (\%)} = \frac{1}{n}\sum_{i=1}^{n}\frac{Ev-Pv}{Ev} * 100 \quad (4)$$

The Root Mean Square Error (RMSE) value for evaluating the prediction model is obtained by the equation (5) and correlation coefficient values were evaluated by equation (6):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_V - P_V)^2} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(Pv-Ev)^2}{\sum_{m=1}^{n}(Ev)^2} \quad (6)$$

Where

'E_V'- experimental values
'P_V' - predicted values respectively,
'n' is the number of observations.

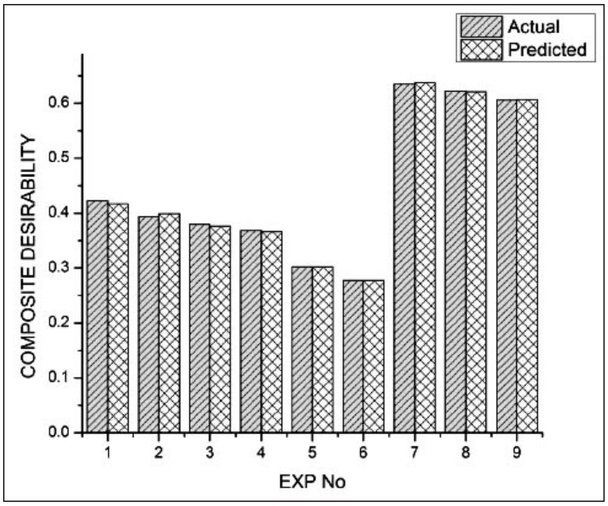

Fig 5. Comparison of Calculated and Predicted Composite Desirability

Table 8: Performance of Developed DFA Based ANFIS Model

Model - ANFIS	Error
Mean Absolute Percentage Error (MAPE)	0.7196
Root Mean Square Error (RMSE)	0.005152
Mean Absolute Error (MAE)	0.00719
Correlation Coefficient	0.9999

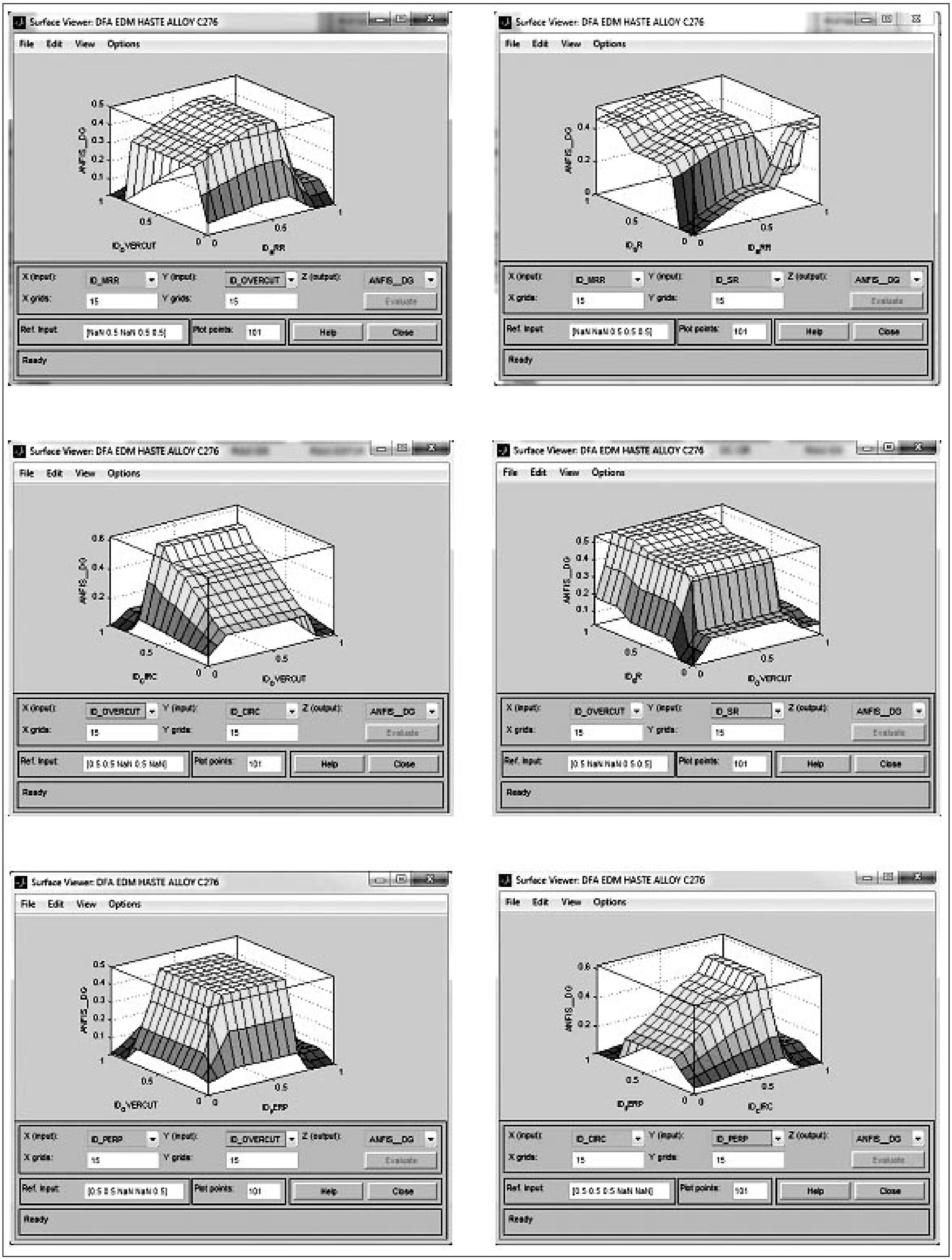

Fig 6. Influence of Process Variables on Composite Desirability

Table 9: Performance Comparison among Initial and Optimum Parameters

Setting level	Optimum machining parameters			
	Initial setting	Prediction	ANFIS	Experiment
	$A_1B_1C_1$	$A_3B_1C_1$	$A_3B_1C_1$	$A_3B_1C_1$
Material Removal Rate (g/min)	0.0435			0.0651
Surface Roughness (microns)	0.30			0.45
Overcut (mm)	0.8842			0.1611
Circularity error (mm)	0.3487			0.0795
Perpendicularity error (mm)	0.6440			0.0230
Composite Desirability	0.4228	0.7411	0.7980	0.7992
Enhancement in Composite Desirability				0.3764

The performance analysis of developed model is depicted in Table 8. It is perceived from the performance analysis that the developed model predicts the desired performance characteristics precisely.

4. CONFIRMATION TEST

As per the outcomes of experimental investigation, the best possible combination of process parameters were ascertained to attain the improved machinability characteristics. To confirm the estimated outcome, the final step is to conduct a confirmation run against experimental value. In this present investigation, the best possible set of process parameters were verified by checking the optimum condition ($A_3B_1C_1$) for spark erosion machining of Haste alloy C276. Comparative results among the initial levels and optimum level performance of process characteristics are presented in Table 9. The performance results of optimum parameter shows that there was a significant improvement in machining performance.

5. CONCLUSIONS

This present experimental investigation details the determination of optimum input process variable for attaining better machining performance on Taguchi's based desirability function analysis and an ANFIS model is evolved to predict the spark erosion machining process parameters based on desirability function approach. Developing a model with high precision for the prediction of machining process is most important for manufacturing domain. The following conclusions were drawn from the exploration:

- The desired performance measures were obtained from the experimental runs which are planned by Taguchi's L_{27} Orthogonal Array.
- The best possible combination of process variables for the desired multi criteria performance measures were ascertained by desirability function approach.
- By applying DFA multi-response optimization tool on spark erosion machining of hastealloy, the optimum values for maximization of MRR and minimization of surface roughness, overcut, circularity error and perpendicularity error were found to be at a current of 15 A, pulse of time of 30 µs, and pulse off time 3 µs.
- From the results of ANOVA, current was identified as the statistical and physical significant parameter followed by pulse on time and pulse off time.
- ANFIS model has been evolved for spark erosion process based on Taguchi - DFA approach.
- The developed DFA based ANFIS approach was employed to ascertain the best possible parameters for Spark erosion machining of Haste alloy C276.
- The results obtained from the evolved ANFIS model were compared with the experimental results and it is concluded that the developed ANFIS model precisely predicts the desired performance characteristics.
- It is affirmed from the confirmation test results, that the determined set of possible parameters are suitable for attaining the better machinability characteristics.
- The proposed DFA based ANFIS approach has

been employed successfully and it has the capability of reducing the uncertainty among the data which results in better prediction of desired performance measure.

- In summary the assessment outcomes prove that the proposed DFA based ANFIS approach is an effective tool and it can be employed for various unconventional machining processes for determining the better machinability characteristics.

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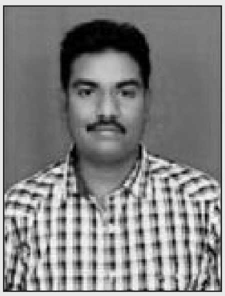

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