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Application of Taguchi Grey Approach and Sustainable Development of Hybrid Machine Learning Model for Wire Electrical Discharge Machining of Low Carbon Steel

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Abstract:
SAE 1010 steel is widely used in the automotive industry for fasteners and in aerospace and other engineering applications. Traditional machining of complicated forms is difficult. Wire Electrical Discharge Machining (WEDM), a specialized form of EDM, is effective for complex machining operations. This study optimises WEDM of SAE 1010 steel while considering environmental impact. A naturally available dielectric medium promotes sustainability without reducing machining efficiency. Pulse on time, pulse off time, and peak current affect material removal rate (MRR), surface roughness (Ra), and tolerance errors. ANOVA is used to determine the significance of the parameters. A hybrid Grey-ANFIS (Adaptive Neuro-Fuzzy Inference System) model improves performance predictions. The results show that Grey-ANFIS provides accurate forecasts, improving machining parameter optimization. The prediction model was highly accurate, with a MAPE of 0.0432, RMSE of 0.00029, and MAE of 0.000432. The model also correlated well with actual values, with a Correlation Coefficient of 0.9997.

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1. INTRODUCTION

Wire Electrical Discharge Machining (WEDM) is a new method for cutting materials. It is also the primary method used to make turbine blades for aircraft engines, nozzles for fuel injectors, and molds, among many other things. Wire Electrical Discharge Machining (WEDM) has many benefits when it comes to improving the performance of machining hard materials that are hard to work with in metal machining. WEDM is often used to make complex shapes instead of the old way of removing material [1–5]. Fig. 1 shows a schematic drawing of WEDM. In this operational process, an electrode wire, often called the tool wire, makes sparks that are used to carefully remove material from the workpiece. The workpiece and the electrode are

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kept at the right distance from each other, and a dielectric medium acts as a protective barrier.

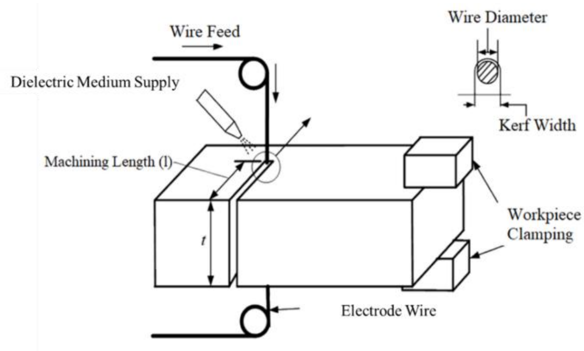

Fig. 1. Outline of WEDM

When sparks are used and the right voltage is applied between the tool and the workpiece, and there is a dielectric medium present, the material starts to melt on the surface. Material is removed [6–8] by the continuous and uninterrupted flow of electricity through the electrode wire and into the substance. Steel alloys are well-known for their natural stiffness and ability to resist corrosion, which makes them very useful in many manufacturing settings. The goal of this technology is to make sure that certain alloy materials have much higher specific strengths. However, to make them work better in complex structural applications, it will be important to improve the current properties of these particles [9]. Steel alloys are very popular in industry because they are light. These materials are very useful in aviation because they are very strong and flexible. SAE 1010 is a type of steel that is known for its high tensile strength and ability to resist corrosion. Empirical evidence has validated that SAE 1010 is an exceptionally suitable material for the structural components of aircraft, including the nozzles of the Space Shuttle SRB and the beam of the external tank SRB in the Inter-tank section. This conclusion is derived from multiple comprehensive analyses. The study of the WEDM of steel showed that the factors had a big effect on how well the materials worked as a whole [10–12]. Prior research has shown that both the ANOVA and Taguchi methodologies surpass the grey theory in accurately determining the effectiveness parameters for materials [13, 14]. The current study employed the grey concept to evaluate the different facets of the operation.

Traditional manufacturing processes for part manufacturing have several problems as well, and there are many factors that can affect the manufacturing quality; hence, WEDM can be an effective tool that can be a replacement for traditional manufacturing [15]. Several tests on different nickel alloys have already been done; also, single-objective optimization is taken into account to see how well each alloy can work in WEDM. The Taguchi optimization enables the proper organization of a large number of readings [16–20]. The GRA method has many advantages, but due to inaccuracy and uncertainty in the output matrices, a replacement is expected. The combination of optimization and fuzzy approaches is used in the grey technique, which makes it more effective [21]. Modern tool use can make this more efficient. Technical advancement in machining can enhance manufacturing efficiency [22]. An adaptive prediction tool is created in the present work by combining neural networks and fuzzy topologies on the ANFIS platform. The main objective of the present study is to strengthen the manufacturer during decision-making. The accurate forecasting of their models' performance leads to productivity enhancement. The effectiveness of the WEDM process improves with the use of a prediction tool like GRA [23-25]. Previous studies have shown that more research is required on the machining of SAE 1010 using the WEDM process [26–28]. The precision standards for the shape and orientation of the machined part are the major factors. These criteria are very important to maintain the manufacturing quality [29-32].

The goal of this exploratory study was to find out how important different factors are for getting certain output metrics, like Material Removal Rate (MRR), Surface Roughness (SR), overcut, and form and orientation tolerance errors of the machined surface. The aim of this study is to ascertain the influence of various factors on achieving specific performance metrics. Taguchi's methodology has been utilized for designing experiments and optimizing specific output metrics. Using the Taguchi-Grey approach, a multi-performance index was made to accurately measure machining performance. A hybrid grey Adaptive Neuro-Fuzzy Inference System (ANFIS) model has been identified as the most effective approach for forecasting the selected output metrics.

2. MATERIALS AND METHODS

Before undertaking any further trials, it is imperative to establish a standardization of the levels and factors. This is accomplished by applying strategies within the framework of the Taguchi experimental research design. A specific plan is known as an orthogonal array (OA). Implementing this approach to examine the input variables is viable. The input parameters are pulse duration (Ton, Toff) and the applied current. The present experiments employ the result measures of MRR, SR, overcut (OC), and errors in form and orientation tolerance. Table 1 presents an exhaustive compilation of the independent factors, along with their corresponding magnitudes and intervals. Upon careful analysis of the characteristics and tolerances of SAE 1010, it was concluded that an L27 OA would be appropriate for WEDM.

The EN24 material has a variety of applications like aerospace, defence and mould manufacturing, etc., due to its ability to retain its strength and anti-corrosive nature against the acidic environment.

Table 1. Factors and levels

Symbols	Variables	Levels		
		1	2	3
A	Pon (μs)	10	20	30
B	Poff (μs)	5	10	15
C	Peak Current (A)	1	2	3

Figs. 2 (a), (b), and (c) depict the WEDM Setup used for experimentation, the Workpiece and CMM Setup used for GD and T Error Measurements, respectively. The present work utilizes the Concord Wire Electron Discharge Machining (WEDM) equipment.

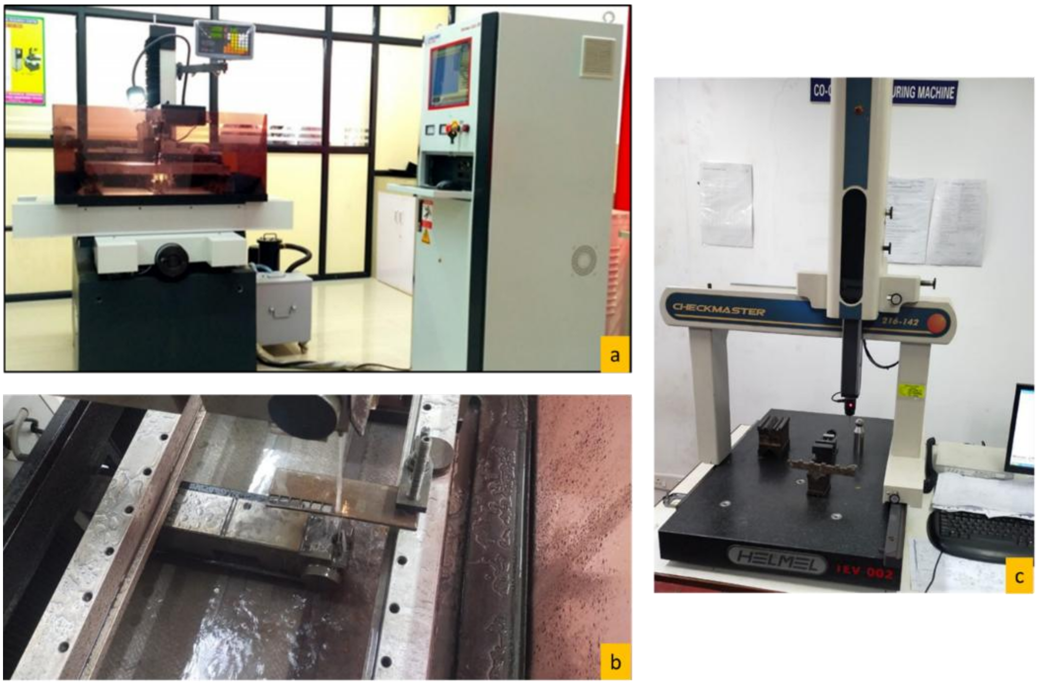

Fig. 2. (a) WEDM Setup used for experimentation, (b) Workpiece and (c) CMM Setup used for GD and T error measurements

2.1 Development of Hybrid Grey-ANFIS Model

At its normal configuration, an ANFIS usually consists of a single output and five input neurons. Input data pertaining to the WEDM of low-carbon steel is fed to the ANFIS model. The provided input information comprises the GRC values for MRR and SR, together with details on form and orientation tolerance defects. A novel ANFIS structure has been created to precisely forecast the values of GRG in the WEDM of SAE 1010 WEDM, utilizing the GRC values as an input factor. It is indeed reasonable to acquire an accurate model that imposes an association between the features of the WEDM and the related performance measures.

This study employed the MATLAB ANFIS-GUI to enable the training of the constructed ANFIS structure. The ANFIS model has 243 rules generated by the application of the 'trimf' membership function on the supplied raw data. Consequently, the set of regulations was developed. The application of the ANFIS model and the ruler for estimating GRG is illustrated in Fig. 3. This approach yielded the expected value as the most beneficial combination.

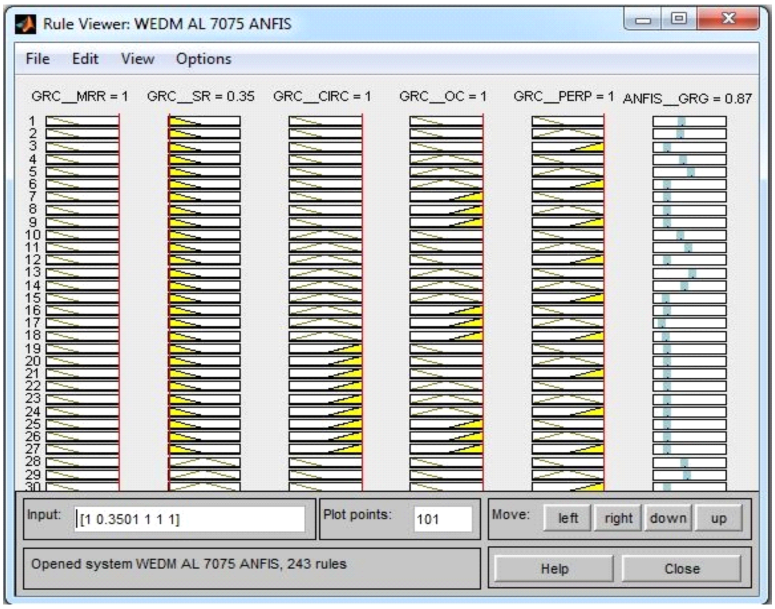

Fig. 3. ANFIS ruler for WEDM of low carbon steel

3. RESULT AND DISCUSSION

An experimental investigation was conducted using a Level 27 OA to study the impact of different input variables on WEDM of SAE 1010. The aspiration of this study was to establish the impact of these factors on the development and progression of the ANFIS model for WEDM of SAE 1010. The objective of the exploration was to recognize the optimum values of these components that would effectively enhance the implementation of the WEDM approach. The optimization of MRR and the minimization of roughness, form orientation tolerance errors, and overcut lead to improved performance.

3.1 Interpretation of Variables on MRR

The MRR response plot for the WEDM method that was applied to the SAE 1010 material is depicted in Fig. 4. The graphic that has been supplied illustrates that there is a positive association between the MRR and the degree of intensity as well as the length of the pulse. It is predominant to note that the variable denoted as "Ton" has a significant impact on MRR. It is possible that increasing the "Ton" ranges will consequences in an intensification in the energy output as well as an escalation in the 'MRR' as well. The same has been decreased with an increasing value of 'Toff', which decreases the frequency of occurrence of sparks, thereby reducing the energy input and consequences in lower MRR.

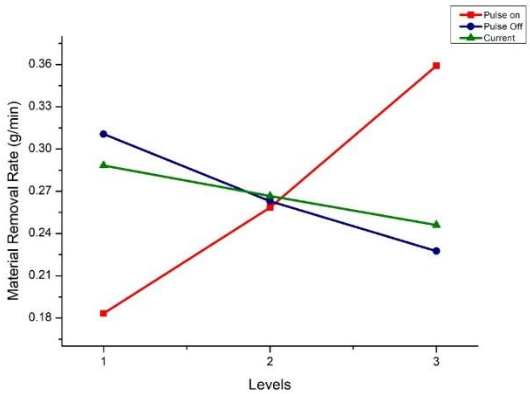

Fig. 4. Response graph for MRR

To optimize the MRR, it is recommended to use the A3B1C1 arrangement of variables. Performance tweaking can be achieved by precisely modifying the parameters "Ton" (30 µs), "Toff" (5 µs), and "Peak current" (1 ampere). The variable exerting the most significant influence is "Toff," trailed by "Ton" and the magnitude of the current supplied.

3.2 Interpretation of Variables on SR

Factors affecting surface roughness during WEDM of SAE 1010 are illustrated in Fig. 5. Empirical evidence indicates that raising the values of "Ton" and "Toff" while evaluating SR in the machined area results in a notable reduction in the overall quality of the work specimen surface. The roughness of the work specimen can be influenced by the timely release of a current from the operational region. The increased roughness of the machined region as a whole indicates a substantial increase in the quantity of energy released. The widely accepted agreement indicates that the 'Ton' component exerts the most influence on accomplishing surface finish.

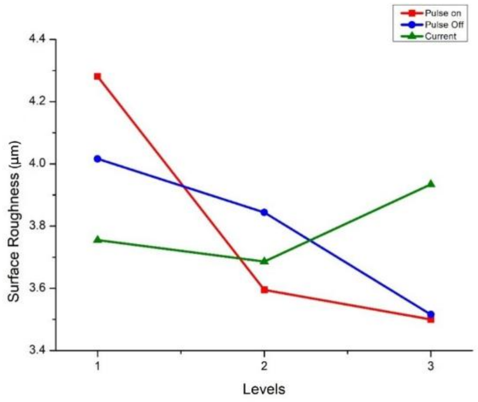

Fig. 5. Response plot for SR

The preliminary aim of this investigation is to optimize the 'SR' that can enhance the complete appearance of the component. The optimum values have been attained with the amalgamations of are as trails: "Ton" might be set to 30 µs, "Toff" might be set to 15 µs, and the "Applied current" might be set to 2 A. The most significant variable that influences the 'SR' is "Ton."

3.3 Interpretation of Variables on Overcut

The graph in Fig. 6 shows how the response to changes in dimensions for WEDM of SAE 1010 was studied. The majority of respondents agree that an increase in peak current values and "Ton" is linked to a reduction in the cutting force applied to the workpiece. After investigation, it can be concluded that the duration of the current application to the working area affects the specimen's surface properties. So, the overcut values made by WEDM might increase. The dependent variable "Ton" has a large effect on overcut patterns.

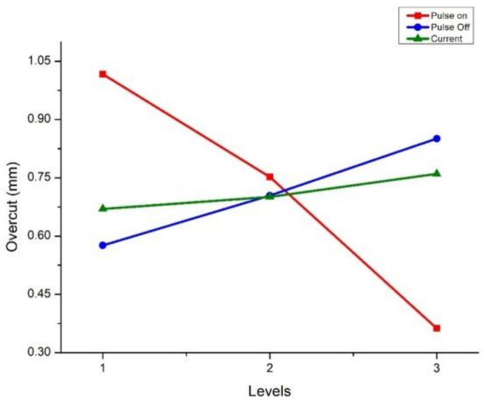

Fig. 6. Response graph for overcut (mm)

The Taguchi method is the most effective approach to minimise the overcut by grouping variables A3B1C1. Hence, the most efficient performance is achieved by employing a 'Ton' of 30 µs, a 'Toff' of 5 µs, and an applied current of 1 A. It suggests that the 'Ton' is the major factor compared to the 'Toff' and peak current.

3.4 Interpretation of Factors on GD&T Errors

The graphical depiction of geometrical and dimensional tolerance errors is represented in Figs. 7 and 8.

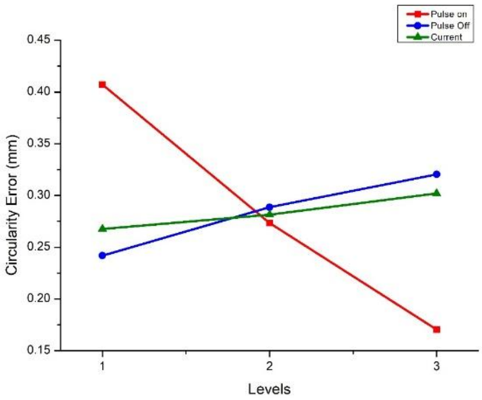

Fig. 7. Response graph for form error

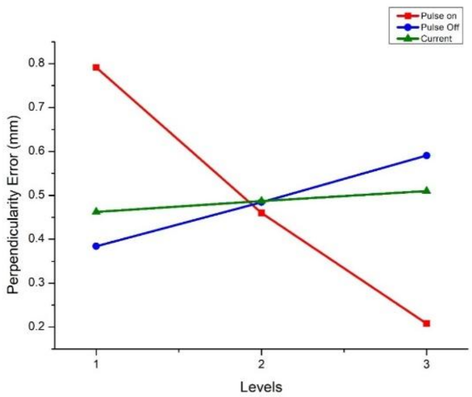

Fig. 8. Response plot for orientation error

Appropriate elimination of debris from the working region can enhance the quality of the part produced. Prolonging the duration of the pulse makes the debris removal from the space between the tool and the work specimen via the dielectric medium. Also, increasing values of 'Ton' makes the discharge effective for a more extended duration, which increases the energy discharged to the machining zone, leading to more removal. But it makes the possibility of more thermal expansion and improper erosion consequences to deviation from the expected geometries. Also, increased levels of current boost the energy of discharge, resulting in aggressive removal of materials and larger craters on the surface, which causes more thermal distortions and uneven removal of material.

A higher 'Toff' lets the molten metal solidify and removes the debris from the gap, which stabilises the sparks, enabling consistent removal of material and decreasing the thermal stress on the work material, thereby reducing the aforementioned GD&T errors.

The analysis has been done on the GD&T errors during WEDM of SAE 1010. The amalgamations of A3B1C2 yield better GD&T errors, thereby minimising the required performance metrics. 'Ton' 30 µs, 'Toff' 3 µs and 1A are the values that need to be set to attain the desired outputs. Also, it is noted that the 'Ton' is the most prevailing factor, and it is trailed by 'Toff' and applied current.

3.5 Interpretation of Variables on GRG

The association among the GRG index and the factors 'Ton', 'Toff', and peak current is depicted in Fig. 9. An escalation in the value of 'Ton' results in a proportional rise in the GRG index, while 'Toff' and peak current oppose this trend. The information created by the GRA procedure is represented in Table 2 and consequently analysed using Taguchi's systematic concept.

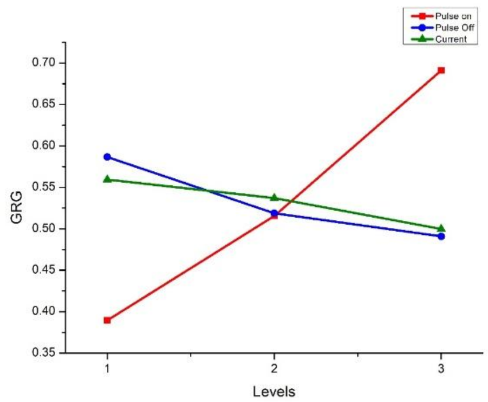

Fig. 9. Response plot for GRG

Table 2. Outcomes of the GRA Approach

S. No.	A	B	C	GRC					GRG	Rank
				MRR	SR	CIRC	OC	PERP		
1	10	5	1	0.4265	0.3891	0.4479	0.4423	0.4390	0.4290	19
2	10	5	2	0.3860	0.3792	0.4348	0.4360	0.4244	0.4121	20
3	10	5	3	0.3710	0.3725	0.4247	0.4278	0.4025	0.3997	21
4	10	10	1	0.3711	0.3806	0.4108	0.4239	0.3991	0.3971	22
5	10	10	2	0.3614	0.3584	0.4028	0.4232	0.3977	0.3887	23
6	10	10	3	0.3498	0.3333	0.3944	0.4225	0.3859	0.3772	25
7	10	15	1	0.3433	0.4550	0.3874	0.3781	0.3457	0.3819	24
8	10	15	2	0.3387	0.4120	0.3872	0.3566	0.3333	0.3656	26
9	10	15	3	0.3333	0.3920	0.3333	0.3333	0.3832	0.3550	27
10	20	5	1	0.5487	0.4801	0.5827	0.6028	0.5806	0.5590	12
11	20	5	2	0.5104	0.5366	0.5744	0.5734	0.5678	0.5525	13
12	20	5	3	0.4725	0.3466	0.5632	0.5005	0.5606	0.4887	15
13	20	10	1	0.4717	0.5557	0.5284	0.4852	0.5471	0.5176	14
14	20	10	2	0.4344	0.8270	0.5211	0.4798	0.5409	0.5606	11
15	20	10	3	0.4130	0.3477	0.5193	0.4696	0.5102	0.4520	18
16	20	15	1	0.4176	1.0000	0.5167	0.4580	0.4992	0.5783	9
17	20	15	2	0.4002	0.5007	0.5021	0.4578	0.4962	0.4714	16
18	20	15	3	0.3848	0.5339	0.4778	0.4479	0.4605	0.4610	17
19	30	5	1	1.0000	0.3501	1.0000	1.0000	1.0000	0.8700	1
20	30	5	2	0.8844	0.4845	0.8226	0.9546	0.9554	0.8203	2
21	30	5	3	0.7122	0.6419	0.7358	0.8533	0.7969	0.7480	3
22	30	10	1	0.7233	0.4890	0.7086	0.7713	0.7402	0.6865	4
23	30	10	2	0.6222	0.5394	0.6622	0.7380	0.6880	0.6500	5
24	30	10	3	0.5519	0.6540	0.6612	0.6612	0.6696	0.6396	6
25	30	15	1	0.5709	0.5596	0.6456	0.6561	0.6439	0.6152	7
26	30	15	2	0.5190	0.6540	0.6341	0.6266	0.6246	0.6117	8
27	30	15	3	0.4783	0.6459	0.6183	0.5492	0.5985	0.5780	10

The combination A3B1C1 offers the greatest benefit in enhancing GRG efficacy. The optimal settings for enhancing the GRG are a 'Ton' (15 µs), 'Toff' (5 µs), and a Peak Current of 1A. The variable that has the greatest influence on enhancing GRG is 'Ton', but 'Toff' and 'peak current' also have a significant influence.

3.6 Interpretation of Variables on GRG

An in-depth exploration and display of a surface plot has produced valuable insights into the chief factor affecting the WEDM process. Fig. 10 (a) exemplifies the influence of MRR and SR in the ANFIS-GRG architecture. Greater values of the GRC of MRR and SR are related to higher GRG, as seen by the visual image. In Fig. 10 (b), the influence of MRR and Overcut GRC on the expected GRG is illustrated. It can be presumed that the depiction precisely foresees a GRG for the midway GRC of both the MRR and overcut. Figs. 10 (c) and 10 (d) exemplify the relationship between GRC values and GD&T errors, as well as the MRR. The data evidently demonstrate that the midway GRC exceeds the anticipated GRG value. The ANOVA analysis results obtained from the output measurements obtained during the WEDM of low carbon steel are presented in Table 3. Fig. 10(e) exemplifies the surface plot analysis accompanied by the GRC of a steel rib and an overcut on the expected GRG. The combination of GRC produces the highest GRG when the SR is moderate and the GRC values are high. The data depicted in Figs. 10(f) and 11(a) suggest a correlation between the desired input and output factors.

Table 3. Outcomes of ANOVA for WEDM of low-carbon steel

MRR (g/min)						
Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	0.14734	0.14734	0.07735	442.60	0
B	2	0.03864	0.03864	0.02300	99.70	0
C	2	0.01538	0.01538	0.01137	26.32	0
Error	20	0.0105	0.01053	0.00751		
Total	26	0.18247				
Surface Roughness (µm)						
A	2	3.27746	3.27746	1.64246	8.867	0.003
B	2	1.16616	1.16616	0.58676	3.797	0.086
C	2	0.30296	0.30296	0.15516	1.717	0.503
Error	20	4.16666	4.16666	0.21536		
Total	26	8.89116				
Overcut (mm)						
A	2	1.95801	1.95801	0.98269	335.18	0
B	2	0.34761	0.34761	0.17748	59.29	0
C	2	0.04519	0.04519	0.02628	7.487	0.007
Error	20	0.06573	0.06573	0.01028		
Total	26	2.39446				
Circularity error (mm)						
A	2	0.253413	0.253413	0.126707	378.36	0
B	2	0.028043	0.028043	0.014021	41.87	0
C	2	0.005421	0.005421	0.002711	8.09	0.003
Error	20	0.006698	0.006698	0.000335		
Total	26	0.293575				
Perpendicularity error (mm)						
A	2	1.5418	1.5418	0.7709	320.22	0
B	2	0.19234	0.19234	0.09617	39.95	0
C	2	0.01031	0.01031	0.00515	2.14	0.144

Table 3. Outcomes of ANOVA for WEDM of low-carbon steel - *Continuation of the table from the previous page*

Error	20	0.04815	0.04815	0.00241		
Total	26	1.7926				
Grey Relational Grade						
A	2	0.412559	0.412559	0.206279	92.81	0
B	2	0.043578	0.043578	0.021789	9.8	0.001
C	2	0.016248	0.016248	0.008124	3.66	0.044
Error	20	0.044452	0.044452	0.002223		
Total	26	0.516836				

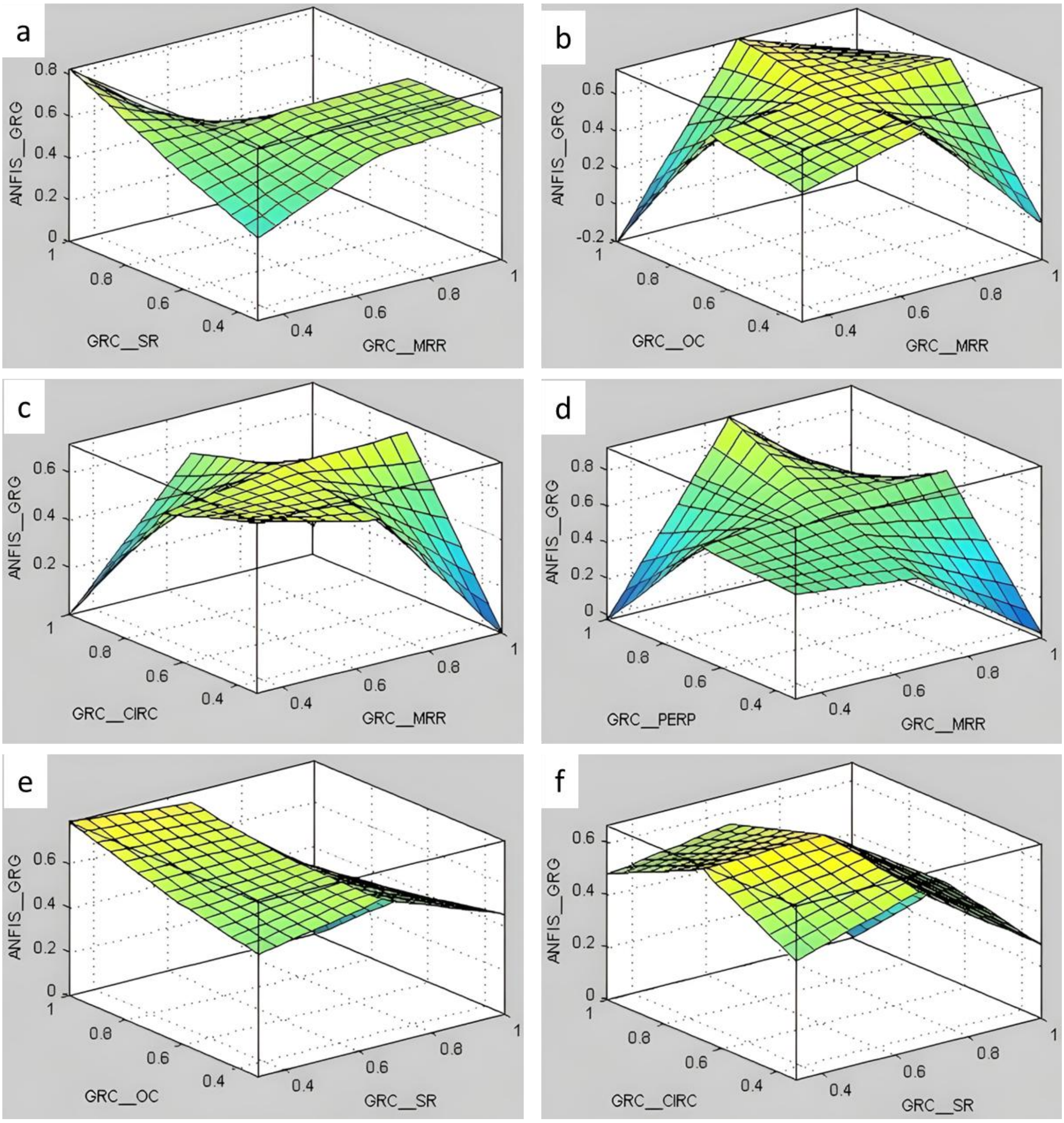

Fig. 10. Surface plot for GRG Vs GRC of MRR, SR, and OC

Fig. 11(a) illustrates the influence of PERP and SR in the ANFIS-GRG architecture. As shown in Fig. 11(b), the projected GRG surface map exhibits a circular reasoning fallacy. Observed investigation of the Overcut and circularity error shows that the anticipated GRG is more beneficial for the intermediate GRC. Fig. 11(c) illustrates the surface topography of the GRC for both overcut and orientation errors. The maximum GRG is seen when the GRC values for overcut and orientation errors are larger. The graphical illustration of how tolerance flaws in form orientation impact the anticipated GRC is shown in Fig. 11(d). The graph illustrates that the GRG achieve their highest values at the centre of the distributions for form and orientation errors.

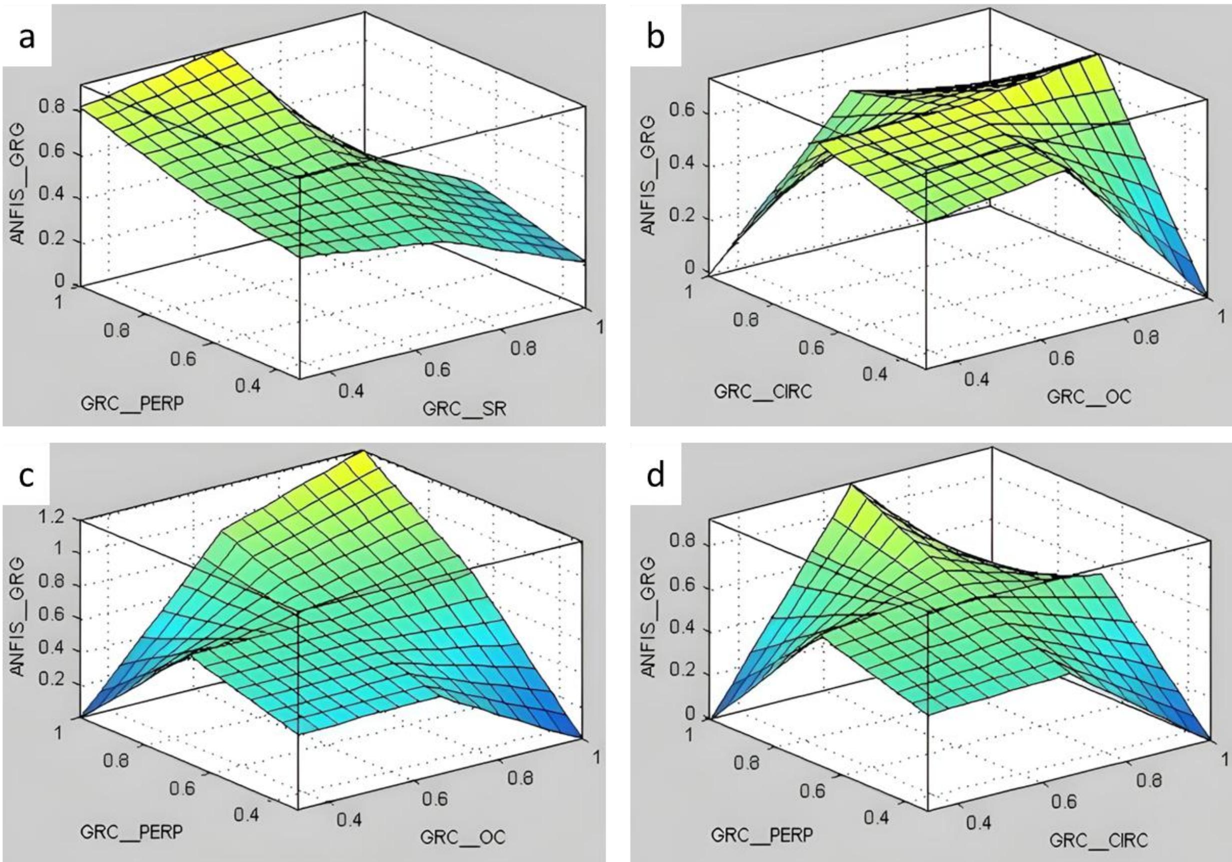

Fig. 11. Surface plot for GRG Vs GRC of GD and T errors

3.7 Comparative Analysis on the GRG Values

By combining traditional and contemporary technologies, the predicted precision of the aforementioned method can be improved. The objective of this preliminary analysis is to develop a forecasting model to assess the GRG's effectiveness. The information obtained using the GRA method serves as the foundation for the model. The structure will then be employed for further analysis and Grey-ANFIS forecasts.

The depiction unequivocally exemplifies the dependable prognostic capability of the (ANFIS) model in accurately foretelling forthcoming necessities. The graphical depiction in Fig. 12 establishes an important relationship between the observed and predicted values, suggesting a greater level of proximity.

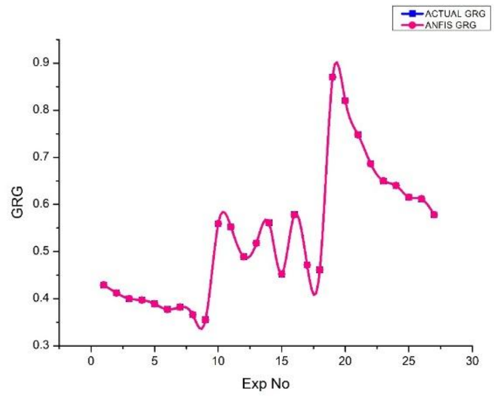

Fig. 12. Comparison of experimental and predicted GRG values

3.8 Study on the Performance of the Developed Predictive Model

An error is the divergence between the outcomes from experimentation and the envisaged data produced by an entrenched predictive model. The efficiency of the generated model is appraised by evaluating the Mean Absolute Percentage Error

(MAPE), which is calculated by means of the associated equations to establish the expected error.

$$\mathrm{MAPE}(\%) = \frac{1}{n}\sum_{i=1}^{n}\frac{E_V - P_V}{E_V}\cdot 100 \tag{1}$$

The values of RMSE and correlation coefficient to assess the resulting predictive model are predicted by Equations 2 and 3, respectively:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_v - P_v)^2} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(Pv - Ev)^2}{\sum_{m=1}^{n}(Ev)^2} \tag{3}$$

where are:
E_V - Experimental data
P_V - Forecast results,
n - is the number of trials.

The efficiency of the ANFIS structure is appraised by a comparison of its results with the data acquired from investigational approaches. The investigation's findings established a more robust association between goals and accomplishments than previously known. To assess the efficacy of the suggested ANFIS model, a set of equations (5, 6, and 7) is employed. This work provides the performance research outcomes of the constructed structures, which are displayed in Table 4.

Table 4. Errors Attained on Hybrid Grey - ANFIS model

Model - ANFIS	Error
MAPE	0.0432
RMSE	0.00029
MAE	0.000432
Correlation Coefficient	0.9997

The values for the mean squared error and standard deviation are shown in Figs. 13 and 14, which present the statistics pertaining to the mean absolute error and the correlation coefficient. Comparative validation of ANFIS models demonstrates their enhanced precision in comparison to conventional models.

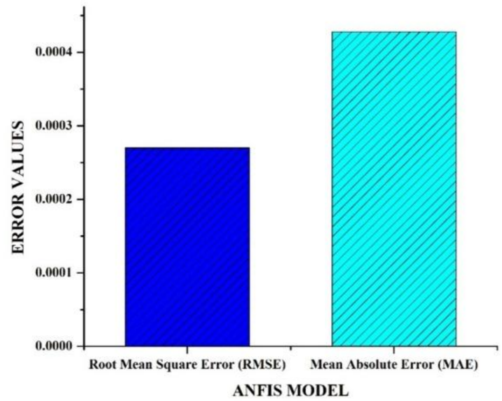

Fig. 13. Performance Analysis on ANFIS Model (RMSE and MAE)

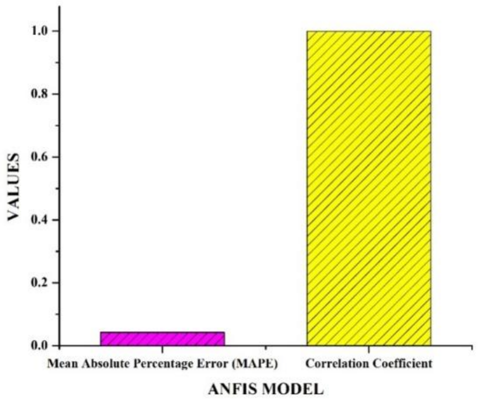

Fig. 14. Performance Analysis on ANFIS Model (MAPE and R2)

4. CONCLUSIONS

Taguchi's approach is used for the development of an optimized WEDM framework for low-carbon steel, which enables the accurate parameter selection to improve machining performance. Effective identification of the influence of independent factors like pulse duration (Ton), which is the most significant parameter for machining efficiency, can be done using the Taguchi method. Grey theory was used to create a multi-performance index, which improves the machining process in different areas. The GRG values are taken as input for the ANFIS model, which results in an advanced ANFIS-GRG prediction system. The system attained an experimental GRG value of 0.8700. The predictive model was thoroughly validated, showing low error values (MAPE – 0.0432, RMSE – 0.00029). These low error values show good results. The present study depicts that ANFIS can help to eliminate data ambiguity and also improve predictive accuracy, which makes it a useful tool for controlling and optimizing processes in real time when using non-traditional machining methods.

The presented results can encourage the production process to utilize advanced tools and algorithms like GA or PSO with a wide range of material scopes. Furthermore, it can enhance accuracy and sustainability in WEDM well before the actual manufacturing. The long-term environmental and economic benefits of eco-friendly dielectric fluids in the WEDM process are also suggested. This approach makes it feasible to deal with practical applications and industrial inputs for intelligent and sustainable manufacturing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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