Multi response Optimization of Al/SiC5 MMC using Integrated GRA-ANFIS Approach.

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Abstract

Now a day's, metal matrix composites (MMCs) are taking a superior position among the available material. The presented work aims to investigate the ease of machining for Aluminium based MMC (AlSiC5- with 5% Silicate) through multi-response optimization. AlSiC is a composite material that combines Aluminum with Silicon Carbide particles which can help to improve efficiency, reliability, and performance of various engineering system and devices. To analyze the process, an effective two techniques i.e. Grey relational analysis (GRA) & Adaptive Neuro-Fuzzy Inference System (ANFIS) has been employed for the investigation, L_{27} plan was used for data collection. The parameters like current (AMP) and pulse on time (TON) are the basically dominant parameters, followed by voltage (VOLT) and pulse off time (TOFF). The outcomes show the optimum parameters to be set for multi-response optimization and effective utilization of process.

Keywords: Machining, Composite Material EDM, $AlSiC_5$, Soft Computing, ANFIS, GRA, Surface roughness, MRR.

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Introduction:

Electrical Discharge Machining (EDM) is a non-traditional machining process that utilizes electrical discharges (sparks) to remove material from a work-piece. It is also known as spark erosion or spark machining. EDM is particularly useful for machining complex and intricate shapes, hard and difficult-to-machine materials, and parts with high precision requirements. Phate Mangesh et.al [1,13] presents a comprehensive investigation into the effects of silicon carbide (SiC) content and various process parameters on the Wire Cut-EDM (Electrical Discharge Machining) of Aluminum/Silicon Carbide Particle (Al/SiCp) Metal Matrix Composites (MMC). Al/SiCp MMCs are advanced engineering materials known for their improved mechanical and thermal properties, making them suitable for various industrial applications**.** The research focuses on Wire Cut-EDM, a non-traditional machining process, to study the machinability and efficiency of Al/SiCp MMCs. The Wire Cut-EDM process employs a thin electrically-charged wire to cut and shape work-pieces accurately. The study aims to optimize the process conditions for better material removal rate (MRR) and reduced tool wear, while maintaining the integrity of the MMC. the investigation sheds light on the challenges and opportunities associated with Wire Cut-EDM of Al/SiCp MMCs. By optimizing SiC content and process parameters, manufacturers can enhance the machining efficiency of these advanced composites while preserving their mechanical properties. The findings of this research contribute to the broader understanding of machining MMCs and can be valuable for industries seeking to utilize Al/SiCp MMCs in their applications. Phate Vikas et.al [2] presented a novel approach for the classification and weighting of Sweet Lime (Citrus Limetta) fruits during the packing process, leveraging a Computer Vision System (CVS). Sweet Lime is a popular citrus fruit known for its sweet and tangy flavor, and it is widely consumed both fresh and in various food products. Efficient and accurate sorting of Sweet Lime based on quality attributes such as size and weight is essential for the fruit packing industry to meet market demands and ensure customer satisfaction. this article demonstrates the successful implementation of a computer vision system for the classification and weighting of Sweet Lime fruits during the packing process. By leveraging advanced image processing techniques, the system ensures consistent fruit quality, optimizes packaging operations, and enhances overall productivity in the fruit packing industry. The research underscores the potential of computer vision technology in revolutionizing agricultural sorting and packing processes, leading to improved efficiency and customer satisfaction.Phate Mangesh et.al [3-8] presented a detailed investigation on the influence of Silicon Carbide (SiC) content and various process parameters on the Wire Cut-EDM (Electrical Discharge Machining) of Aluminum/Silicon Carbide Particle 20% (Al/SiCp20) Metal Matrix Composites (MMC). Al/SiCp20 MMCs are a specific type of metal matrix composite known for containing 20% SiC particles, offering enhanced mechanical and thermal properties suitable for numerous industrial applications.The investigation highlights the challenges and opportunities associated with Wire Cut-EDM of Al/SiCp20 MMCs. By optimizing SiC content and process parameters, manufacturers can enhance the machining efficiency of these advanced composites while preserving their mechanical properties. The findings contribute to the broader understanding of machining MMCs and provide valuable insights for industries seeking to employ Al/SiCp20 MMCs in various applications. Moreover, the research opens avenues for further exploration and refinement of the Wire Cut-

EDM process to improve the overall productivity and cost-effectiveness of machining Al/SiCp20 MMCs. Pradhan M.K et.al [9] presented the application of Multiple Criteria Decision Making (MCDM) techniques for optimizing the Electrical Discharge Machining (EDM) process of LM6 Silicon Carbide (SiC) Boron Carbide (B4C) hybrid composite. LM6 is an aluminum alloy known for its lightweight and excellent castability, while SiC and B4C are reinforcing ceramic particles that enhance the mechanical and wear properties of the composite. The article demonstrates the successful application of MCDM techniques for optimizing the EDM process of the LM6 SiC B4C hybrid composite. By systematically evaluating and selecting the most suitable combination of process parameters, the MCDM approach offers an efficient and practical solution to enhance the machining performance and surface quality of this advanced composite material. The findings of this research contribute to the broader field of advanced materials processing and highlight the importance of leveraging MCDM techniques to optimize non-conventional machining processes for complex materials like LM6 SiC B4C hybrid composites. Sahani P. et.al [10] presented the effect of Aluminum (Al) addition on the properties of SiC-B4C cermets prepared using two different sintering methods: pressure less sintering and spark plasma sintering (SPS). Cermets are composite materials composed of a ceramic phase (SiC and B4C) and a metallic phase (Al), known for their enhanced mechanical and thermal properties. The article provides valuable insights into the impact of Aluminum addition on the properties of SiC-B4C cermets prepared using pressure less sintering and spark plasma sintering methods. The research demonstrates that the Al content significantly affects the mechanical and thermal properties of the cermets. Additionally, the study highlights the influence of the sintering technique on the microstructure and final properties of the cermets. These findings contribute to a better understanding of cermet material design and fabrication processes, enabling potential applications in industries that require materials with improved mechanical strength and thermal performance. Bodukuria Anilkumar. et.al [11] demonstrates the successful fabrication of Al-SiC-B4C metal matrix composites using the powder metallurgy technique. The study highlights the influence of Silicon Carbide and Boron Carbide content on the mechanical properties of the composites, emphasizing their enhanced strength and wear resistance compared to pure Aluminum. The research findings contribute to the understanding of MMCs and open up possibilities for using Al-SiC-B4C composites in various engineering applications that demand high-performance materials with improved mechanical characteristics. Debnath S. et. al. [12] demonstrates the successful application of the Fuzzy-TOPSIS method for multi-objective decision-making optimization of the EDM process of Al-4.5Cu-SiC composite. By considering multiple conflicting objectives and handling uncertainties in the process data, the Fuzzy-TOPSIS method offers an efficient and practical approach to achieve an optimized EDM process for this composite material. The findings of this research contribute to the broader understanding of multi-objective optimization techniques and their application in advanced materials processing, facilitating the use of Al-4.5Cu-SiC composite in industries that require improved mechanical and wear properties. Sreenivasa Rao et. al. [14] showcases the successful utilization of Response Surface Methodology and Particle Swarm Optimization for the parametric optimization of the machining process for Nimonic-263 alloy. By systematically optimizing the machining parameters, the RSM-PSO approach offers an efficient and practical solution to enhance the machining efficiency and surface quality of this high-temperature superalloy. The research contributes to the broader understanding of optimization techniques in machining applications and highlights their significance in improving the performance of advanced materials like Nimonic-263 in critical industrial sectors. Tamang, S.K and Chandrasekaran [15] showcases demonstrates the successful use of both conventional and soft computing techniques for modeling and optimizing the turning process of Al/SiCp MMC to minimize surface roughness and tool wear. The research provides valuable insights into the complex relationships between process parameters and responses in machining advanced composites. By employing soft computing techniques for multi-objective optimization, the study offers an efficient and practical approach to enhance the machining performance of Al/SiCp MMCs. The findings contribute to the broader understanding of optimization techniques in the machining of MMCs and highlight their significance in achieving improved surface quality and extended tool life in critical industrial applications.Prosun Mandal and Subhas Chandra Mondal [16] explores the surface characteristics of mild steel machined using EDM with a Cu-MWCNT composite electrode. The addition of MWCNTs to the Cu electrode aims to enhance the EDM performance and surface quality of mild steel. The study demonstrates the potential advantages of using composite electrodes in EDM to improve surface characteristics and optimize machining efficiency. The findings contribute to the understanding of advanced electrode materials and their application in non-conventional machining processes for improved surface finishing and machining performance. Ravindranadh Bobbili et. al. [17] demonstrates the successful multi-response optimization of Wire-EDM process parameters for machining ballistic grade aluminum alloy. By considering multiple responses simultaneously and employing optimization techniques, the study offers an efficient and practical approach to enhance the Wire-EDM process for tough materials like ballistic grade aluminum alloy. The findings contribute to the broader understanding of optimization techniques in machining aerospace and defense materials, with the potential to improve the manufacturing process and performance of ballistic grade aluminum alloy components. Jibin T. Philip et. al. [18] demonstrates presents experimental investigations on the tribological performance of Electric Discharge Alloyed Ti-6Al-4V (Titanium-6% Aluminum-4% Vanadium) at elevated temperatures ranging from 200 to 600 °C. Electric Discharge Alloying (EDA) is a surface modification technique that introduces alloying elements into the surface of a base material using electrical discharges. Ti-6Al-4V is a widely used titanium alloy known for its excellent mechanical properties and high-temperature applications.N. Manikandan et. al. [19] demonstrates the experimental investigations on the tribological performance of Electric Discharge Alloyed Ti-6Al-4V at elevated temperatures (200–600 °C). The study demonstrates the potential benefits of EDA treatment in enhancing the wear and friction properties of the titanium alloy at high temperatures. The findings contribute to the understanding of surface modification techniques for improving the performance of titanium alloys in challenging environments and high-temperature applications. These results may have practical implications in the design and development of advanced materials for aerospace and other industries that require reliable and high-performance components operating at elevated temperatures. Devarasiddappa Devarajaiah and Chandrasekaran Muthumari [20] present a novel methodology that integrates Fuzzy Logic with Particle Swarm Optimization (PSO) for the optimization of machining parameters in the end milling process of Aluminum/Silicon Carbide Particle Metal Matrix Composites (Al/SiCp MMCs). Al/SiCp MMCs are advanced materials with enhanced mechanical properties, widely used in aerospace and automotive industries. The study focuses on improving the machining efficiency and surface quality of Al/SiCp MMCs through the optimization of end milling parameters.

2. Materials and methods

Electrical Discharge Machining (EDM) is a non-traditional machining process that utilizes electrical discharges (sparks) to remove material from a workpiece. Here's an overview of the EDM machining process.

1. Principle of Operation: EDM is based on the principle of erosion caused by a series of electrical discharges between the workpiece and the electrode. The workpiece and the electrode are immersed in a dielectric fluid (usually deionized water) to act as a coolant and an electrical insulator.
2. Electrode and Tooling: The tool used in EDM is called an electrode, which can be made from graphite, copper, or other conductive materials. The electrode is typically designed to have the desired shape and dimensions required for the machining process. The electrode does not physically contact the workpiece during the machining process; rather, the sparks created by the electrical discharges remove material from the workpiece through a series of successive discharges.
3. Spark Generation: A voltage difference (typically several thousand volts) is applied between the electrode and the workpiece. When the voltage difference reaches a critical point, an electrical discharge or spark occurs between the electrode and the workpiece.
4. Material Removal: As the spark occurs, a high-intensity heat is generated, causing the localized area of the workpiece to melt and vaporize. This vaporization, along with the flushing action of the dielectric fluid, removes small particles of the workpiece material.
5. Dielectric Fluid: The dielectric fluid plays a crucial role in the EDM process. It serves as both an electrical insulator and a coolant. It prevents arcing between the electrode and the workpiece, helps in flushing away the eroded material, and cools the workpiece and electrode during the machining process.
6. Finish and Accuracy: The surface finish of the machined part in EDM is influenced by the spark gap, the pulse duration, and the flushing rate. EDM can achieve very fine surface finishes, even on hard and difficult-to-machine materials. The process is also capable of producing high accuracy and intricate shapes with tight tolerances.

EDM is widely used in various industries, including aerospace, automotive, tool making, medical, and electronics, for applications that require high precision and machining of complex shapes. It is particularly valuable for materials that are difficult to machine using conventional methods, such as hardened steels, exotic alloys, and electrically conductive ceramics. However, EDM is a relatively slow process compared to conventional machining, and it is best suited for small and medium-sized production runs and prototyping. The EDM machining set up is as show in figure 1.

Figure 1: Experimental set up

2.1 Preparation of MMC

In the presented work, aluminum-based matrix composite (MMC) with Aluminum is used as an alloying element and 5 % Silicate with dimensions 35mm x 35 mm x 10 mm was used. The experiments were carried out on Sprconix 25 ampere machine work bed size 1000x500x500 mm machine (Figure 1). The EDM performance was measured in the form of machined product roughness of the surface (Ra) which was measured using portable digital surface roughness tester (Mitutoyo SJ-201).

2.2 Experimental plan :

In the initial stage of the experimentation various process parameters were identified. After fixing input parameters and the target response, the experimentation were carried out with three replicates using Taguchi's L_{27} plan of experimentation. Finally the experimental was used to carry out the analysis using ANN and RSM techniques. In this research, MATLAB E2015 has been used to carry out the experimental data analysis and getting technical result. The lists of parameters associated with the experimentation are as tabulated in Table 2. The experimental result is tabulated in Table 3.

Table2: Process parameters associated with the presented work.

Sr. No	Parameters	Dimensions	Levels		
			Low [1]	Medium [2]	High [3]

1	Pulse_on_ time [PON]	Micro-sec	5	6	7
2	Pulse_off_time [POFF]	Micro-sec	5	6	7
3	Current [AMP]	Amp	7	8	9
4	Voltage [VOLT]	Volts	50	60	65

Table3: Experimental plan and data.

Sr No	TON	TOFF	AMP	VOLT	Ra	MRR
1	5	5	7	50	2.25	3.218
2	5	5	7	50	2.27	3.3
3	5	5	7	50	2.29	3.149
4	5	6	8	60	3.01	3.251
5	5	6	8	60	2.96	3.285
6	5	6	8	60	2.98	4.176
7	5	7	9	65	3.37	3.255
8	5	7	9	65	3.42	2.847
9	5	7	9	65	3.51	3.368
10	6	5	8	65	3.29	1.87
11	6	5	8	65	3.5	3.3
12	6	5	8	65	3.69	3.41
13	6	6	9	50	3.94	3.87
14	6	6	9	50	4.01	3.23
15	6	6	9	50	4.09	4.01
16	6	7	7	60	2.43	3.39
17	6	7	7	60	2.36	3.34
18	6	7	7	60	2.68	3.36
19	7	5	9	60	3.62	2.5
20	7	5	9	60	3.75	3.6
21	7	5	9	60	3.78	2.521
22	7	6	7	65	2.91	3.125
23	7	6	7	65	2.89	4.567
24	7	6	7	65	2.96	2.314
25	7	7	8	50	3.49	3.587
26	7	7	8	50	3.61	5.637
27	7	7	8	50	3.69	2.367

2.3 Grey Relational Analysis :

Grey Relational Analysis (GRA) is a method used for comparing and evaluating the relationships between multiple variables or factors. It is commonly employed in decision-making processes, optimization, and performance evaluation in various fields such as engineering, management, and social sciences. The concept of Grey Relational Analysis was introduced by Deng Julong in 1982 as part of Grey System Theory, a mathematical approach for dealing with systems with uncertain or insufficient information. GRA is particularly useful when dealing with systems with limited data or systems where conventional statistical methods may not be applicable. Here's an overview of how Grey Relational Analysis works.

1. Data Collection: GRA requires data from multiple factors or variables to be compared. These factors are typically represented as time series or arrays.
2. Data Normalization: To ensure that all the factors are on a comparable scale and contribute equally to the analysis, the data is often normalized using a specified normalization method, such as linear normalization or min-max normalization.
3. Determining Reference Series: In GRA, one of the time series or arrays is selected as the reference series. The reference series is the basis for comparison and evaluation against other series.
4. Calculating Grey Relational Coefficients: Grey Relational Coefficients (GRC) are computed to quantify the similarity between the reference series and each of the other series. Various approaches, such as the absolute difference method, the mean difference method, or other grey relational generation methods, can be used to calculate GRC.
5. Computing Grey Relational Grades: The Grey Relational Coefficients obtained from the previous step are then used to calculate the Grey Relational Grades (GRGs) for each factor or variable. The GRG represents the overall similarity or closeness to the reference series.
6. Rank Ordering: The factors are ranked based on their Grey Relational Grades. The higher the GRG, the closer the factor's relationship to the reference series.
7. Interpretation: Decision-makers can use the ranking results to identify the factors that have the closest relationship to the reference series, which can lead to insights, optimization, or better decision-making.

It's important to note that Grey Relational Analysis is just one of many techniques available for data analysis and decision-making. Its suitability and effectiveness depend on the specific problem, data characteristics, and the underlying assumptions of the Grey

System Theory. Researchers and practitioners often combine GRA with other statistical or machine learning methods to enhance the analysis and draw more robust conclusionsGrey Relational Analysis (GRA) holds several key importance and advantages, making it a valuable tool in various fields. Here are some of the main reasons why GRA is considered significant:

1. Handling Limited Data: GRA is particularly useful when dealing with systems that have limited or incomplete data. It can work effectively even when there is insufficient information available, making it applicable to real-world situations where data collection may be challenging or expensive.
2. Dealing with Uncertainty: Many real-world problems involve uncertainty, and GRA, as part of Grey System Theory, is designed to handle such situations. It can cope with systems where data may be imprecise or when there are uncertainties in the relationships between variables.
3. Comparing Multiple Variables: GRA allows for the comparison and evaluation of multiple variables simultaneously. This capability is essential in decision-making processes, where various factors need to be considered together to make informed choices.
4. Identifying Key Factors: GRA can help identify the most influential or critical factors among the variables being analyzed. By ranking the factors based on their Grey Relational Grades, decision-makers can focus on the most relevant variables that significantly affect the system's performance or outcomes.
5. No Distribution Assumptions: Unlike some traditional statistical methods, GRA does not require strict assumptions about the data distribution, making it more robust and applicable to a wider range of problems.
6. Simple and Intuitive: GRA is relatively straightforward to understand and implement. It doesn't demand advanced mathematical expertise, which makes it accessible to a broader audience, including practitioners and decision-makers.
7. Complementary Analysis: GRA can complement other data analysis techniques, such as statistical methods or machine learning algorithms. It can be used in conjunction with these methods to gain deeper insights into the data or enhance the validity of the results.
8. Optimization and Decision-making: GRA's ability to rank variables allows decision-makers to make better choices and optimize processes. By identifying the factors with

the highest grey relational grades, managers can focus their efforts on improving those factors for better overall system performance.

9. Interdisciplinary Application: GRA is applicable in various domains, including engineering, management, finance, social sciences, and more. Its versatility allows it to be adapted and utilized across different industries and research areas.

While Grey Relational Analysis has its advantages, it's essential to recognize that no single analysis technique is suitable for all scenarios. Depending on the specific problem, data characteristics, and research objectives, other statistical or machine learning methods may also be necessary for a comprehensive and accurate analysis. Combining GRA with other techniques can provide a more robust and reliable basis for decision-making and problem-solving.

Grey Relational Analysis (GRA) is based on the principles of Grey System Theory, which was introduced by Deng Julong in the early 1980s. GRA involves several mathematical steps to compare and evaluate the relationships between multiple variables. Here's a breakdown of the key mathematical components of Grey Relational Analysis:

1. Data Normalization: Before conducting GRA, it is essential to normalize the data to ensure that all variables are on a comparable scale. Normalization transforms the original data into a dimensionless range to avoid biases during the analysis. Various normalization methods can be used, such as linear normalization, min-max normalization, or mean normalization.
2. Grey Relational Coefficients (GRC): The Grey Relational Coefficients (GRC) quantify the similarity or closeness between the reference series (often denoted as X0) and each of the other series (X1, X2, ..., Xn) being compared. There are different methods to calculate GRC, but one common approach is the absolute difference method.

   For a reference series X0 and another series Xi, the absolute difference between them is calculated for each data point:

$$|\Delta i(k) = |X0(k) - Xi(k)|$$

   where k represents the position of the data point in the time series.

   After computing the absolute differences for all data points, a cumulative sum is obtained for each series:

$$C_i = \sum_{k-1}^{N} \Delta_i\,(k)$$

where N is the total number of data points in the time series.

Next, the Grey Relational Coefficient for each series is calculated using the formula:

$$GRC_i = \frac{Min\ (C)}{C_i + \varepsilon}$$

where min min(C) is the minimum value of the cumulative sums among all series, and ε is a small positive constant (usually set to a small value, such as 0.0001) to avoid division by zero.

3. Grey Relational Grade (GRG): The Grey Relational Grade (GRG) is a measure of the overall similarity or closeness of each series to the reference series. It is calculated as follows:

$$GRG_i = \frac{\sum_{j=1}^{N} GRC_i}{n}$$

where n is the total number of series being compared.

4. Ranking: After computing the Grey Relational Grades for all series, they are ranked in descending order. The higher the GRG, the closer the series' relationship to the reference series, indicating its higher importance or similarity.

   By following these mathematical steps, Grey Relational Analysis provides a ranking of the variables based on their similarity to the reference series, helping decision-makers identify the most relevant factors and make informed decisions in various applications and disciplines.

2.4 Adaptive Neuro-fuzzy inference System (ANFIS)

ANFIS is a hybrid intelligent system that combines the adaptive capabilities of neural networks with the interpretability of fuzzy logic. ANFIS was first proposed by Jang in 1993 and has since become a popular tool for system modeling, identification, and control in various fields.

The main components of an ANFIS model are:

1. Fuzzy Logic: ANFIS uses fuzzy logic to handle linguistic variables and fuzzy rules. Fuzzy logic allows for the representation and manipulation of uncertain or imprecise information by using fuzzy sets and membership functions. It provides a systematic framework to model human-like reasoning and decision-making processes.

2. Neural Networks: ANFIS employs neural networks to adaptively adjust the parameters of fuzzy systems based on data. The neural network's learning capability allows ANFIS to learn from the input-output data and optimize the fuzzy inference rules to fit the underlying system or data pattern.

The ANFIS architecture is typically based on Takagi-Sugeno-Kang (TSK) fuzzy models, which are a class of fuzzy models widely used for system identification and control. TSK fuzzy models use rules of the form "IF (antecedent) THEN (consequent)," where the antecedents are defined by fuzzy sets and the consequents are linear functions of the input variables. The training of an ANFIS model involves two main stages:

a. Forward Pass (Fuzzy Inference): In the first stage, the input data is fuzzified using membership functions, which represent the degree of membership of each data point in the fuzzy sets. The fuzzified values are then used to determine the firing strengths of each fuzzy rule (antecedent).

b. Backward Pass (Parameter Optimization): In the second stage, the parameters of the consequent (linear functions) are optimized using gradient descent or other optimization algorithms. The gradient descent method adjusts the parameters to minimize the error between the ANFIS output and the target output based on the training data.

ANFIS is widely used in various applications, including system modeling, function approximation, time series prediction, and control systems. Its key advantages include its ability to handle nonlinear systems, its interpretability due to the fuzzy rule-based structure, and its capability to learn from data and adapt to changing environments.However, ANFIS may require a sufficient amount of training data and careful tuning of its parameters to achieve accurate results. Additionally, for more complex problems, the size of the rule base in ANFIS can grow quickly, potentially leading to a computationally expensive model. As with any modeling technique, it is essential to validate the ANFIS model's performance on unseen data and consider the trade-offs between model complexity, accuracy, and interpretability.

2.5 ANFIS methodology;

The methodology for building an Adaptive Neuro-Fuzzy Inference System (ANFIS) involves several key steps, including data preprocessing, setting up the fuzzy rules, defining the architecture, and training the model. Here's a step-by-step guide to the ANFIS methodology:

1. Data Preprocessing: Before constructing the ANFIS model, it's essential to preprocess the input-output data. This step may involve tasks such as normalization or scaling of input data to bring all variables to a similar range and dealing with missing values if present. Proper data pre-processing ensures better convergence during training and prevents issues related to data inconsistencies.
2. Fuzzy Rule Base: The next step is to design the fuzzy rule base, which consists of a set of fuzzy rules. Each rule typically has an antecedent (IF-part) and a consequent (THEN-part). The antecedent consists of fuzzy sets defined for each input variable, and the consequent contains linear functions associated with each fuzzy rule.
3. The number of fuzzy sets for each input variable and the number of fuzzy rules depend on the complexity of the problem. Common methods to determine the number of fuzzy sets include expert knowledge, data clustering, or using heuristics.
4. Fuzzification: In this step, the input data is mapped to the corresponding membership degrees in the fuzzy sets of the antecedents. The membership functions describe how each data point belongs to each fuzzy set.
5. Rule Activation: The activation level of each rule (firing strength) is determined based on the membership degrees obtained in the fuzzification step. This quantifies how well each rule applies to the input data.
6. Rule Aggregation: The activation levels of the rules are combined to obtain the overall contribution of each rule to the model's output. This aggregation process typically involves using a fuzzy AND operator for "and" logic or a fuzzy OR operator for "or" logic when multiple rules are activated.
7. Defuzzification: In this step, the aggregated rule outputs are combined to produce a crisp output value. The defuzzification process transforms the fuzzy output into a single numerical value that represents the ANFIS model's final prediction.
8. Parameter Optimization: The parameter optimization stage involves adjusting the parameters of the consequent (linear functions) to minimize the discrepancy between the ANFIS output and the target output based on the training data. Common optimization techniques include gradient descent algorithms or least-squares methods.

2.6 Training the ANFIS Model: The ANFIS model is trained using a suitable optimization algorithm. The training process iteratively adjusts the model's parameters to minimize the error between the predicted output and the actual target output. Training continues until a convergence criterion is met or a specified number of iterations is reached.

Model Evaluation: After training, the ANFIS model's performance is evaluated using a separate validation dataset to assess its generalization capabilities. The model's accuracy and predictive capabilities are measured based on metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), or other relevant performance metrics.

Model Application: Once the ANFIS model is trained and validated, it can be used to make predictions for new, unseen data.Remember that the success of ANFIS depends on the proper selection of fuzzy rules, the quality and quantity of training data, and the appropriate tuning of model parameters. ANFIS is a powerful tool for system modeling, but it requires careful consideration of the problem's characteristics and suitable preprocessing and model evaluation to obtain accurate and reliable results.

3. Results and Discussion:

Aluminum-Silicon Carbide (Al-SiC) Metal Matrix Composites (MMCs) offer several advantages that make them attractive for various engineering applications. These composites are created by embedding silicon carbide particles in an aluminum matrix. The resulting material exhibits a combination of properties that are not achievable with either the individual constituents alone. Some of the major advantages of Al/SiC are lightweight metal, specific strength and specific stiffness of the composite. High Strength and Stiffness, higher tensile strength, compressive strength, and modulus of elasticity compared to pure aluminium. Silicon carbide is known for its exceptional wear resistance and hardness. Silicon carbide has excellent thermal stability and can withstand high temperatures without significant degradation. Al-SiC MMCs exhibit good thermal stability, making them suitable for applications in high-temperature environments, including thermal management systems and heat exchangers. Silicon carbide is a good thermal conductor. It has a lower coefficient of thermal expansion compared to aluminum. It exhibit good damping capacity due to the viscoelastic behavior of the aluminum matrix. Due to these advantages, Aluminum-Silicon Carbide MMCs find applications in various industries, including aerospace, automotive, electronics, and defense, where their unique combination of properties makes them well-suited for a wide range of engineering challenges.

Table 4 : Calculation for Normalized Value & Deviation Sequence

	Normalized Value		**Deviation Sequence**	
Sr No	**Ra (LB)**	**MRR(HB)**	**Ra (LB)**	**MRR(HB)**
1	1	0.3578444	0	0.6421556
2	0.9891304	0.3796124	0.01086957	0.6203876
3	0.9782609	0.3395275	0.02173913	0.6604725
4	0.5869565	0.3666047	0.41304348	0.6333953
5	0.6141304	0.3756305	0.38586957	0.6243695
6	0.6032609	0.6121582	0.39673913	0.3878418
7	0.3913043	0.3676666	0.60869565	0.6323334
8	0.3641304	0.2593576	0.63586957	0.7406424
9	0.3152174	0.3976639	0.68478261	0.6023361
10	0.4347826	0	0.56521739	1
11	0.3206522	0.3796124	0.67934783	0.6203876
12	0.2173913	0.4088134	0.7826087	0.5911866
13	0.0815217	0.5309265	0.91847826	0.4690735
14	0.0434783	0.36103	0.95652174	0.63897
15	0	0.5680913	1	0.4319087
16	0.9021739	0.4035041	0.09782609	0.5964959
17	0.9402174	0.390231	0.05978261	0.609769
18	0.7663043	0.3955402	0.23369565	0.6044598
19	0.2554348	0.1672418	0.74456522	0.8327582
20	0.1847826	0.4592514	0.81521739	0.5407486
21	0.1684783	0.1728166	0.83152174	0.8271834
22	0.6413043	0.3331564	0.35869565	0.6668436
23	0.6521739	0.7159543	0.34782609	0.2840457
24	0.6141304	0.1178657	0.38586957	0.8821343
25	0.326087	0.4558004	0.67391304	0.5441996
26	0.2608696	1	0.73913043	0
27	0.2173913	0.1319352	0.7826087	0.8680648

Table 5: Calculation for grey relational grade and Grey relational grade

	Grey Relational Coefficient			
Sr No	**Ra (LB)**	**MRR(HB)**	**GRG**	**Rank**
1	1	0.437768739	0.71888	1
2	0.9787234	0.446274138	0.7125	2
3	0.95833333	0.430858973	0.6946	4
4	0.54761905	0.44115236	0.49439	12
5	0.56441718	0.444693661	0.50456	11
6	0.55757576	0.563163403	0.56037	9
7	0.45098039	0.441566053	0.44627	15
8	0.44019139	0.403017011	0.4216	22
9	0.42201835	0.453582179	0.4378	16
10	0.46938776	0.333333333	0.40136	23
11	0.42396313	0.446274138	0.43512	17
12	0.38983051	0.458216762	0.42402	21
13	0.35249042	0.515956718	0.43422	19
14	0.34328358	0.438993124	0.39114	24
15	0.33333333	0.536533257	0.43493	18
16	0.83636364	0.455998063	0.64618	6
17	0.89320388	0.450544193	0.67187	5
18	0.68148148	0.452710011	0.5671	8
19	0.40174672	0.375161836	0.38845	25
20	0.38016529	0.480423415	0.43029	20
21	0.3755102	0.376737674	0.37612	27
22	0.58227848	0.428506427	0.50539	10
23	0.58974359	0.637717962	0.61373	7
24	0.56441718	0.361759339	0.46309	13
25	0.42592593	0.478835643	0.45238	14
26	0.40350877	1	0.70175	3
27	0.38983051	0.365479771	0.377655	26

GRA-ANFIS integrated approach :

The integrated approach of Grey Relational Analysis (GRA) and Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the strengths of both methods to enhance data analysis, modeling, and decision-making in complex systems. This integrated approach leverages the complementary characteristics of GRA and ANFIS to improve the accuracy and robustness of the analysis. Here's how the integrated GRA-ANFIS approach works:

ANFIS takes the Grey Relational Grade (GRG) values obtained from GRA as inputs and aims to learn the underlying mapping between these inputs and the target output. By training the ANFIS model, it can capture the non-linear relationships and improve the accuracy of the predictions or decisions.

Integration: The integration of GRA and ANFIS involves feeding the GRG values obtained from GRA into the ANFIS model as inputs. The ANFIS model then learns the relationship between these inputs and the target output based on the training data. The combined approach allows for a more comprehensive analysis of the data and a more accurate model for prediction or decision-making.

Advantages of GRA-ANFIS Integrated Approach:

1. Improved accuracy: The integrated approach leverages the strengths of both GRA and ANFIS to enhance the accuracy of the analysis and predictions.
2. Handling uncertainties: GRA is effective in handling uncertainties and limited data, which benefits the ANFIS model's training process.
3. Non-linear modeling: ANFIS can handle complex non-linear relationships, and its integration with GRA enables the modeling of intricate systems with limited data.
4. Robustness: The integrated approach provides a more robust analysis and decision-making process, considering both the relative importance of variables (GRA) and the non-linear relationships (ANFIS).

Overall, the GRA-ANFIS integrated approach is a powerful and versatile method for data analysis, modeling, and decision-making in various fields, including engineering, finance, management, and other complex systems. It provides an effective way to leverage the benefits of both GRA and ANFIS, resulting in a more accurate and reliable analysis and model. The membership function and designer used in as shown in Fig 2 -4. The rule based used is as shown in fig 5 & 6.

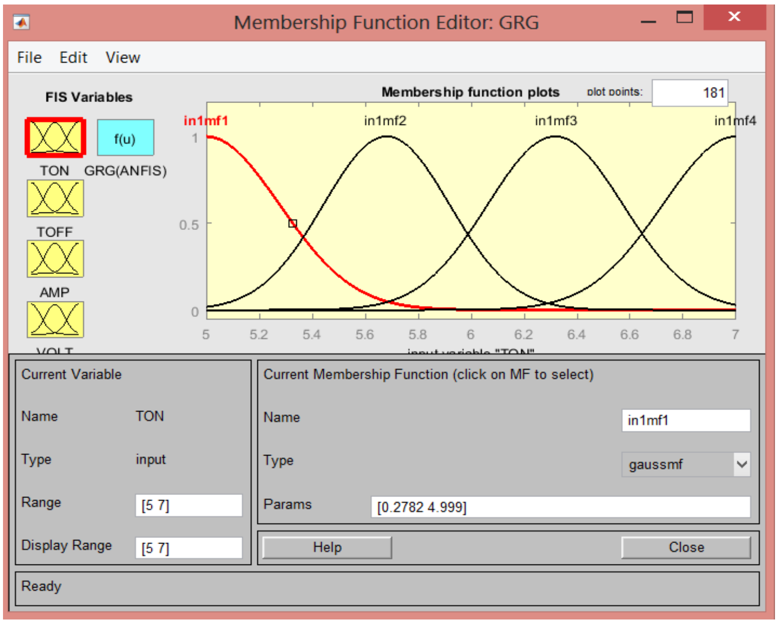

Fig 2 : membership function used in ANFIS

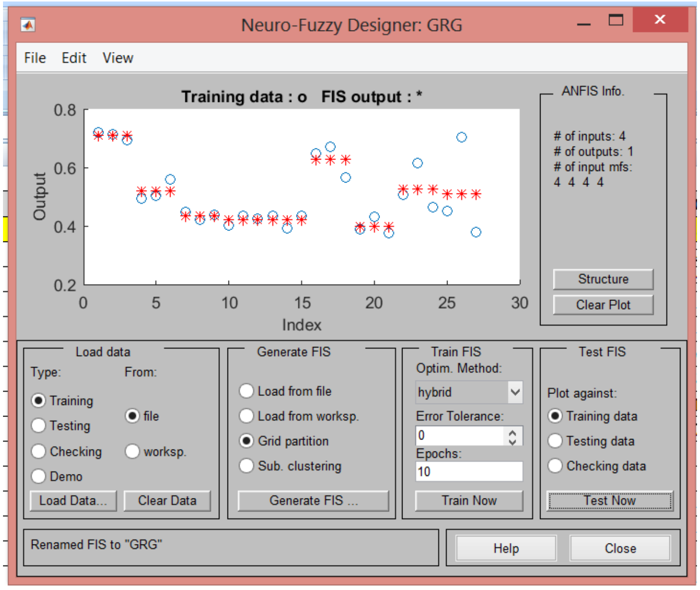

Fig 3 : Neuro-fuzzy designer used in ANFIS

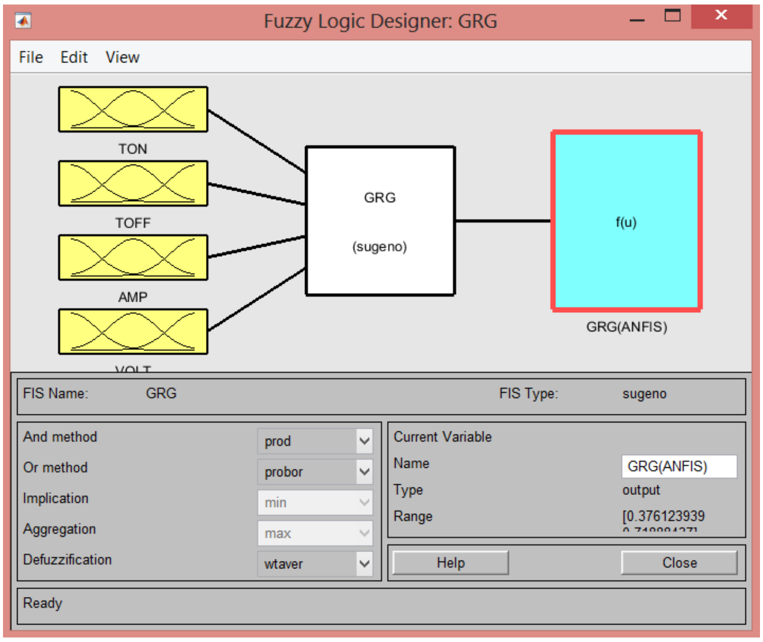

Fig 4 : Fuzzy logic designer used in ANFIS

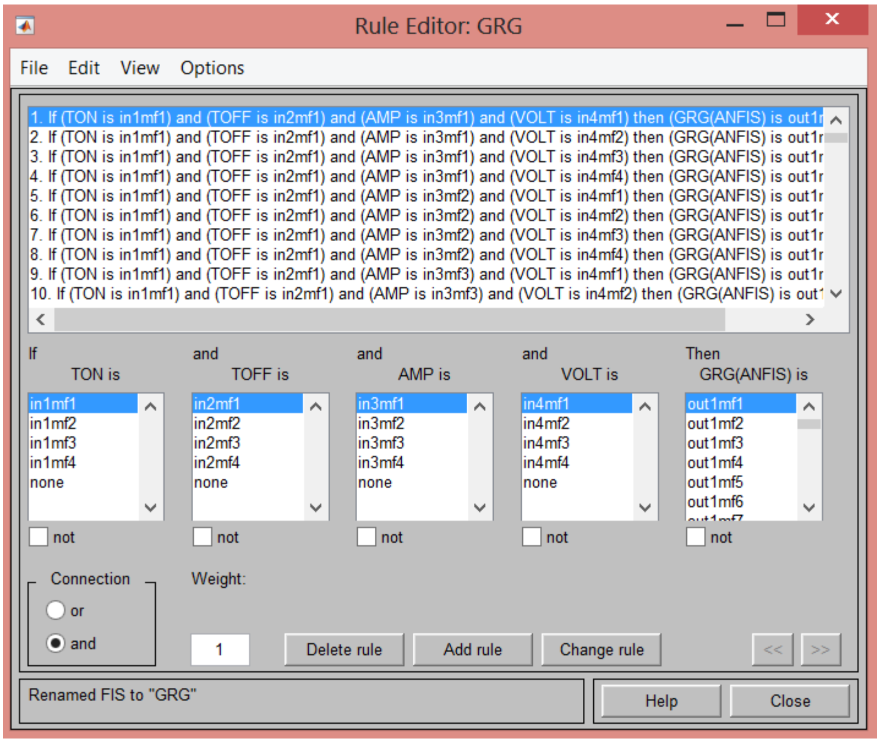

Fig 5 : Rule based use in ANFIS

Fig 6 : Rule viewer use in ANFIS

Minimum SiC Content: The minimum SiC content in Al-SiC MMCs is typically around 5% by weight. Below this threshold, the reinforcement effect of SiC may not be significant enough to yield notable improvements in mechanical properties.

The pulse on time refers to the duration of the electrical discharge during which the current flows between the electrode and the workpiece. A longer pulse on time generally results in higher energy input, which leads to a higher material removal rate (MRR). As the energy input increases, more material is melted and vaporized, resulting in a faster material removal rate.However, a longer pulse on time can also lead to increased electrode wear due to more significant erosion and crater formation on the electrode surface. This may negatively impact the machining accuracy and increase the operating costs due to frequent electrode replacements.

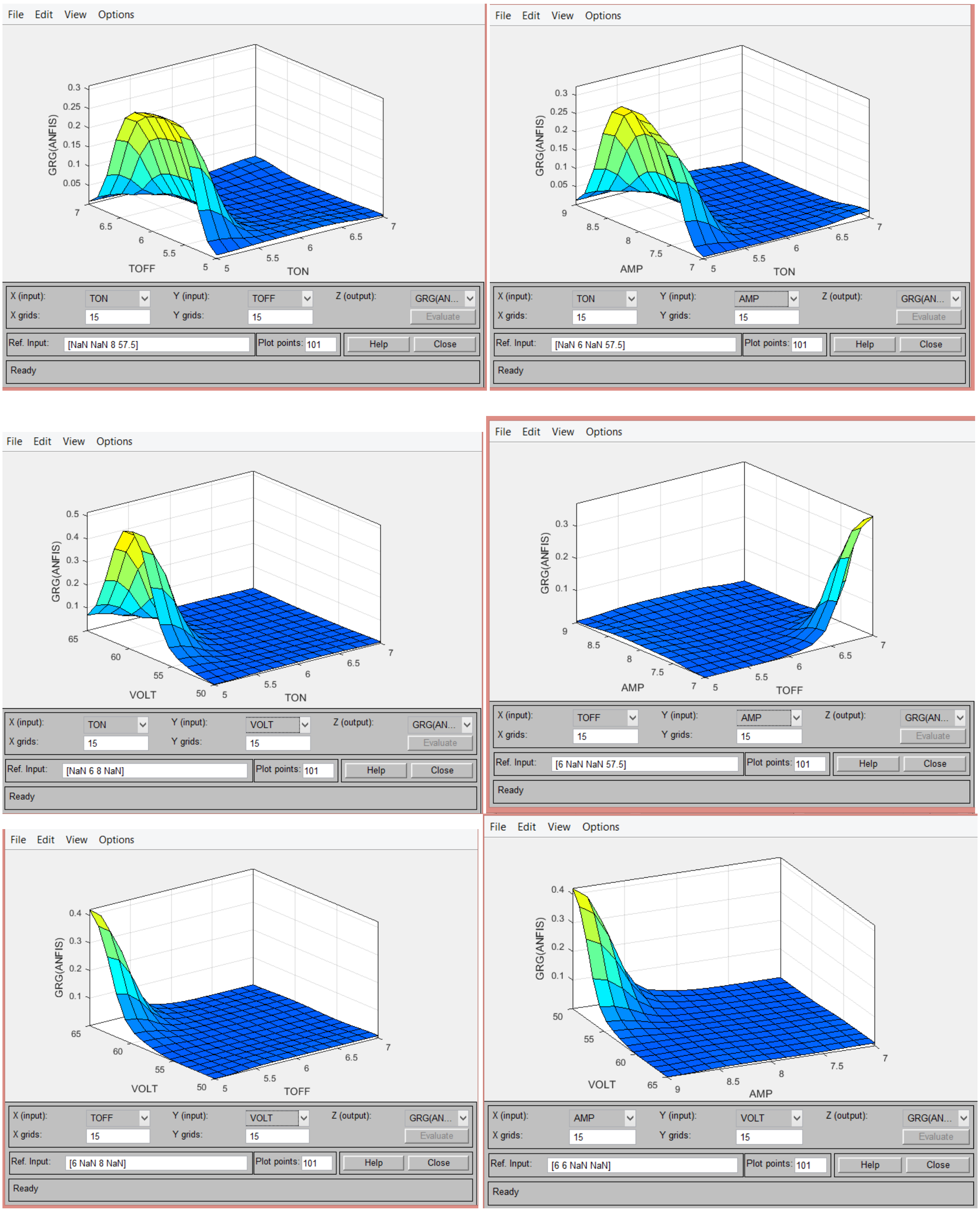

Fig 7 : ANFIS based surface plot to show the impact of various Process Parameters on Responses

The pulse off time refers to the duration between successive electrical discharges, during which the current flow is stopped. The pulse off time allows time for debris to be flushed away, cooling to occur, and dielectric fluid to return to the gap.A longer pulse off time allows for better cooling and debris removal, resulting in reduced recast layer thickness and improved surface finish. It also helps reduce the re-attachment of particles to the workpiece surface, leading to improved surface quality. However, a very long pulse off time may lead to a decrease in material removal rate due to reduced energy input and fewer discharges per unit time.

Higher voltage results in increased energy in each discharge, leading to a higher MRR. The higher energy input causes more material to be melted and vaporized, resulting in a faster material removal rate. Higher voltage can lead to a rougher surface finish due to the formation of larger craters and recast layers on the workpiece surface. The increased energy in each discharge may create deeper and wider craters, resulting in a less smooth surface.Higher current increases the amount of charge delivered during each electrical discharge, leading to a higher MRR. A higher current results in a more substantial electrical discharge and more material removal from the workpiece. Higher current can also lead to a rougher surface finish. The higher energy of the discharge may cause more significant thermal effects, resulting in a rougher surface with recast layers.

From the analysis ,it is observed that the optimum i.e. maximum MRR of 0.4377 mm3/min and minimum surface roughness of 1 microns is obtain through GRA-ANFIS intergrated approach. The optimum parameters are TON (5)-TOFF(5)-AMP(7)-Volt(50).

Sr No	**Ra (LB)**	**MRR(HB)**	**GRG**	**Rank**
1	1	0.437768739	0.71888	1

Sr No	**TON**	**TOFF**	**AMP**	**VOLT**	**Ra**	**MRR**
1	5	5	7	50	2.25	3.218

CONCLUSION

In the presented work, machining of AlSiCp5 was presented. The well known machining i.e. EDM ease has been carried out in the analysis. From the analysis, it has been observed that the integrated approach GRA-ANFIS is a very competent method of modelling. The optimum setting is obtain through the GRA-ANFIS intergrated approach for TON (5)-TOFF(5)-AMP(7)-Volt(50).

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Conflicts of interest:

Authors shows no conflicts of interest.

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