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*Research Article*

# Development of Hybrid Optimization Model Using Grey-ANFIS-Jaya Algorithm for CNC Drilling of Aluminium Alloy

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Aluminium alloys are gaining popularity in a diversity of engineering applications because of their extraordinary features such as strength, resistance to oxidation, and so on. AA5052 (Al-Mg series) is generally used in antirust uses, particularly in desalination related activities, due to its better resistance to corrosion in marine applications at temperature ranges up to 125°C, lower cost, better heat-carrying capacity, and nontoxicity of its corrosion components. Drilling is one of the most commonly adopted material removal processes that is adopted in numerous engineering uses. Taguchi's technique is engaged to arrange and examine the tests, by treating the drilling diameter and speed and as independent process factors. The studies were carried out using an L27 orthogonal array. Material removal rate (MRR), surface roughness (SR), and form/orientation error are deemed as output characteristics. Taguchi's analysis was engaged to discover the best process factors. ANOVA is used to examine the influence of process variables. Suitable application of artificial intelligence tools for making effective decision assists the manufacturer in accomplishing the benefits in numerous engineering domains. To obtain the maximum material removal and minimum roughness, circularity (circ), and perpendicularity errors (perp), the process variables have been optimized with the help of grey-ANFIS-amalgamated with Jaya algorithm. The multiperformance index was developed using grey theory. Statistical error analysis is used to estimate the performance of the established optimization model. Based on the investigative outcomes, the best-suited process variable combinations will be used to provide improved and enhanced multiperformance characteristics.

## 1. Introduction

Making of the drill is one of the most general processes of material removal adopted in various engineering industries. In general, machining aluminium alloys is easier than machining other metals (such as steel and titanium); yet, drilling can be difficult. Because of the high ductility of aluminium alloys, continuous lengthy chips and burrs frequently occur at the entry and exit of drill holes. The burr is a plastically distorted work material that, because of the strain hardening effect, is often tougher than the original material. Aluminium 5xxx series products are known for their superior corrosion resistance and formability. They are generally engaged in various industrial and aerospace uses. AA5052 is deemed as one amidst the appropriate materials for automobile structure applications owing to its higher

weldability, excellent forming properties, and outstanding corrosive resistance [1–5].

Traditional machine tools are usually used to remove layers of material by cutting them using a wedge-shaped tool. The energy consumption of these tools is separated into two parts. One of these is the amount of power that is used during the cutting process. The other is the amount of heat that is converted into energy. During the removal of the layers of plastic, the chip or metal adheres to the face of the rake, causing the force to increase [6]. The usage of cutting fluids is commonly used in metal-cutting processes to improve the life of the tool and improve surface finish. They also help in the transfer and breakdown of chips. Unfortunately, when used on the shop floor, the fluids can lead to airborne smoke, dust as well as other kinds of contaminants [7]. Cutting fluids are known to create various health and safety concerns. Their cost is significantly higher than that of tool pricing. Due to this issue, research has been conducted to limit their use in certain metal production processes. As an alternate to regular fluids, the usage of minimal quantity lubricant (MQL) and dry machining have gained widespread interest among experts and researchers in the field of machining. Despite the efforts to eliminate the need for cutting fluids, cooling is still very important in certain uses, such as those involving complex materials. The use of minimal quantity lubricant can be advantageous due to its ability to reduce the consumption of fluids while also improving the cooling performance of the tool. In most of the cases, it is not necessary to use a lot of oil to prevent the material from adhering to the surface. In addition, it can be used in combination with other MQL systems to overcome the limitations of dry operations [8–11].

Various methods are available to enhance the surface and reduce the overall production costs. One of these is the adoption of cutting liquid that can penetrate through the interaction areas of the chip-tool and the workpiece. These can efficiently remove the heat created during the machining. In addition, they can also help in improving the flow of the chip. Due to the widespread use of synthetic mineral oils, it has been estimated that the disposal and recovery of these materials pose a significant environmental issue. This can be especially true for surfaces used in biomedical applications [12].

This section covers various environmental effects of metal working fluids. Due to the rising prices of crude oil, vegetable-based fluids have been developed more commonly. Some of these are commonly used in manufacturing processes. New technologies were discovered that can be used to reduce the environmental and economic disadvantages of flood machining. These include the use of high pressure coolants, cold and nanofluid cooling, and dry machining. Compared to conventional fluid lubrication procedures, these new techniques offer superior results [13–16]. Predictive model development is a process utilized in manufacturing to predict the performance of a product or service. It helps the manufacturer make informed decisions and improve the efficiency of their operations [17–20].

An optimization strategy can be used to enhance the performance of a process by identifying the optimal machining parameters. This process can then be used to develop a predictive model that can be used to improve the accuracy of future predictions [21–24]. Although optimization techniques are typically regarded as inefficient, single-aspect optimization techniques can still deliver superior results. This is because most of the procedures in a multiaspect model can fail at the same time. There is a need for improved methods that can deal with different variables and improve the performance of the process [24–28].

It is surmised from the existing literature that the development of the artificial intelligence-based optimization algorithm for the sustainable manufacturing process (CNC drilling of aluminium alloy) by considering the rate of material removal (MRR), roughness of the drilled surface (SR), and form/orientation tolerance errors needs much intentness. In this exploratory analysis, an attempt was taken to evolve a hybrid artificial intelligence model by using the grey approach, ANFIS model, and Jaya algorithm.

## 2. Materials and Methods

AA5052 is opted as a work specimen in this present exploration that possesses various engineering uses. Experimentation has been performed in a LMW JV 55 machine by various considered input variables as illustrated in Figure 1. Table 1 represents various machining combinations that have been adopted in the exploration. The experimentation was performed using an L27 orthogonal array (OA).

The aspiration of this investigational study is to analyse the various output characteristics of a material, such as the MRR, SR, and the form/orientation tolerance errors. The weight loss methodology is utilized in the evaluation of MRR, whereas the Mitutoyo SJ410 tester is utilized in the determination of the surface roughness of the drilled part. The evaluation of orientation and form tolerance errors was performed by the Helmelmake Coordinate Measuring Machine (CMM). The outcomes of the experimentation presented in Table 2 were then analysed and used for future studies.

## 3. Methodology

The present investigation adopted ANOVA to examine the level of influence of process variables. To obtain efficient machining performance, the process variables have been optimized with the help of grey-ANFIS-amalgamated with the Jaya algorithm as shown in Figure 2. The development of the multiperformance index included the use of grey theory, while the estimation of the performance of the created optimization model was conducted via the utilization of statistical error analysis. The process variable combinations that provide better and enhanced multiperformance features will be selected based on the investigation findings.

## 4. Results and Discussion

The investigation was completed using the L27 OA. The outcomes of the studies are discussed as follows.


Figure 1: Experimental setup.

Table 1: Machining process parameters.

| Symbols | Machining parameters | Levels | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| A | Diameter (mm) | 10 | 12 | 14 |
| B | Speed (rpm) | 1250 | 1750 | 2250 |
| C | Feed | 0.05 | 0.1 | 0.15 |

Table 2: Outcomes of the experimentation.

| Exp no. | Input | | | Output | | | |
|---|---|---|---|---|---|---|---|
| | Dia | Speed | Feed | Ra | MRR | Perp | Circ |
| 1 | 10 | 1250 | 0.05 | 1.624 | 81.8452 | 0.023 | 0.0795 |
| 2 | 10 | 1250 | 0.1 | 1.854 | 163.6905 | 0.5163 | 0.2838 |
| 3 | 10 | 1250 | 0.15 | 2.845 | 245.5357 | 0.2917 | 0.1914 |
| 4 | 10 | 1750 | 0.05 | 2.731 | 114.5833 | 0.2628 | 0.1693 |
| 5 | 10 | 1750 | 0.1 | 1.983 | 229.1667 | 0.2433 | 0.2489 |
| 6 | 10 | 1750 | 0.15 | 3.364 | 343.7500 | 0.1935 | 0.1266 |
| 7 | 10 | 2250 | 0.05 | 2.553 | 147.3214 | 0.9948 | 0.1994 |
| 8 | 10 | 2250 | 0.1 | 2.682 | 294.6429 | 0.4354 | 0.2143 |
| 9 | 10 | 2250 | 0.15 | 2.669 | 441.9643 | 0.3928 | 0.2744 |
| 10 | 12 | 1250 | 0.05 | 2.116 | 117.8571 | 0.4039 | 0.2055 |
| 11 | 12 | 1250 | 0.1 | 2.101 | 235.7143 | 0.644 | 0.3487 |
| 12 | 12 | 1250 | 0.15 | 3.755 | 353.5714 | 0.7444 | 0.5163 |
| 13 | 12 | 1750 | 0.05 | 3.298 | 165.0000 | 0.315 | 0.1909 |
| 14 | 12 | 1750 | 0.1 | 3.997 | 330.0000 | 0.0457 | 0.3927 |
| 15 | 12 | 1750 | 0.15 | 2.51 | 495.0000 | 0.349 | 0.4252 |
| 16 | 12 | 2250 | 0.05 | 3.35 | 212.1429 | 0.1468 | 0.2413 |
| 17 | 12 | 2250 | 0.1 | 4.277 | 424.2857 | 0.374 | 0.2961 |
| 18 | 12 | 2250 | 0.15 | 3.878 | 636.4286 | 0.5922 | 0.2817 |
| 19 | 14 | 1250 | 0.05 | 2.497 | 160.4167 | 0.4252 | 0.2359 |
| 20 | 14 | 1250 | 0.1 | 2.36 | 320.8333 | 0.5104 | 0.1579 |
| 21 | 14 | 1250 | 0.15 | 3.39 | 481.2500 | 0.759 | 0.4248 |
| 22 | 14 | 1750 | 0.05 | 3.74 | 224.5833 | 0.6821 | 0.3182 |
| 23 | 14 | 1750 | 0.1 | 3.589 | 449.1667 | 0.9427 | 0.3634 |
| 24 | 14 | 1750 | 0.15 | 2.405 | 673.7500 | 1.805 | 0.2802 |
| 25 | 14 | 2250 | 0.05 | 3.758 | 288.7500 | 0.7961 | 0.4033 |
| 26 | 14 | 2250 | 0.1 | 4.199 | 577.5000 | 0.4895 | 0.3753 |
| 27 | 14 | 2250 | 0.15 | 4.549 | 866.2500 | 0.7546 | 0.4148 |

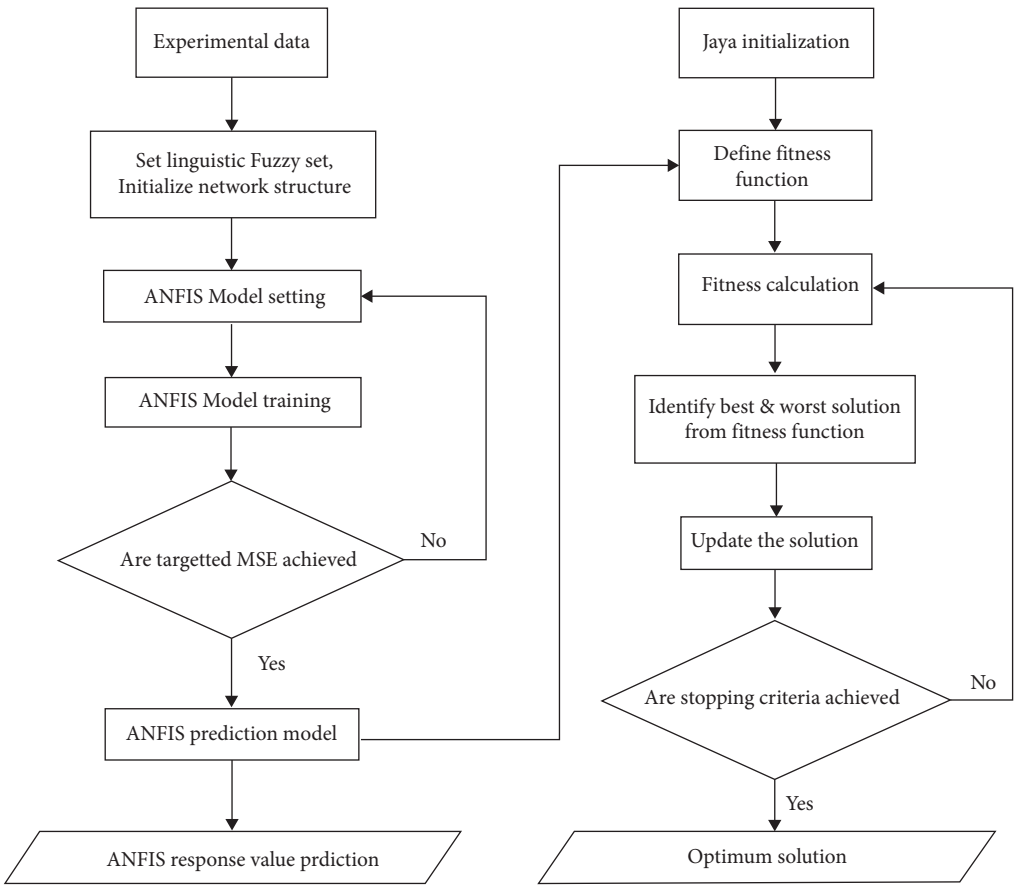


Figure 2: Flow chart for optimum solution using the grey–ANFIS-based Jaya algorithm.

*4.1. Ascendency of Factors on SR.* Figure 3 displays the response analysis that was performed for the roughness of the drilled surface.

The graphical representation clearly illustrates that the roughness has increased as the value of the input variables has increased. The optimal process variable for accomplishing minimum roughness is ascertained with the help of response analysis, as shown in Table 3.

*4.2. Ascendency of Factors on MRR.* The study of the response plot for MRR is depicted in Figure 4. The graphical representation makes it clear that an increase in the value of the input variables has resulted in augmentation in the MRR. With the aid of assistance response analysis, Table 4 determines the ideal process variables for achieving the maximum removal rate.

*4.3. Ascendency of Factors Variable on Orientation Tolerance Error.* Figure 5 depicts the response analysis that was done for the orientation tolerance error. The graphical representation makes it clear that the perpendicularity error has grown with drill diameter, speed, and feed. With the aid of response analysis, Table 5 identifies the best process variable for minimising the perpendicularity error.

*4.4. Ascendency of Process Variable on Circularity Error.* The examination of the circularity error response plot is shown in Figure 6.

The graphical representation makes it clear that as the input variable values have increased, the circularity error has also grown. With the aid of response analysis, Table 6 determines the ideal process variable for achieving the lowest circularity error.

*4.5. Influence of Process Variable on GRG.* The examination of the response graph for the GRG is depicted in Figure 7. The graphical representation makes it clear that the GRG value has fallen with rising input variable values.

With the aid of assistance response analysis, Table 7 determines the ideal process variable for achieving the maximum GRG.

*4.6. Evolution of ANFIS Model for Drilling of AA5052.* The anticipated structure of the ANFIS was developed with the assistance of three input neurons and one output neuron. The drill diameter, speed, and feed rate are the pieces of information that are provided to the ANFIS structure as input data when WEDM AA5052 alloy. The enhanced ANFIS model will provide an estimate of the

Table 3: Response analysis for surface roughness.

| Level | Drill diameter | Speed | Feed |
|---|---|---|---|
| 1 | 2.478 | 2.505 | 2.852 |
| 2 | 3.254 | 3.069 | 3.005 |
| 3 | 3.387 | 3.546 | 3.263 |
| Delta | 0.909 | 1.041 | 0.411 |
| Rank | 2 | 1 | 3 |

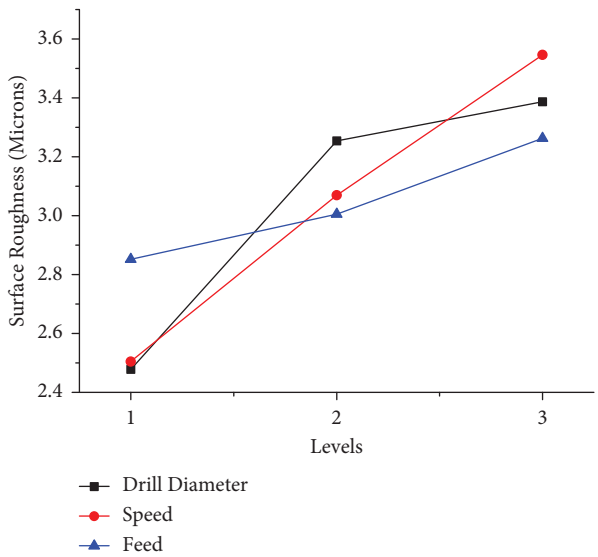


Figure 3: Response plot for surface roughness.

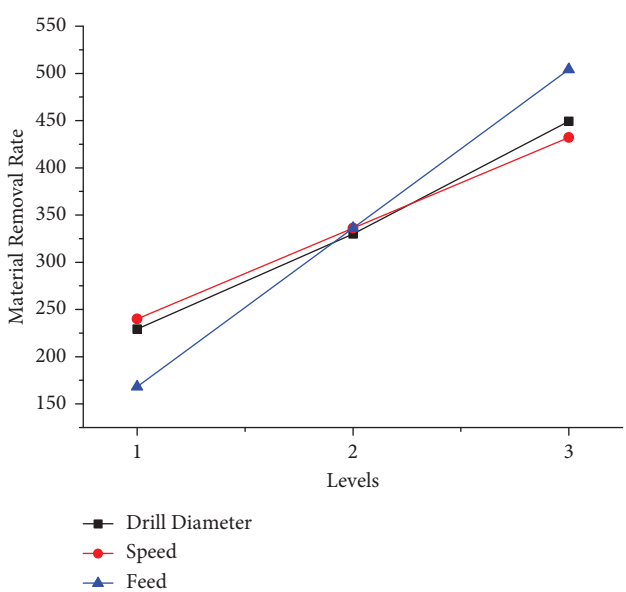


Figure 4: Response plot for the material removal rate.

GRG values that will be encountered during drilling of the AA5052 alloy. It is possible to obtain a model that is accurate and that successfully links the drilling parameters to the appropriate performance data. For the purpose of training the newly developed ANFIS model, the

Table 4: Response analysis for the material removal rate.

| Level | Drill diameter | Speed | Feed |
|---|---|---|---|
| 1 | 229.2 | 240.1 | 168.1 |
| 2 | 330 | 336.1 | 336.1 |
| 3 | 449.2 | 432.1 | 504.2 |
| Delta | 220 | 192.1 | 336.1 |
| Rank | 2 | 3 | 1 |

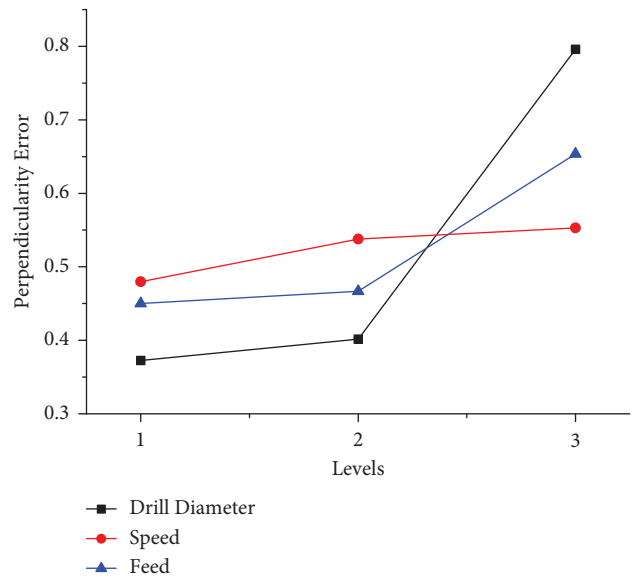


Figure 5: Response plot for the perpendicularity error.

Table 5: Response analysis for the perpendicularity error.

| Level | Drill diameter | Speed | Feed |
|---|---|---|---|
| 1 | 0.3726 | 0.4798 | 0.45 |
| 2 | 0.4017 | 0.5377 | 0.4668 |
| 3 | 0.7961 | 0.5529 | 0.6536 |
| Delta | 0.4234 | 0.0731 | 0.2036 |
| Rank | 1 | 3 | 2 |

graphical user interface (GUI) for ANFIS in MATLAB was utilized. The "trimf" membership function was used to generate the eight rules that make up the ANFIS model. These rules, which are based on the input information set, were produced by the ANFIS model. Figure 8 depicts the editor that is used for ANFIS. Following construction of the ANFIS model, it was applied to the ANFIS rule viewer in order to make a prediction regarding GRG, as shown in Figure 9.

*4.7. Inferences on Forecast of ANFIS-GRG.* Figure 10 represents the combinatorial effect of various independent process factors considered in this investigation. The ANFIS-GRG will be supreme for the amalgamation of the middle level of speed and lesser levels of drill diameter. Similarly, lower levels of drill diameter and higher levels of feed offer better and improved ANFIS-GRG. The amalgamations of lower levels of feed and speed produce

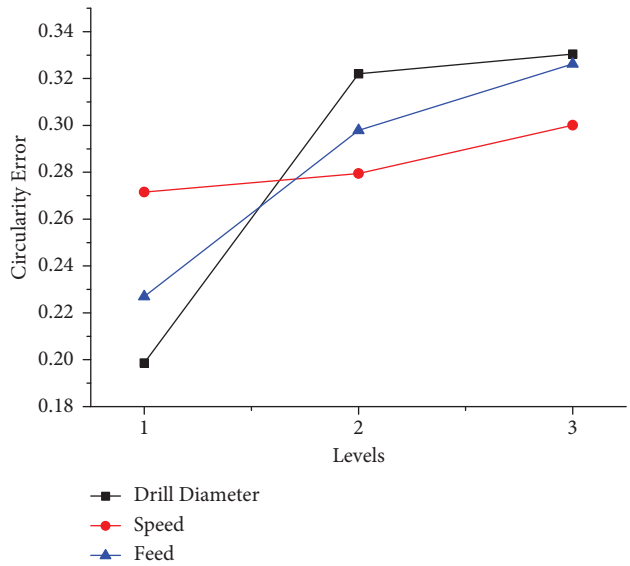


Figure 6: Response plot for the circularity error.

Table 6: Response analysis for the circularity error.

| Level | Drill diameter | Speed | Feed |
|---|---|---|---|
| 1 | 0.1986 | 0.2715 | 0.227 |
| 2 | 0.322 | 0.2795 | 0.2979 |
| 3 | 0.3304 | 0.3001 | 0.3262 |
| Delta | 0.1318 | 0.0285 | 0.0991 |
| Rank | 1 | 3 | 2 |

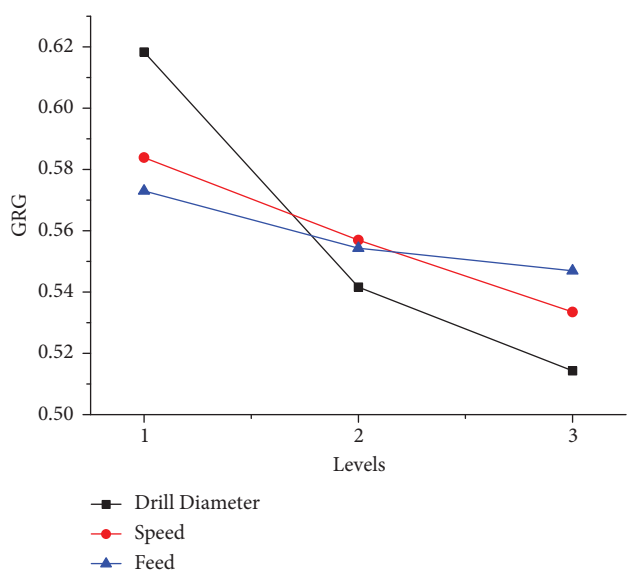


Figure 7: Response plot for GRG.

Table 7: Response analysis for GRG.

| Level | Drill diameter | Speed | Feed |
|---|---|---|---|
| 1 | 0.6183 | 0.5839 | 0.573 |
| 2 | 0.5416 | 0.5569 | 0.5543 |
| 3 | 0.5143 | 0.5335 | 0.5469 |
| Delta | 0.104 | 0.0504 | 0.0261 |
| Rank | 1 | 2 | 3 |

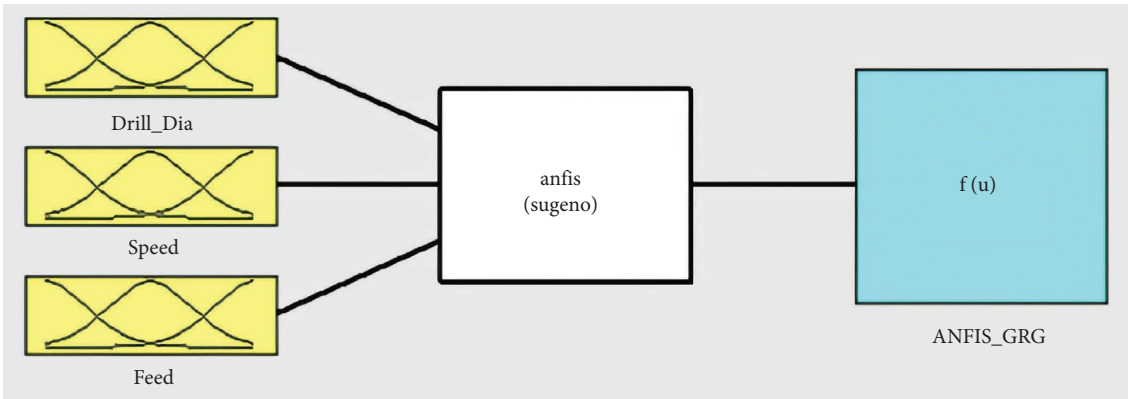


Figure 8: ANFIS editor.

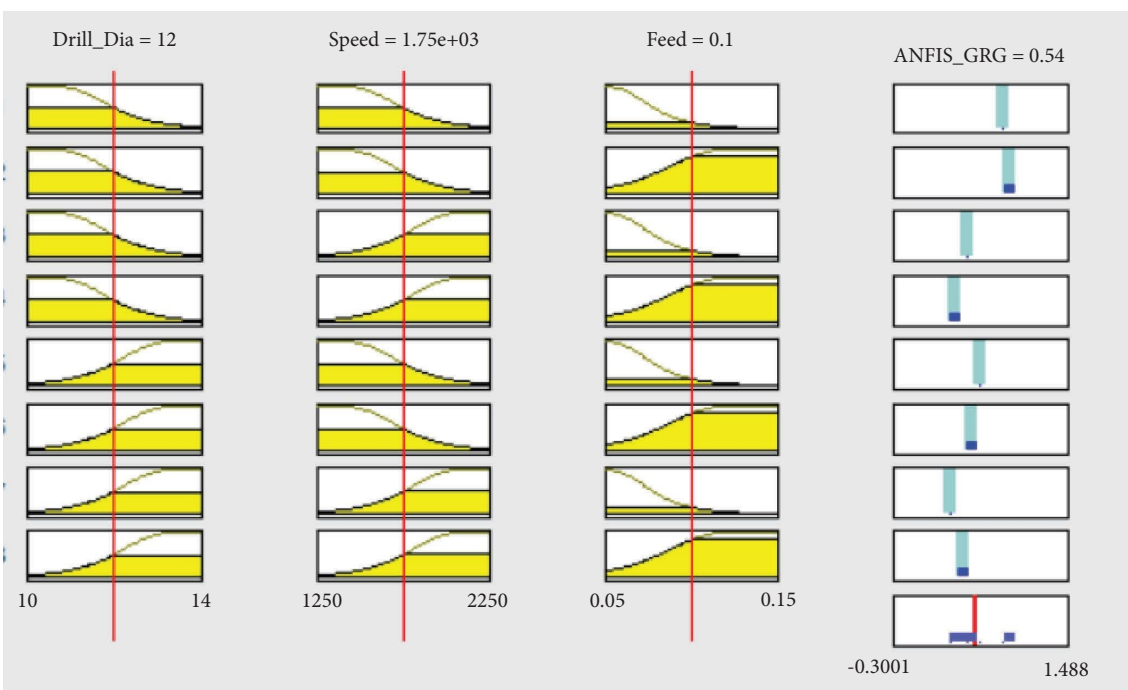


Figure 9: ANFIS rule viewer.

improved multiperformance machining. Same kinds of tendencies have been noticed for remaining combinations of process variables and levels.

*4.8. Comparative Analysis on Actual and Prophesied GRG.* The performance of forecast models can be enhanced by developing a hybrid approach with improved intelligence technologies. The purpose of this investigation is to use the ANFIS tool to develop a prediction model for the GRG. The GRA methodology is used in the procedure to get the values of the different ledger components. The model's objective is to forecast future ANFIS-GRG data. It demonstrates that the modified model represents the organization's needs properly. The model's graphic representation in Figure 11 demonstrates that the foretold GRG is much confined to the actual GRG, and the data are presented in Table 8.

*4.9. Performance Analysis of Evolved ANFIS Model.* With the help of statistical error analysis and efficiency coefficients, the constructed ANFIS structure performance is evaluated. The evaluation of model error and model efficiency is performed as follows.

*4.9.1. Determination of Errors for Evolved ANFIS Structure.* $E_i$ is experimental data, $P_i$ is foretold data attained from the structure, $\overline{E}$ is average of experimentation data, and "$n$" is

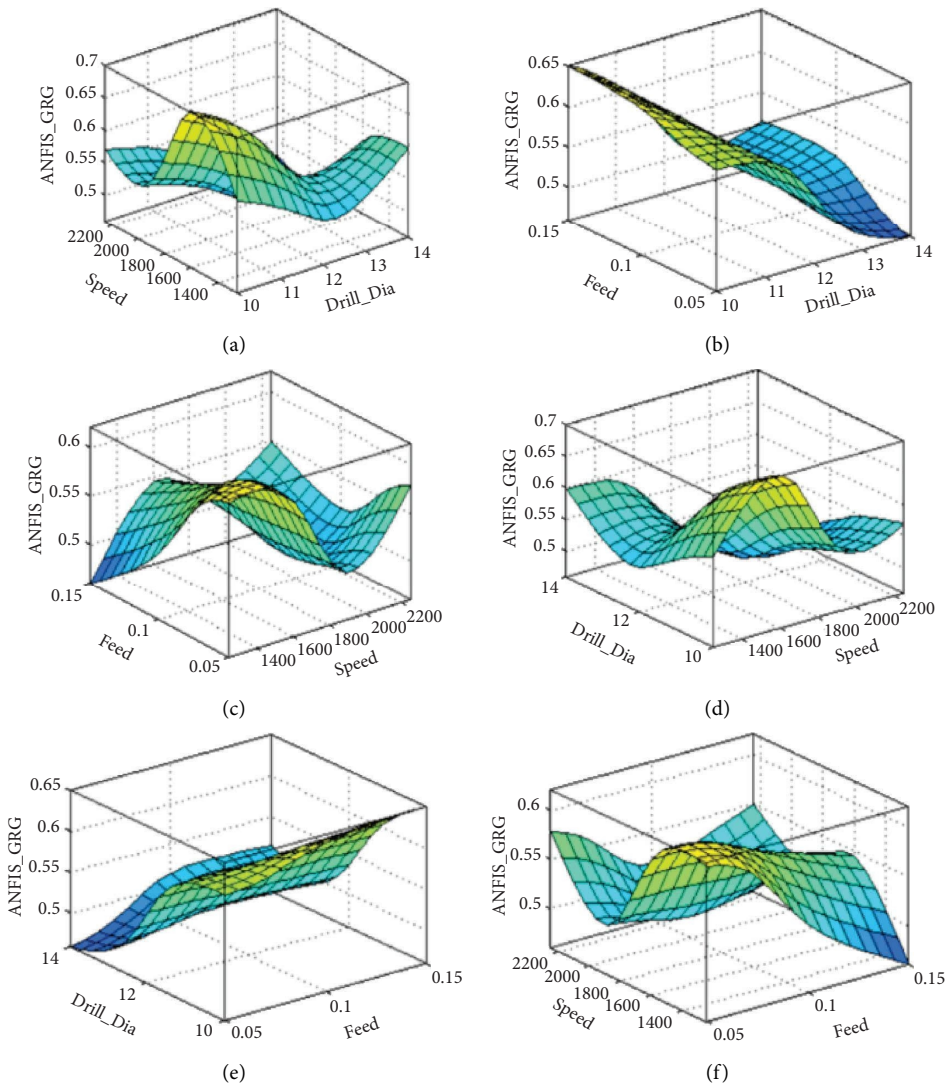


Figure 10: Inferences on ANFIS-GRG vs. independent factors.

the number of experimental runs. Statistical error values are evaluated for the developed model and tabulated in Table 9. The created ANFIS model can successfully forecast the GRG values, according to error analysis.

*4.9.2. Model Efficiency: ANFIS Prediction Model.* Model efficacy is measured using the correlation coefficient and Nash Sutcliffe efficiency coefficient (NSE) and are shown in Table 10. Both values are showing the values near to 1. Hence, the evolved model is efficient to foretell the GRG values.

*4.10. Multiobjective Optimization (ANFIS-Jaya).* The hybrid multiobjective optimization model was evolved to corroborate the foremost suitable amalgamation of factors for effectuating multiple performance measures. The ANFIS

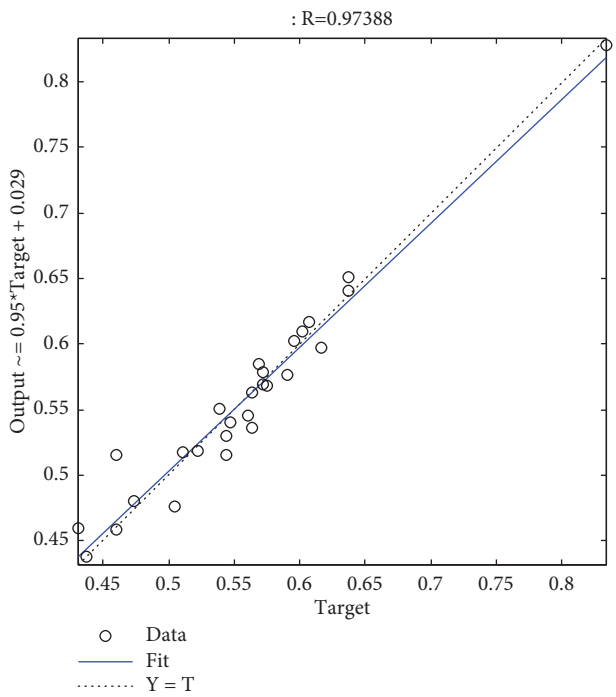


Figure 11: Regression plot for experimental GRG and predicted GRG using ANFIS.

Table 8: Comparison between actual and predicted values.

| Exp no. | Actual GRG | ANFIS output |
|---|---|---|
| 1 | 0.8333 | 0.8280 |
| 2 | 0.5957 | 0.6027 |
| 3 | 0.5904 | 0.5761 |
| 4 | 0.6022 | 0.6097 |
| 5 | 0.6372 | 0.6405 |
| 6 | 0.6369 | 0.6512 |
| 7 | 0.5221 | 0.5186 |
| 8 | 0.5723 | 0.5693 |
| 9 | 0.5747 | 0.5687 |
| 10 | 0.6067 | 0.6172 |
| 11 | 0.5437 | 0.5299 |
| 12 | 0.4316 | 0.4600 |
| 13 | 0.5601 | 0.5451 |
| 14 | 0.5474 | 0.5403 |
| 15 | 0.5639 | 0.5358 |
| 16 | 0.5715 | 0.5785 |
| 17 | 0.5112 | 0.5176 |
| 18 | 0.5384 | 0.5501 |
| 19 | 0.5638 | 0.5630 |
| 20 | 0.6164 | 0.5973 |
| 21 | 0.4732 | 0.4805 |
| 22 | 0.4602 | 0.4588 |
| 23 | 0.4595 | 0.5150 |
| 24 | 0.5443 | 0.5153 |
| 25 | 0.4373 | 0.4383 |
| 26 | 0.5048 | 0.4758 |
| 27 | 0.5692 | 0.5848 |

prediction model for the multiperformance index (GRG) is applied as fitness function in the Jaya algorithm. The flowchart for obtaining the optimum solution Grey ANFIS-based Jaya algorithm is presented in Figure 2. The convergence graph shown in Figure 12 indicates that the optimum results are obtained with less computational

Table 9: Statistical error values.

| Type | Equation | Value |
|---|---|---|
| Mean absolute error | $\mathrm{MAE} = \sum_{i=1}^{n} \lvert E_i - P_i \rvert / n$ | 0.012996 |
| Mean squared error | $\mathrm{MSE} = \sum_{i=1}^{n} (E_i - P_i)^2 / n$ | 0.000312 |
| Root mean squared error | $\mathrm{RSME} = \sqrt{\sum_{i=1}^{n} (E_i - P_i)^2 / n}$ | 0.017677 |
| Mean absolute relative error | $\mathrm{MARE} = \sum_{i=1}^{n} \lvert (E_i - P_i / E_i) \rvert / n$ | 0.024498 |
| Mean squared relative error | $\mathrm{MSRE} = \sum_{i=1}^{n} (E_i - P_i / E_i)^2 / n$ | 0.001250 |
| Root mean squared relative error | $\mathrm{RMSRE} = \sqrt{\sum_{i=1}^{n} (E_i - P_i / E_i)^2 / n}$ | 0.035354 |
| Mean absolute percentage error | $\mathrm{MAPE} = \sum_{i=1}^{n} \lvert (E_i - P_i / E_i) \rvert / n$ | 2.449834 |
| Root mean squared percentage error | $\mathrm{RMSPE} = \sqrt{\sum_{i=1}^{n} (E_i - P_i / E_i * 100)^2 / n}$ | 3.535395 |

Table 10: Model efficiency coefficient values.

| Types of correlation | Equation | Value |
|---|---|---|
| Correlation coefficient | $R = (n * (\sum_{i=1}^{n} E_i P_i) - ((\sum_{i=1}^{n} E_i) * (\sum_{i=1}^{n} P_i)) / \sqrt{(n * \sum_{i=1}^{n} E_i^2 - (\sum_{i=1}^{n} E_i)^2)} * \sqrt{(n * \sum_{i=1}^{n} P_i^2 - (\sum_{i=1}^{n} P_i)^2)})$ | 0.97388 |
| Nash Sutcliffe efficiency coefficient (NSE) | $\mathrm{NSE} = 1 - ((\sum_{i=1}^{n} (E_i - P_i)^2) / \sum_{i=1}^{n} (E_i - \overline{E})^2)$ | 0.9484 |

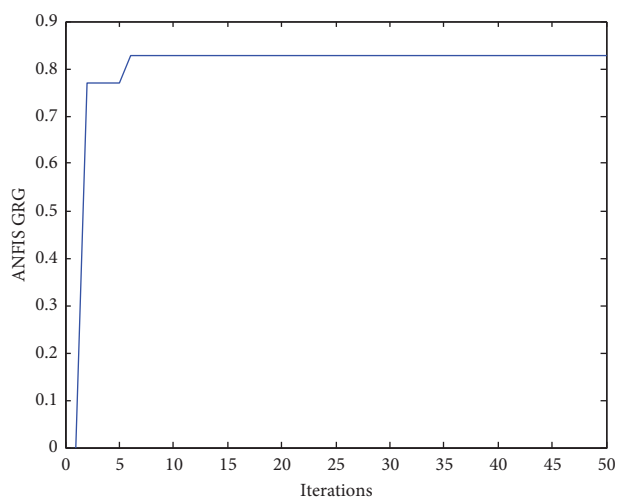


Figure 12: Convergence graph from the Jaya algorithm for ANFIS_GRG.

complexity. The optimal combination has been determined as diameter 10 mm, speed 1250 rpm, and feed 0.05 mm/rev.

## 5. Conclusions

Drilling is one of the fundamental metal removal methods which are used in various engineering applications.

It is very challenging for manufacturers to choose the optimal processing parameters for their products when it comes to improving their drilling performance. In this paper, a grey-ANFIS-Jaya algorithm for achieving improved multiple performances in the drilling process has been developed. The extrapolations accomplished from this investigation are presented as follows:

(1) The analysis by Taguchi's approach was adopted to assess the significance of factors on the targeted performance metrics. According to the findings, drill diameter is a major process variable impacting the overall machining performance for the drilling of AA5052.

(2) The performance of the predictive model was appraised using a hybrid grey-ANFIS approach. It is noticed that the improved model predicts the required performance metric more accurately.

(3) The independent factors for accomplishing a better multiperformance index (GRG) have been ascertained by adopting the ANFIS-Jaya algorithm as

drilling diameter 10 mm, speed 1250 rpm, and feed 0.05 mm/rev with optimum values of fitness as 0.810022.

(4) The use of ANFIS-Jaya algorithm helps in ascertaining the optimal amalgamation process variables for the drilling of the AA5052 alloy.

## Data Availability

The data used to support the findings of this study will be made available on reasonable request to the corresponding author through email.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Authors' Contributions

All authors contributed equally for the preparation of this manuscript.

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