Parametric optimization of CNC turning on glass-fibre-reinforced plastic (GFRP) pipes: A grey-fuzzy logic approach

Vimal Pradhan\textsuperscript{a}, Partha Protim Das\textsuperscript{b}

\textsuperscript{a} Mechanical Engineering Department, Sikkim Manipal Institute of Technology, Majitar, 737136, India
\textsuperscript{b} pradhanvimal30@gmail.com, parthaprotimdas@ymail.com

Abstract: Glass-fibre-reinforced plastic (GFRP) is an advanced polymeric glass fibre reinforced composite material being widely used in various applications such as aircrafts, robots and machine tools. An attempt was made by the past researchers on optimizing the cutting parameters of CNC turning on these filament wounded GFRG pipes with coated carbide tool inserts (K20 grade) as cutting tool by desirability function analysis using Taguchi technique. Machining process parameters such as cutting velocity, feed rate and depth of cut are optimized, while response parameters considered are surface roughness, flank wear, crater wear and machining force respectively. In this paper, grey relational analysis (GRA) combined with fuzzy logic is applied to this multi-objective optimization problem and the derived parametric mix is compared to that obtained by the past researchers. The predicted results of the parametric mix obtained using the proposed approach shows a significant improvement of approximately 14% in the quality of response parameters as compared to that of the past researchers. Lastly, ANOVA is applied so as to identify the significant factors which positively contribute to the cutting process.

1. Introduction

Glass-fibre-reinforced plastic (GFRP), an advanced polymeric matrix composite material, is widely used. It is cheaper and more flexible than carbon fibre, it is stronger than many metals by weight, and can be moulded into complex shapes. Applications include aircraft, boats, automobiles, bath tubs and enclosures, swimming pools, hot tubs, septic tanks, water tanks, roofing [1]. High dimensional accuracy and better surface integrity are the necessary qualities of the machined surfaces of the GFRP. Generally, GFRP composite pipes are manufactured either by hand layup process or by the filament winding method. High quality surface finish GFRP composite pipes can be manufactured by different machining processes. Machining on fibre-reinforced composite differs than conventional machining processes as metals and alloys, owing to the behaviour of matrix material, reinforcement and diverse properties of fibre, matrix and orientation of fibre and volume fraction of fibres [2]. If the fibre orientation angle is greater than 90\textdegree, the three distinct deformation zones will appear chipping, pressing and bouncing [3]. It is an most important think to select combination of machining parameters as slight changes in a single parameter significantly affects the process adversely. While controlling the process parameters it should be capable of producing required dimensional accuracy and quality surface finish. Many researchers have attempted to obtain the optimal machining parameters of several machining process while machining on GFRP pipes. Existing well known approaches such as grey relational analysis (GRA), analytic network process (ANP), preference ranking organization method for enrichment evaluation (PROMETHEE), VIKOR method etc. can be applied in these direction. Aravindan et al. [4] investigated the machinability of hand layup GFRP pipes using statistical techniques. Palanikumar [5] used Taguchi’s method and response surface methodologies for maximum minimising surface roughness in machining of GFRP using polycrystalline diamond tool. Paulo Davim [6] attempted to study the influence of cutting conditions on the surface roughness during turning and by design of experiments and regression analysis.
Deng [7] first introduced Grey systems. It is a powerful tool that deals with poor, unknown and vague data [8]. In recent years, a grey system has been effectively used to solving many multi usually conflicting criteria’s in various fields of manufacturing [9, 10]. Fuzzy sets were first introduced by Zadeh [11] which can successfully deals with improper, uncertain and vague data. Fuzzy logic aided with GRA can further improve its performance in solving the multi-objective optimization problems. Many researchers have effectively employed grey fuzzy logic in optimizing multi-objective problems [8, 10]. Soepangkat et al. [12] applied integrated fuzzy-logic based GRA in optimizing wire EDM processes. Pandey et al. [13] proposed a modified algorithm (grey based fuzzy algorithm) which they used to optimize multiple performance characteristics in drilling of a bone. Das et al. [14] optimized the process parameters for a CNC milling of Al–4.5%Cu–TiC composites using grey-fuzzy logic that optimizes the response parameters. Tamiloli et al. [15] focused to find the optimum end milling process parameters by considering multiple performance characteristics using grey fuzzy approach to optimize three response parameters: centre line average roughness (Ra), root mean square roughness (Rq) and MRR. Chakraborty et al. [16] adopted grey-fuzzy technique to obtain the optimal parametric combination of abrasive water-jet machining (AWJM), electrochemical machining (ECM) and ultrasonic machining (USM) processes.

**Table 1: Process parameters of CNC turning process [17]**

| Process Parameters    | Unit       | Symbol | 1  | 2  | 3  |
|-----------------------|------------|--------|----|----|----|
| Cutting velocity (v)  | m/min      | A      | 100 | 150| 200|
| Feed rate (f)         | mm/rev     | B      | 0.05| 0.1| 0.2|
| Depth of cut (d)      | mm         | C      | 0.5 | 1.0| 2.0|

**Table 2: Experimental Data [17]**

| Exp. No. | Speed (m/min) | Feed rate (mm/rev) | Depth of cut (mm) | Flank Wear (mm) | Crater Wear (mm) | Rₐ (μm) | Fₘ (N) |
|----------|---------------|--------------------|-------------------|-----------------|------------------|---------|--------|
| 1        | 100           | 0.05               | 0.5               | 0.059           | 0.011            | 2.35    | 57.23  |
| 2        | 100           | 0.1                | 1                 | 0.066           | 0.009            | 4.06    | 83.18  |
| 3        | 100           | 0.2                | 2                 | 0.088           | 0.007            | 3.95    | 95.68  |
| 4        | 150           | 0.05               | 0.5               | 0.068           | 0.009            | 2.81    | 51.78  |
| 5        | 150           | 0.1                | 1                 | 0.078           | 0.008            | 3.61    | 77.47  |
| 6        | 150           | 0.2                | 2                 | 0.109           | 0.006            | 3.65    | 86.48  |
| 7        | 200           | 0.05               | 1                 | 0.085           | 0.007            | 3.71    | 71.48  |
| 8        | 200           | 0.1                | 2                 | 0.108           | 0.006            | 4.07    | 68.14  |
| 9        | 200           | 0.2                | 0.5               | 0.112           | 0.006            | 3.67    | 43.98  |
| 10       | 100           | 0.05               | 2                 | 0.067           | 0.009            | 3.63    | 58.24  |
| 11       | 100           | 0.1                | 0.5               | 0.064           | 0.01             | 2.87    | 50.39  |
| 12       | 100           | 0.2                | 1                 | 0.079           | 0.008            | 3.13    | 47.91  |
| 13       | 150           | 0.05               | 1                 | 0.071           | 0.009            | 3.88    | 74.57  |
| 14       | 150           | 0.1                | 2                 | 0.087           | 0.007            | 2.74    | 83.32  |
| 15       | 150           | 0.2                | 0.5               | 0.09            | 0.007            | 3.39    | 69.61  |
| 16       | 200           | 0.05               | 2                 | 0.096           | 0.007            | 3.26    | 132.97 |
| 17       | 200           | 0.1                | 0.5               | 0.089           | 0.007            | 2.58    | 40.66  |
| 18       | 200           | 0.2                | 1                 | 0.122           | 0.005            | 3.99    | 66.29  |

An attempt has been made earlier by the past researchers in obtaining the optimal parametric setting of CNC turning operation while machining of glass-fibre-reinforced plastic (GFRP) pipes using Taguchi method. Sait et al. [17] considered three level variations for each input parameters viz. cutting speed, feed rate, and depth of cut.
velocity, feed rate, depth of cut while optimizing the performance measures viz. flank wear, cutter wear, Rₜ and Fₘₐₓ. Taguchi method is a single response optimization technique which deals with optimizing a single response while it does not takes into account the effect on other performance measures. In this paper, emphasis has been made in optimizing the process parameters of this CNC turning process in machining of Glass-fibre-reinforced plastic (GFRP). GRA aided with fuzzy logic has been applied to above problems so to obtain the optimal parametric combinations in order to further enhance the results than that obtained by past researchers. Lastly ANOVA is also applied to to identify the significance of each process parameters in CNC turning process.

2. Methodology

2.1. Design of experiments

The experiments are designed as per Taguchi’s L₁₈ orthogonal array of experiments with flank wear, cutter wear, surface roughness (Rₜ), and machining force (Fₘₐₓ) as machining responses. The three level variations for each of cutting velocity, feed rate, depth of cut is chosen for this experimentation is shown in Table 1. The experimental results for all the eighteen experiments are shown in Table 2.

2.2. Grey relational analysis

In grey system, the data in the decision matrix are needed to be normalized (data pre-processing) in a range between 0 and 1 so as to make the data dimensionless and comparable. The following expressions are utilized for data pre-processing depending on the type of the considered criterion, i.e. equation (1) for larger-the-better and equation (2) for smaller-the-better type [9, 10].

\[
x'_{i}(k) = \frac{x_{i}(k) - \min x_{i}(k)}{\max x_{i}(k) - \min x_{i}(k)} \quad i = 1, 2, ..., m \text{ and } k = 1, 2, ..., n
\]

(1)

\[
x''_{i}(k) = \frac{\max x_{i}(k) - x_{i}(k)}{\max x_{i}(k) - \min x_{i}(k)}
\]

(2)

where \( x_{i}(k) \) and \( x'_{i}(k) \) are the observed and normalized data respectively for \( i^{th} \) alternative and \( k^{th} \) criterion. After normalization, the grey relational coefficient (GRC) is calculated using equation (3).

\[
\xi_{i}(k) = \frac{\Delta_{min} + \zeta \Delta_{max}}{\Delta_{max}}
\]

(3)

Where \( \Delta_{i}(k) \) is the difference between \( x''_{i}(k) \) and \( x^*(k) \) (\( x^*(k) \) is the ideal sequence). The distinguishing coefficient \( \zeta \) lies between 0 and 1, usually considered as 0.5. \( \Delta_{min} = \bigvee_{j=n}^{m} \bigwedge_{k=1}^{n} \left| x_{i}(k) - x_{j}(k) \right| \) is the smallest value of \( \Delta_{i} \); and \( \Delta_{max} = \bigvee_{j=n}^{m} \bigwedge_{k=1}^{n} \left| x_{i}(k) - x_{j}(k) \right| \) is the largest value of \( \Delta_{i} \). A higher value of GRC for an alternative indicates that it is closer to the optimal solution with respect to a particular criterion. Grey relational grade (GRG) for an alternative is computed by averaging the GRC values corresponding to each criterion using equation (4).

\[
\gamma_{i} = \frac{1}{n} \sum_{k=1}^{n} \xi_{i}(k)
\]

(4)

where \( n \) is the number of criterion. A higher value of GRG indicates that the corresponding alternative is the best choice for the said application.

2.3. Fuzzy logic in grey relational analysis

Fuzzy set deals with imprecise and inadequate information in an efficient way to arrive at a logical conclusion for any decision making problem. Fuzzy set theory states that, in a universe of discourse \( X \), a fuzzy subset \( \tilde{A} \) of \( X \) is defined by a membership function \( f_{\tilde{A}}(x) \), which takes each element \( x \) in \( X \) to a real number \( R \) in the interval of \([0,1]\). The function value \( f_{\tilde{A}}(x) \) represents the grade of membership of \( x \) in \( \tilde{A} \). The larger the value of \( f_{\tilde{A}}(x) \), the stronger is the grade of membership for \( x \) in \( \tilde{A} \).
In GRA, the use of lower-the-better and higher-the-better characteristics results in some uncertainty in the derived results which can be effectively controlled using fuzzy logic. A fuzzy logic unit consists of a fuzzifier, fuzzy membership functions, a fuzzy rule base, an inference engine and a defuzzifier. In the fuzzy logic, the membership functions are the inputs to the fuzzifier in order to fuzzify the GRC values. The inference engine performs a fuzzy reasoning of the developed fuzzy rules to generate a fuzzy value. The defuzzifier finally converts the fuzzy value into an understandable value known as grey fuzzy reasoning grade (GFRG). A fuzzy rule base comprising a set of if-then control rules is developed to represent the inference relationship between the input and output. A set of such fuzzy rules is provided as below:

Rule 1: if \( x_1 \) is \( A_1 \) and \( x_2 \) is \( B_1 \) and \( x_3 \) is \( C_1 \) and \( x_4 \) is \( D_1 \), then output \( (G) \) is \( e_1 \), else

Rule 2: if \( x_1 \) is \( A_2 \) and \( x_2 \) is \( B_2 \) and \( x_3 \) is \( C_2 \) and \( x_4 \) is \( D_2 \), then output \( (G) \) is \( e_2 \), else

Rule \( n \): if \( x_1 \) is \( A_n \) and \( x_2 \) is \( B_n \) and \( x_3 \) is \( C_n \) and \( x_4 \) is \( D_n \), then output \( (G) \) is \( e_n \). (5)

where \( A_i \), \( B_i \), \( C_i \) and \( D_i \) are the fuzzy subsets defined by the corresponding membership functions, i.e. \( \mu_{A_i} \), \( \mu_{B_i} \), \( \mu_{C_i} \) and \( \mu_{D_i} \), respectively. The inference engine performs fuzzy reasoning on fuzzy rules while taking max-min inference to generate a fuzzy value, \( \mu_{G_i}(G) \).

\[
\mu_{G_i}(G) = (\mu_{A_i}(x_1) \land \mu_{B_i}(x_2) \land \mu_{C_i}(x_3) \land \mu_{D_i}(x_4) \land \mu_{G_i}(G)) \lor \ldots \ldots .
\]

\[
(\mu_{A_i}(x_1) \land \mu_{B_i}(x_2) \land \mu_{C_i}(x_3) \land \mu_{D_i}(x_4) \land \mu_{G_i}(G)) \lor \ldots \ldots .
\]

\[
(\mu_{A_i}(x_1) \land \mu_{B_i}(x_2) \land \mu_{C_i}(x_3) \land \mu_{D_i}(x_4) \land \mu_{G_i}(G))
\]

where \( \land \) and \( \lor \) is the minimum and maximum operation. Finally, a central fuzzification method is utilized to transform the fuzzy multi-response output, \( \mu_{G_i}(G) \) into a crisp value of GFRG \( (G_0) \).

\[
G_0 = \frac{\sum G \mu_{G_i}(G)}{\sum \mu_{G_i}(G)}
\]

The GFRG values are then arranged in descending order. The alternative with the maximum value of GFRG signifies it to the best choice with respect to a set of criteria/attributes.

3. Results and discussion

3.1. Grey-fuzzy analysis

The pre-processed data of experimental results is done using equation (1) and (2) where MRR is of ‘higher-the-better’ characteristics and TWR, RWR and SR is of ‘lower-the-better’ characteristics. GRC and GFRG values are calculated using equation (3) and (4) and the results for each of the combination of parameters is given in table 3. In order to obtain an improved quality in the performances and to decrease the vagueness in the data, grey-fuzzy logic method is additionally used for computing the GFRG. In this paper, four inputs (GRC) and one output (GFRG) fuzzy-logic system is used as shown in figure 1. Mamdani inference engine is used which performs fuzzy reasoning with fuzzy rules for generating a fuzzy value [18]. In total 9 fuzzy rules is developed based on ‘if-then’ control rule that shows inference relationship between the input GRC and output GFRG. One of such rule is depicted below.

If Flank wear= Highest, Crater wear= Lowest, \( \text{R}_c \) = Highest and \( F_m \) = High, then GFRG = Highest.

GRC values of cutter wear, flank wear, \( \text{R}_c \) and \( F_m \) are the inputs to the fuzzy logic system. The linguistic membership function for instance lowest (LT), low (L), medium (M), high (H) and highest (HT) are used to represent GRC of input variables. Likewise the output GFRG is being represented by the membership functions such as lowest (LT), very low (VL), low (L), medium low (ML), medium (M), medium high (MH), high (H), very high (VH), highest (HT). In this study triangular shaped membership function to define these membership functions and are shown in figure 2 and 3. The rule-based fuzzy-logic reasoning is shown in figure 4. Maximum–minimum compositional operation by tracking the fuzzy reasoning yields a fuzzy output. At last, the defuzzifier converts the fuzzy predicted values into a crisp GFRG value by using MATLAB (R2013a) fuzzy toolbox. This GFRG values are
tabulated in table 3. It can be seen from the table that experiment number 1 is having the highest GFRG value signifies it to be most preferred.

![Diagram of Fuzzy System](image1)

**Figure 1:** Four input–one output fuzzy system

![Input Membership Function](image2)

**Figure 2:** Input membership function

![Output Membership Function](image3)

**Figure 3:** Output membership function
Figure 4: Rule viewer

Table 3: Normalized data, GRC, GRG and GFRG

| Exp. No. | Flank Wear (mm) | Crater Wear (mm) | R_a (μm) | F_m (N) | Flank Wear (mm) | Crater Wear (mm) | R_a (μm) | F_m (N) | GRG | GFRG |
|----------|----------------|------------------|----------|---------|----------------|------------------|----------|---------|-----|------|
|          | Normalized Data | Grey relational coefficient |          |         |                |                   |          |         |     |      |
| 1        | 0.8205          | 1                 | 0.3333   | 0.7358  | 0.7673         | 0.753           | 0.5255   | 0.5294  |     |      |
| 2        | 0.3058          | 1                 | 0.4286   | 0.3346  | 0.5008         | 0.505           | 0.4816   | 0.4993  |     |      |
| 3        | 0.4043          | 1                 | 0.6151   | 0.4563  | 0.6659         | 0.656           | 0.5214   | 0.5071  |     |      |
| 4        | 0.5207          | 1                 | 0.6515   | 0.8058  | 0.5630         | 0.556           | 0.4524   | 0.4392  |     |      |
| 5        | 0.6238          | 1                 | 0.6563   | 0.8058  | 0.5630         | 0.556           | 0.4524   | 0.4392  |     |      |
| 6        | 0.3865          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
| 7        | 0.5478          | 0.6               | 0.3874   | 0.5996  | 0.5337         | 0.529           | 0.5337   | 0.529   |     |      |
| 8        | 0.3913          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
| 9        | 0.5478          | 1                 | 0.3874   | 0.5996  | 0.5337         | 0.529           | 0.5337   | 0.529   |     |      |
| 10       | 0.6661          | 0.6               | 0.3874   | 0.5996  | 0.5337         | 0.529           | 0.5337   | 0.529   |     |      |
| 11       | 0.3728          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
| 12       | 0.3728          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
| 13       | 0.3728          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
| 14       | 0.3728          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
| 15       | 0.3728          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
| 16       | 0.3728          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
| 17       | 0.3728          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
| 18       | 0.3728          | 0.75              | 0.3981   | 0.5018  | 0.5091         | 0.508           | 0.5091   | 0.508   |     |      |
Table 3 and figure 5 shows the response table and corresponding graph for GFRG. It is obtained by calculating the average value of each input machining parameter at its corresponding level. The max–min column indicates that depth of cut is the most significant factor among the three input parameters. In order to obtain the best responses, the optimal combination of the parameters as depicted from the table shows that all the three input parameters i.e cutting velocity, feed rate, depth of cut must maintained at level 1 respectively. Analysis of variance is also carried out for this problem and the results are presented in table 5. In this analysis, it can be seen from the table that depth of cut has a p-value less than 0.05 which indicates it to be a significant parameter at 95% confidence level thus validating the above made conclusion.

Table 4: Response table of GFRG

| Parameters       | unit | levels | Max-Min | Rank |
|------------------|------|--------|---------|------|
| Cutting velocity | m/min| 1      | 0.6198  |      |
| Feed rate        | mm/rev| 2      | 0.5925  |      |
| Depth of cut     | mm   | 3      | 0.5347  |      |

Figure 5: Response graph for GFRG

Table 5: ANOVA for GFRG

| Source          | DoF | Adj SS  | Adj MS  | f-value | p-value |
|-----------------|-----|---------|---------|---------|---------|
| Speed           | 2   | 0.013840| 0.006920| 1.99    | 0.183   |
| Feed rate       | 2   | 0.003733| 0.001867| 0.54    | 0.599   |
| Depth of cut    | 2   | 0.051919| 0.025959| 7.48    | 0.009   |
| Error           | 11  | 0.038198| 0.003473|         |         |
| Total           | 17  | 0.107690|         |         |         |

3.2. Predicted GFRG

Optimum level of machining input parameters obtained from GFRG is A1 B1 C1 which differs from the obtained parameter settings by past researchers. The predicted GFRG for the parametric combination can be estimated using the formulae.

\[
G_p = G_m + \sum_{i=1}^{N} (G_i - G_m)
\]

where, \(G_p\) is the predicted GFRG, \(G_m\) is the mean GFRG for all the 18 experiments, \(G_i\) is the mean GFRG of the corresponding optimal response and \(N\) is the total number of input parameters. As shown in table...
the predicted GFRG for both the previous and obtained input parametric combinations signifies that there is an improvement in the GFRG value from 0.6190 to 0.7059, which equals to 0.089 i.e. improvement by 14%.

Table 6: Comparison table for initial and obtained input parameters

| Levels          | Machining parameters previously obtained | Optimum machining parameters by our method |
|-----------------|------------------------------------------|-------------------------------------------|
| A3 B3 C2        | Speed= 115m/min, Feed rate= 0.1mm/rev and Depth of cut= 0.5mm | Speed= 100m/min, Feed rate= 0.05mm/rev and Depth of cut= 0.5mm |
| GFRG            | 0.6190                                   | 0.7059                                    |
| Improvement in GFRG |                                          | 0.0869                                    |
| % improvement   |                                          | 14.04                                     |

4. Conclusion

Thus from the above analysis it was found that at Cutting velocity 100m/min, Feed rate= 0.05mm/rev and Depth of cut= 0.5mm is the optimal combination. It is also verified by the predicted results that the parametric combination found by the adopted approach significantly increases the output performance by 14%. Therefore, it is concluded that the optimization procedure proposed in this present paper significantly improved the turning of Glass-fibre-reinforced plastic (GFRP) by CNC turning process.

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