Optimization of Magnetic Abrasive Finished Aluminum 2024 alloy Using Jaya Algorithm, Genetic Algorithm and Grey Relational Analysis

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Abstract

Magnetic Abrasive Finishing (MAF) is one of the advanced finishing processes that produce a surface finish at the nano scale for magnetic and non-magnetic materials. The surface finish of the material can be enhanced significantly by optimizing the major process parameters of MAF process. The present paper investigates the optimization of MAF process parameters. Grey relational analysis (GRA), Genetic algorithm (GA) and the Jaya Algorithm (JA) were used and compared to analyze the best optimum solution for MAF process parameters while processing aluminum 2024 alloy (Al 2024) plate. The process parameters such as voltage (V), speed of the electromagnet (RPM) and weight ratio of abrasives (%) were considered as input variables, whereas percentage improvement of surface finish (%ΔR_a) was considered as response. Based on the literature and trial experiments, the range of each process parameters were decided and L9 orthogonal array was designed. The analysis of variances (ANOVA) analysis and regression equation were obtained with the help of Minitab17 software. The regression equation was used to get the optimum set of process parameters using GRA, GA and JA algorithms. These optimum results were compared and JA was shown to be the best optimization technique, which gave the best optimum solution.

Keywords: Magnetic abrasive finishing; Aluminum 2024 alloy; Grey relational analysis; Genetic algorithm; Jaya algorithm; Surface finish

1. Introduction

Surface finish is highly important in different industrial processes. However, traditional methods to design advanced materials is a challenging task and it is difficult to process tough materials. Therefore non-conventional finishing processes such as Magnetic abrasive finishing (MAF), Abrasive Flow Machining (AFM), and Electro Chemical Honing etc. have been developed in recent years [1]. MAF process is one among them which is an alternative to conventional machining processes. MAF process is becoming more important due to its capability to achieve good surface finish up to nano level. Optimization is required to improve the surface finish of the products, and to reduce the machining costs and increase the machining effectiveness, it is very important to select the optimum process parameters to improve the effectiveness of MAF process[2]. Many advanced optimization techniques have been developed by researchers based on the population in the past two decades. Researchers have widely applied these heuristic algorithms to solve complex engineering optimization problems of continuous and discrete nature. Greyscale (GRA) analysis based on grayscale analysis can be used to effectively solve complex interrelationships between different functions [3]. Grey analysis provides a grey correlation score to evaluate multiple functions. Therefore, the optimization of complex multiple power functions can be converted to optimization of a single relationship grey level. Genetic algorithm (GA) is one of the basic optimization techniques in which the best solution is obtained by comparing each candidate group's best value in the entire search. This process mainly works based on the survival of fittest by comparing individuals[4]. GA does not depend on initial conditions, it gives a robust global solution. Jaya algorithm (JA) was first developed by Rao for solving both unconstrained and constrained problems. It gives better results for many problems compared to other optimization techniques. Jaya algorithm (JA) is one of the population-based optimization techniques. The key feature of JA is that it depends on only two parameters, size of the population and the number of iterations. The beauty of this algorithm is it gives the optimal solution and it reduces the worst solution in the same iteration[5].

Yan et al. [6]investigated the optimization of machining parameters of magnetic force assisted EDM process using grey relational analysis. They also reported the influence of optimum input machining parameters on responses material removal rate (MRR), electrode wear rate (EWR) and surface roughness. The researchers also observed that the most influencing optimum input parameters are peak current, pulse duration and voltage. The optimization of process parameters of dry drilling process for machining of Ti-6Al-4V material using grey relational analysis was studied by Prasanna et al.[7]. They reported spindle speed and air pressure have the most significant impact on the dimensional accuracy of the hole;the investigators also reported that spindle speed and feed rate control the thrust force. Durairaj et al. [8] noticed that for multi objective optimization, grey relational analysis was one of the best optimization techniques. As a result, the optimized input parameters for both objectives (surface finish and kerf width) are 50V voltage, 233/min wire feed, 4µs for both pulse on time and pulse of time. They also conducted Taguchi's optimization for individual objectives and ANOVA analysis for finding out the most influential input parameter. As a result, they observed that the most influencing process parameter for minimization of both objectives is pulse on time. The influence of input parameters on joining Inconel -625 through microwave hybrid heating was investigated by Ravindra et al. [9]. They optimized the microwave process using grey relation analysis for finding out the optimum input parameters for maximizing the responses (ultimate tensile strength, flexural strength). The researchers also conducted ANOVA analysis and observed that the most significant factor for improving bond strength is size of the interface filler powder. Doriana et al. [10]. investigated the genetic algorithm-based optimization of cutting parameters in turning processes. They reported that genetic algorithm gives near optimum solution in less time and it can be applied for any complex machining processes. The investigators also tried to compare the genetic algorithm with other optimization techniques. A multi objective genetic approach to domestic load scheduling in an energy management system was investigated by Soares et al. [11]. As a result of that, they modified existing genetic algorithm into NSGA-II (non-dominated sorting genetic algorithm). They also observed the global solutions of both GA and NSGA-II and reported NSGA-II gave better results compared to existing GA. Sreenivasan et al. [12] optimized the processes variables of friction welding process for AA7075-SiC composite using GA. The researchers reported that the responses at optimum process parameters are hardness and ultimate tensile strength. They also observed that when using genetic algorithm for multi objective optimization the computation time was very less and global optimum solution was obtained in fewer iterations. The optimization of surface grinding process using JA was studied by Rao et al. [13]. They compared the JA results with other optimization techniques such as GA, PSO, ABC, TLBO etc. The researchers also observed that computation time and number of generations required for JA very few compared to other techniques. Rao et al. [14] investigated the optimization of submerged arc welding process parameters using quasi-oppositional based Jaya algorithm (QO – JA). As a result, they compared the results of JA and QO- JA with GA, PSO, TLBO and Imperialist competitive algorithm (ICA). They observed both JA and QO-JA showed better results compared to other optimization techniques in terms of obtaining optimum solutions in less generations. The researchers also compared JA and QO-JA results, where QO-JA showed faster convergence time compared to JA.

From the literature review, some of the experimental studies reported on MAF process for finishing of different materials (EDM, Drilling, Wire EDM etc..) while others focused on experimental studies with regard to different hybrid MAF processes (Turning, scheduling, welding etc.…) for better surface finish improvement. Some of the numerical studies validating experimental results focused on materials (Surface grinding, Welding, EDM etc.) Very few researchers have reported the comparison of surface finish capabilities of magnetic and nonmagnetic materials and the effect of different process parameters on surface finish improvement (ΔR_a). The objectives of the present work are (i) to design experiments on nonmagnetic material (Al 2024 ally) using orthogonal array L9 by varying various parameters such as percentage (%) weight of abrasives (20-30%), speed of the electromagnet (1000-2100 rpm) and supply voltage to electromagnet (30-50 V) (ii) to conduct the analysis of variances (ANOVA) with the help of Minitab 17 software in order to find out the most influential parameters to obtain better surface finish of materials (iii) to optimize the regression equation using commonly used optimized techniques GRA,GA and JA (iv) to compare three optimization techniques based on their optimum solution value.

2. Experimental details

In this experiment, a vertical milling machine was used in which the experimental MAF setup designed is shown in Fig. 1. The workpiece can be moved horizontally or vertically based on the requirement. The electromagnet is placed in the place of spindle and external power is supplied with the help of dimmer stat. The dimmer stat is used to change the magnetic flux of the electromagnet with the help of slip ring, attached to an electromagnet. Work piece dimensions of 10 × 10 × 0.8 cm and SiC abrasives of 400 mesh size and 600 mesh size magnetic particles were used. Magnetic abrasive finishing (MAF) process consists of a flexible magnetic abrasive brush (FMAB) composed of abrasive particles and magnetic particles which are used for fine finishing of metallic and nonmetallic materials. The working principle of MAF consists of an FMAB formed between the workpiece and the electromagnet in this process.

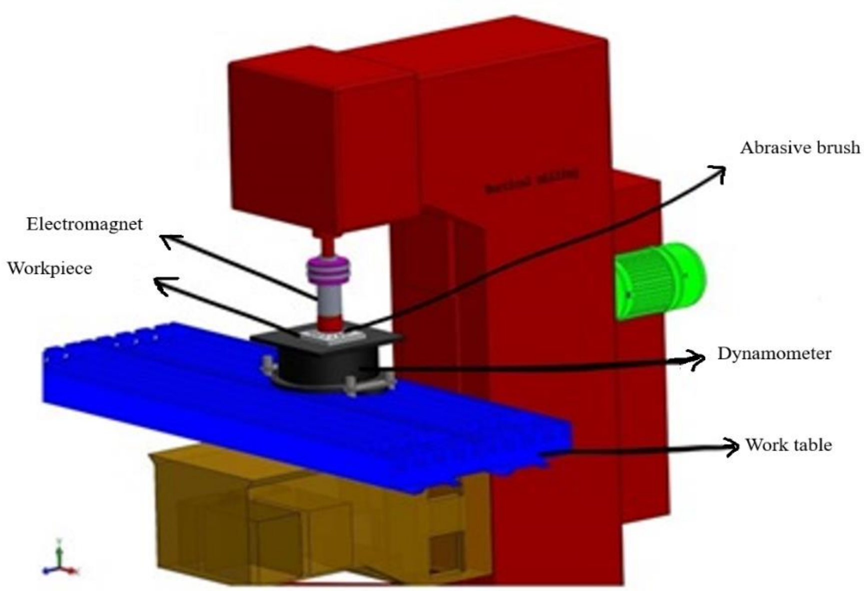

Fig. 1: MAF set up on a vertical milling machine

2.1 Design of experiments

In most practical studies, the design of the experiment is a very important step. The purpose of experimenting is to establish the relationship between process parameters and response or output. In the present work, orthogonal arrays L9 design is used for the analysis [15]. The levels and the parameter ranges are given in Table1, and the results obtained are given in Table 2. The ANOVA and regression analysis of the obtained results were computed using minitab17 and presented in Table 3. It is observed that input parameters that exercise high impact on response are the speed of the electromagnet, voltage and abrasive % based on their P- Values as mentioned. The values of obtained R-sq., Adj. R- Sq., Pred. R- sq. value shows the model is fit and acceptable.

Table 1. Parameters and levels

	Level 1	Level 2	Level 3
% of Abrasives (C1)	20	180	30
Speed of electromagnet, C2 (RPM)	25	350	40
Voltage, C3 (V)	30	500	50

The change in surface finish value of each experiment is calculated by the below equation [16].

$$\%\Delta R_a = \frac{Final\ R_a - Initial\ R_a}{Final\ R_a} \times 100 \tag{1}$$

Table 2. Experimental results based on orthogonal array L9.

S. No	C_1	C_2	C_3	$\%\Delta R_a$
1	20	1000	30	17.00
2	20	1400	40	33.25
3	20	2100	50	59.00
4	25	1000	40	25.50
5	25	1400	50	44.65
6	25	2100	30	38.45
7	30	1000	50	37.00
8	30	1400	40	38.25
9	30	2100	30	42.50

Table 3. The ANOVA of process parameters

Source	DF	Adj. SS	Adj. MS	F- Ratio	P-Value
C_1	2	17.38	8.689	3.20	0.0238
C_2	2	684.81	342.404	126.30	0.008
C_3	2	480.99	240.496	88.71	0.0011
Error	2	5.42	2.711		
Total	8	1525.20			
Model Summary	S	**R- Sq.**	**Adj. R- Sq.**	**Pred. R- Sq.**	
	1.26	0.9896	0.9834	0.9565	
Regression equation	**C_4 = -39.44 - 0.127 C_1 + 0.01888 C_2 + 1.2169 C_3**				

Based on the ANOVA analysis the most effecting input parameters on response are C_2, C_3, and C_1

2. 2 Optimization of Process parameters

Optimization of cutting parameters is often a daunting task [17], which requires the following aspects: empirical equations related to tool life, force, performance, surface finish, etc. One needs to develop realistic constraints; machine tool capability specifications, effective optimization criteria and knowledge of mathematical and numerical optimization techniques. In each optimization process, the most important result must be determined, the so-called optimization goal or optimization criterion. The most commonly used optimization criteria in the production process are the specific costs incurred by researchers. Gray's theory can provide solutions for systems with insecure models or incomplete information. It also provides an effective solution to the problem of uncertainty, multiple inputs and discrete data. Gray's relationship analysis can be used to determine the relationship between processing parameters and performance[18]. Genetic algorithms have received wide attention as a powerful method for optimizing multiple targets, because genetic algorithms can develop a population of solutions for generations that are not characterized by the exploration of complex research spaces and the use of genetic resources. The use of GA to solve a specific problem involves the correct design of the solution (coding), elimination of operators, fitness functions and constraints; this is needed in order to obtain an effective method with satisfactory results[19]. Due to the nature of the problem and the goal of assigning load operations during the planning period, the individual (solution) consists of n genes. Jaya algorithm that does not require any adjustments to specific algorithm parameters. The algorithm is simple to apply, uses an equation to update the solution, and values the best and worst solutions in the current population. JA has good exploration and utilization capabilities.

2.2.1 Jaya algorithm

A JA doesn't require any algorithm-based parameters, it requires only two tuning parameters population size and number of variables. The simple JA follows the following steps to optimize for any complex constrained and unconstrained machining processes.

Step1. Initialize the population size, number of variables

Step 2. Find the $f(x)$ values for each population and tabulated, also note the $f(x)_{best}$ and $f(x)_{worst}$ values.

Step 3. For maximization case the highest $f(x)$ value taken as $f(x)_{best}$ and in case of minimization case lowest $f(x)$ value taken as $f(x)_{best}$.

Step 4. Calculate new variables values based on the below equation [20]

$$X_{i\ new} = X_{i\ old} + r_1 (X_{i\ best} - |X_{i\ old}|) - r_2 (X_{i\ worst} - |X_{i\ old}|) \quad (2)$$

Step 5. Calculate new $f(x)$ values for new variables with same population size and tabulated

Step 6. Check condition $f(x)_{new} > f(x)$ values

Step 7. Compare the two tables $f(x)$ values and condition in step 6 are tabulated in new table.

Step 8. Repeat the steps from 4 to 7 for next iteration up to termination criteria.

The Jaya Algorithm flowchart is shown in Fig. 2

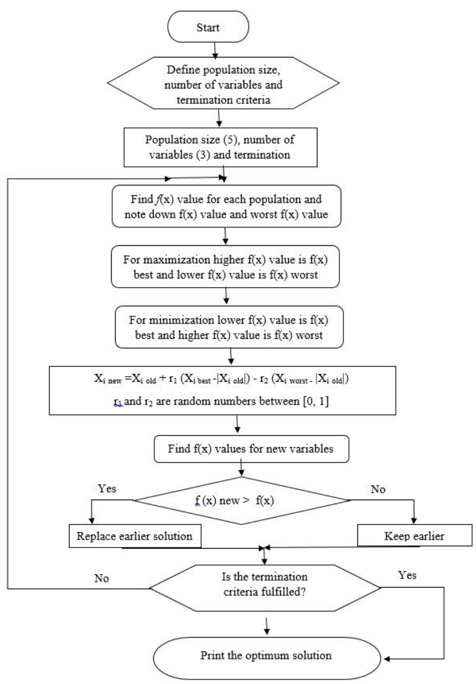

Fig. 2: Flow chart of JAYA Algorithm

2.2.2 Genetic Algorithm

The genetic algorithm iterations consist of three steps: selection, crossover, and Mutation. They form the core of genetic algorithms with powerful research capabilities. They are the primary carriers for natural selection and reproduction simulation. Hybridization and mutations occur during genetic processes [21].Get the best optimum solution for any complex problem. GA method is escribed in detail below.

1. You must choose a type of code that represents the most influential parameters in MAF process
2. GA parameters are to be carefully selected, such as the length of the chromosome, the size of the population, the selector, the crossover operator, the crossover probability, the mutation probability, and the adaptive parameters.
3. Initialize the process by randomly generating the overall scale chain required for the problem parameters within the defined limits.
4. Select the allowed algebra or maximum number of iterations. Set i= 0.
5. Process variables must be decoded from binary to decimal.
6. To evaluate each string, a regression equation must be used to construct the fitness function to predict the objective function, such as surface finish improvement.
7. When the objective function reaches the optimum value or i > i max, take the optimum solutions for next generation
8. Reproduce new population.
9. The crossing between the two randomly selected chains at the selected intersection has a probability of crossing.
10. Mutations occur in the entire population chain with the possibility of mutation.
11. Decode the new overall chain according to steps 5 and 6. The iteration value is incremented by i = i + 1 to indicate the end of the corresponding iteration and the process of step 7 is repeated.

The flow chart of genetic algorithm as shown in Fig. 3

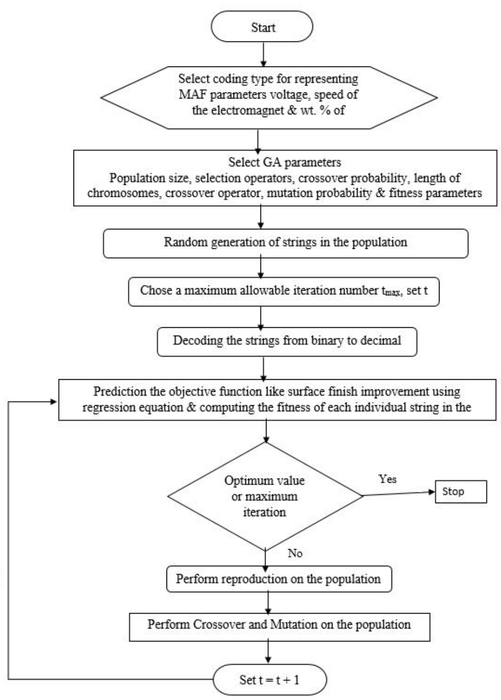

Fig. 3: Flow chart of Genetic Algorithm

2.2.3 Grey Relational Analysis

Grey relational analysis (GRA) is an effective analysis method to get optimum relation between input parameters and responses of any machining process. It is also used to obtain better results for complex relationships between multi-objective functions. That explains the relationship between input parameters (voltage, speed of the electromagnet and wt. % of abrasives) and response surface finish improvement of MAF process. Based on grey theory, systems can be examined through quantification, modeling, forecasting, and relationship decisions.

- Normalization of date is required to compare it with any other response due to the difference in size or magnitude. The conversion formula is given by [22]. The% of improvement of surface finish is higher the better criterion

  $$x_i^*(k) = \frac{x_i(k) - min\, x_i(k)}{max\, x_i(k) - min\, x_i(k)} \quad (3)$$

- According to the proposed problem, maximum surface finish improvement is required. Absolute deviation is determined as follows:

  $$\Delta_{0i} = \|x_o(k) - x_i(k)\| \quad (4)$$

  Difference of absolute value $x_o(k)$ and $x_i(k)$

  Here $x_o(k)$ =1, let delta=difference of absolute value

- Calculation of Grey Correlation Coefficient: This relationship essentially represents the difference in the geometry of the curve, so the difference value of the curve can be used as a criterion for evaluating the relevant grey level. The formula for calculating gamma is as follows:

  The Grey relational coefficient $\xi_i(k)$ is

$$\xi_i(k) = \frac{\Delta_{\min} + \psi\Delta_{\max}}{\Delta_{0i}(k) + \psi\Delta_{\max}} \quad (5)$$

  Ψ is the distinguishing coefficient $0 \le \psi \le 1$

  $\Delta min^{min\|x_o(k)-x_j(k)\|}{}_{min}$=the smallest value of Δ_{0i}

  $\Delta max^{max\|x_o(k)-x_j(k)\|}{}_{max}$= the largest. Generally, $\psi=0.5$

- The grey relational grade (GRG) γ_i can be computed as

  $$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \quad (6)$$

- Ranking based on GRG value close to 1

3. Results and Discussions

3. 1 Optimization of MAF process parameters

3.1.1 Jaya Algorithm

In the present study, the parameters bound chosen are as given below

$20 \le C_1 \le 30$ (7)

$1000 \le C_2 \le 2100$ (8)

$30 \le C_3 \le 50$ (9)

Whereas the objective function is:

$F(x) = \%\Delta R_a = C_4 = -39.44 - 0.127\, C_1 + 0.01888\, C_2 + 1.2169\, C_3$ (10)

Jaya Algorithm is applied with the help of MATLAB 201a. The initial population size was taken as 5 and the number of iterations was taken as 50. The random numbers considered for each input variable are taken between 0 to 1. After the application of Jaya algorithm to the objective function F(x) the initial solution is noted in Table 4 and first and second iterations are noted in Table 5 and Table 6. The final optimal solution is obtained in just 3 iterations and the optimum values are given in Table 7.

Table 4. Initial values consider for JA

Population	C_1	C_2	C_3	$\%\Delta R_a$	
1	23	1200	32	19.2358	**f worst**
2	24	1500	36	29.6404	
3	21	1000	47	33.9673	
4	20	1800	41	41.8969	
5	30	2000	43	46.8367	**f best**

In Table 4, C_1, C_2 and C_3 values are taken randomly between operating ranges C_1 [20 to 30], C_2 [1000 to 2100] and C_3 [30 to 50]. The new parameters are calculated based on equation 2

$X_{i\ new} = X_{i\ old} + r_1 (X_{i\ best} - |X_{i\ old}|) - r_2 (X_{i\ worst} - |X_{i\ old}|)$

Table 5. First iteration after applying JA

Population	C_1	C_2	C_3	$\%\Delta R_a$	
1	24.89	1504	38.38	32.49911	**f worst**
2	25.85	1843	43.3	44.76466	
3	22.97	1278	50	42.61645	
4	22.01	2100	49.45	57.58844	**f best**
5	30	2100	50	57.243	

The new parameters are calculated based on equation 2 and noted in Table 5. The r_1 and r_2 values were taken for C_1, C_2 and C_3 are [0.27, 0.23], [0.38, 0.51] and [0.58, 0.81]. The $f(x)_{worst}$ and $f(x)_{best}$ values showed improvement compared to initial solution such as $f(x)_{best}$ value from 46.84 to 57.58 and $f(x)_{worst}$ value from 19.23 to 32.49.

Table 6. Second iteration after applying JA

Population	C_1	C_2	C_3	$\%\Delta R_a$	
1	23.6516	1706.64	47.0146	46.98968	
2	24.794	2100	50	57.90416	
3	21.3668	1435.44	50	45.79252	**f worst**
4	20.2244	2100	50	58.4845	**f best**
5	29.7325	2100	50	57.27697	

The new parameters are calculated based on equation 2 and shown in Table 5. The r1 and r2 values were taken for C_1, C_2 and C_3 are [0.43, 0.62], [0.34, 0.54] and [0.78, 0.84]. The $f(x)_{worst}$ and $f(x)_{best}$ values also improved compared to initial solution such as $f(x)_{best}$ value from 57.58 to 58.48 and $f(x)_{worst}$ value from 32.49 to 45.79.

Table 7. Final optimum values after applying JA

Population	C_1	C_2	C_3	$\%\Delta R_a$	
1	30	2100	50	60.989	
2	30	2100	50	60.989	
3	30	2100	50	60.989	**f worst**
4	30	2100	50	60.989	**f best**
5	30	2100	50	60.989	

Figure 4 shows variations between optimum value for the number of generations. From the graph, optimum surface finish was observed after 2 generations and the optimum value is 60.989.

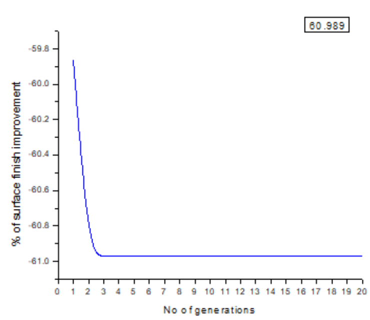

Fig. 4: variation of optimum value and number of generations

3.1.2 Genetic Algorithm

GA was applied with the help of an optimization toolbox using MATLAB 2014a. After the application of GA to **the objective function**, the optimum parameters and their levels were noted. Fig. **5** shows a converged plot for the % of surface finish improvement and no. of generations. It is revealed that optimum surface finish was observed after 200 generations and the optimum value is 60.969. In this work the same optimum input parameters ware observed for both Jaya and GA technique. Performance improvements were verified based on the optimal level of MAF process parameters. The optimum process parameter levels can be calculated while considering only those process parameters that have a significant impact on performance characteristics. Table 8 shows the comparison of test results with optimal process parameters. The conformation runs were conducted at optimum input parameters and average response value was taken and compared with predicted values of Jaya and GA in Table 8.

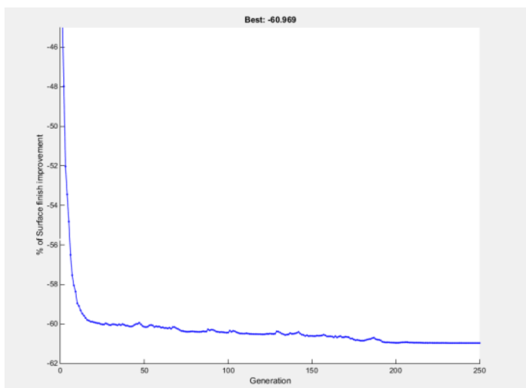

Fig. 5: variation of optimum value and number of generations by using GA

Table 8: confirmation experiments are conducted at optimum parameters using JA and GA also observed the % of the error

C_1	C_2	C_3	$\%\Delta R_a$			%Error	
			Actual	Predicted		Compared	
				GA	JA	GA	JA
30	500	50	60.95	60.968	60.968	0.3	0.29

3.1.3 Grey Relational Analysis

In this present work, Maximization of $\%\Delta R_a$ is GRA required and the steps are followed based on**.** Based on GRG ranking, 3rd experiment was considered the optimal best treatment compared to other treatments listed in Table 9.

Table 9: GRA to table 2 the result shown in the table along with ranking

S. No	C_1	C_2	C_3	$\%\Delta R_a$	GRG Rank
1	20	1000	30	17.00	9
2	20	1400	40	33.25	7
3	20	2100	50	59.00	1
4	25	1000	40	25.50	8
5	25	1400	50	44.65	2
6	25	2100	30	38.45	4
7	30	1000	50	37.00	6
8	30	1400	40	38.25	5
9	30	2100	30	42.50	3

The optimum average GRG value at each factor for different level are noted in Table 10. The average GRG value at each level represents the impact of each factor on surface finish improvement. By comparing each factor with another factor, it can estimate which level of each factor is optimum.

Table 10: Average gray relational grade at each level of the factor

Factor	Average GRG at different levels for each factor		
	1	2	3
C_1	0.594167	0.494932	0.517122
C_2	0.402342	0.515417	0.688472
C_3	0.466249	0.445838	0.694144

Figure 6 shows the impact of each input factor on surface finish improvement at each level based on average GRG value. Based on Fig 6 the most influential input parameter on response is speed of the electromagnet in descending order from 2100, 1400 and 1000 rpm and voltage in descending order 50, 40 and 30 V.

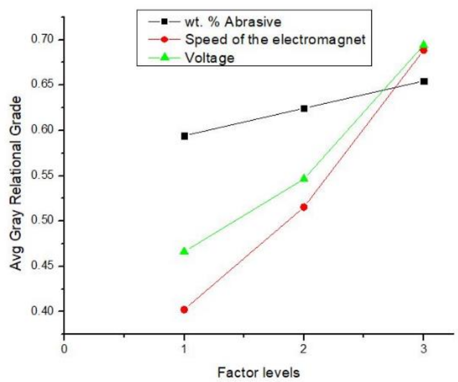

Fig. 6: Avg grey relational grade at each level of the factor

4. Conclusions

In the present paper,

- Magnetic abrasive finishing (MAF) process is a versatile finishing process for both metals and non-metals.
- MAF process parameters have great effect on %ΔR_a; improvement and optimum parametric input parameters selection is also important for getting the desired response.
- Mathematical modelling was done using L9 orthogonal array technique for %ΔR_a. The objective equation and ANOVA analysis was done by Minitab 17.
- Optimal parametric settings were obtained by JA and GA algorithms: for maximization of % ΔR_a it is: voltage (V) = 30 V, speed of the electromagnet (rpm) = 2100 rpm, % of abrasives (%) = 30 % and the output response value 60.968 %
- GA result is very close to actual response value for this particular problem. But it took almost 200 iterations to get global optimum value of 60.968. However, with JA within 2 iterations the optimum result was observed as 60.969.
- GRA always gives comparatively optimum value compared to other values.
- JA and GA algorithms are found to be very effective to optimize the MAF process and to get global optimum value; GRA is found to be very effective for getting local optimum value.

- From the grey relational grade, the most influential parameters on surface finish improvement are speed of the electromagnet and voltage.
- Compared to GRA, GA and JA, the JA optimization is best compared to other techniques in terms of best optimum solution in fewer number of iterations.

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