

Exploration of GRA Based Multiobjective Optimization of Magnetic Abrasive Finishing Process using Simulated Annealing

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Magnetic abrasive finishing (MAF) process is an advanced super-finishing process that is capable of achieving surface-finish in micro to nano range. In this study a hybrid module, Taguchi based grey relational analysis (GRA) coupled with simulated annealing (SA) approach is developed for multi-objective optimization of micro-finished aluminium 6060 via MAF process. The performance responses 'change in roughness', 'raise in temperature' and 'change in hardness' are considered to minimize their impact on micro-finished aluminium 6060. These responses are used to calculate the grey relational coefficient for individual response and are then converted into a single response variable i.e. grey relational grade (GRG) value. The meta-heuristic based simulated annealing algorithm is used to predict the most desired process parameter setting i.e. working gap (2 mm), abrasive weight (15 g), voltage (6 V) and rotational speed (50 rpm). This setting has been selected based on the highest GRG value predicted by hybrid Taguchi based SA-GRA approach..

Keyword: *Magnetic abrasive finishing, Surface roughness, Surface temperature, Hardness, Grey relational analysis, Simulated annealing.*

1. INTRODUCTION

Magnetic abrasive finishing process was introduced to improve the surface texture of novel materials such as metals-composites, superalloys and ceramics [1]. This process uses the magnetic field to control the flexible magnetic abrasive brush (FMAB) responsible for removal of material from the target surface. FMAB is formed with the alignment of magnetic particles (ferrous particles) and abrasive particles (alumina, silicon carbide) under the magnetic field in the working gap. Magnetic abrasive particles arrange themselves in the form of FMAB in a magnetic field due to their ferromagnetic nature, the strength of FMAB depends on the magnetic flux density in the working gap. Finishing is achieved when these magnetic abrasive particles are placed into working gap between target surface and magnetic poles [2]. Finishing is achieved by relative motion between target surface and FMAB [3]. This FMAB acts as multi-point cutters which removes the material from the surface in form of micro-chips. During finishing a substantial amount of heat is generated on the target surface due plastic deformation, fracture and frictional heat. This heat might affect the surface integrity of workpiece target surface and basic aim is to minimize the generated heat. Hardness is another surface property which affect the surface quality of workpiece surface

To understand the effects of surface temperature on

the target surface of workpiece, both theoretical and experimental studies was done. Komanduri et al. did theoretical temperature analysis using silicon nitride ceramic (Si_3N_4) workpiece and chromium oxide (Cr_2O_3) abrasive particles to derive a thermal solution based on moving heat theory of Jaeger. That model considerably calculated the produced flash temperature during finishing and flash time at an interaction point [4]. Other attempt was made by Kumar et al. in developing a finite element model to reveal the effect of surface temperature on the target surface. Conclusions were drawn that surface temperature was elevated due to escalation in magnetic abrasive particle velocity and magnetic potential [5]. Further, Mulik et al. did an experimental investigation of surface temperature on the workpiece-FMAB interface during Ultrasonic MAF process (UAMAF) and they took ferrous alloy as a workpiece for conducting the experiment. Temperature directly depends on voltage, weight of abrasive particles and pulse on time were the key finding of their work [6].

To reveal the influence of MAF process on the hardness of target surface, M.naif studied the effect on hardness of a brass plate when finishing was done using MAF process [7]. He did a regression analysis for predicting the most significant process parameter affecting the response parameters. It was founded that value of hardness increases when powder volume and coil current increases and it decreases with an increase in rotational speed and machining gap. Further, Shather et al. did an experimental study to reveal the impact of design parameters and process parameters on mechanical properties (micro-hardness, surface roughness and material removal) of the processed surface through MAF process [8]. They applied analysis of variance (ANOVA) for finding the most significant process

Received: March 2019, Accepted: July 2019

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doi:10.5937/fmet2001195R

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FME Transactions (2020) 48, 195-203 195

parameters affecting the response parameters. It was concluded that amplitude of pole geometry, finishing time and current were the most significant factors on which hardness of processed surface depended.

To study the role of multi-objective optimization in the machining and finishing process for the appraisal of their performance, numerous studies were also conducted. The multi-objective optimization results enhance the manufacturing process performance and were also very well adopted for industrial applications. Lakshminarayanan et al. used Taguchi based L_9 orthogonal arrangement (OA) and ANOVA test for classifying the important factor altering the strength of friction stir welded RDE-40 Al alloy joints [9]. Taguchi philosophy has a limitation to solve multi-optimization problem but it can be overcome by converting multi-objective problem into a single response with a use of grey relational analysis (GRA). Chan et al. integrated the artificial neural network with simulated annealing to enhance the surface finish of pure tungsten workpiece machined through wire electro discharge machining (WEDM). This hybrid approach had effectively optimized the performance of the WEDM and optimal settings were obtained for improving the productivity [10]. Kolahan et al. also successfully implemented simulated annealing algorithm with GRA to optimize the multi-responses in the turning operation. Simulated annealing (SA) was used to enhance the optimal process parametric setting for maximum productivity and performance of turning process. Combination of GRA-SA approach was successful in achieving the objective of the work performed [11].

Azhiri et al. developed a hybrid multi-objective optimization approach by combining adaptive neuro-fuzzy system with GRA. Objective was to optimize the cutting velocity and surface roughness of an aluminium based metal matrix composite processed by WEDM. Their experimentations were based on the Taguchi's orthogonal arrays were ANOVA revealed the most significant process parameter [12]. Kumar et al. optimized four performance response of the WEDM using desirability function based on Box-behnken design. They opted for titanium to study the performance characteristics between six process parameters to four responses. Finally, their design successfully optimized the optimal setting required for maximum productivity of WEDM [13].

Goswami et al. investigated the rate of material removal, wire wear ratio and surface integrity of WEDM on Nimonic 80A alloy using Taguchi method and GRA. Their study reveals that an interaction between process parameters was significant. Scanning electron microscope (SEM) was later performed to investigate about the changes in micro-structure after doing machining process [14]. Tripathy et al. applied technique for order of preference by similarity to ideal solution (TOPSIS) and GRA to optimize the multi-response of powder-mixed-EDM. Their results showed an enhancement in the performance characteristics of 0.161689 and 0.2593 in preference values by using TOPSIS and GRA, respectively [15]. Mittal et al. used response surface methodology and desirability approach to optimize the performance measure of abrasive flow machining. They used Aluminium based SiC metal-

matrix composite that is highly needed in the industries as the workpiece. Also, significance of process parameters was obtained using the ANOVA method. Their results were improved by using the above approaches [16]. Agarwal et al. developed a hybrid (GRAANN) model to predict optimal setting of electrochemical machining (ECM) parameters with highest GRG value for material removal rate, under-cut and etch factor [17]. The artificial neural network (ANN) component also delivers an acceptable performance for trends investigation for a specified set of tests. In this study, a surface curve is a plot which represents the machining characteristic in a better way. Gopal et al. used multi-criteria optimization module based on Taguchi-GRA-TOPSIS to minimize the effect of cutting force, temperature and surface roughness in end milling of Mg hybrid MMC. Their developed module had successfully achieved 0.198 μ m surface roughness, 63.92N cross feed force, 42.6N thrust force, 68.96°C temperature and 139.48N feed force [18].

Literature review reveals that most of the multi-objective optimization was done on machining process by using hybrid optimization approaches. To fill the voids of previous investigations, the present study focuses on conducting Taguchi based grey relational analysis of aluminium 6060. The material is finished through MAF process. Here, for enhancing the results of GRA, metaheuristic based simulated annealing is coupled with Taguchi based GRA. In this study, an attempt has been made to develop a robust optimization module using SA-GRA based Taguchi optimization philosophy. This approach is used to optimize the performance measures of aluminium 6060 when micro-finished via MAF process. The performance responses 'change in roughness', 'raise in temperature' and 'change in hardness' are opted for multi-objective optimization to minimize their effect in order to get desired micro-finishing value. Further, the contribution of process parameters is analysed by ANOVA in respect to Taguchi based GRG, this inclusive step helped in better development of the predictive meta-heuristic SA-GRA module.

2. EXPERIMENTATION ON ALUMINIUM 6060 USING MAF PROCESS

In this study, aluminium 6060 was opted as a workpiece (100X100X10 mm³) for micro-finishing through MAF process. Taguchi L_9 orthogonal array is used in determining the appropriate number of experiments. Before micro-finishing operation, surface roughness and hardness of workpiece were measured [19]. Surface roughness measurement was done by Handysurf surface tester and the initial surface roughness of workpiece were between '1.43 μ m to 1.56 μ m'. Then, hardness test was performed using vicker's hardness. Vicker's hardness of workpieces was found between '31 HV - 34 HV'. In order to measure the surface temperature during micro-finishing, three 2.0 mm through hole at the specific location were drilled into considered workpieces. After these K-type thermocouples with 1.6 mm probe were inserted in the former holes. Figure (1) shows the schematic representation of surface temperature measuring methodology [20].

Then, aluminium 6060 workpiece with thermocouples was placed on the worktable of MAF set-up as shown in figure (2). The required working gaps between electromagnetic tool and workpiece were maintained by using slip gauges. The magnetic flux density in the working gap is measured using EMF-PORTABLE digital gaussmeter (range 0-2.0 T). Magnetic flux density in working gap is found to be between 0.65 T to 1.02 T when voltage between 10-18 V is provided as input.

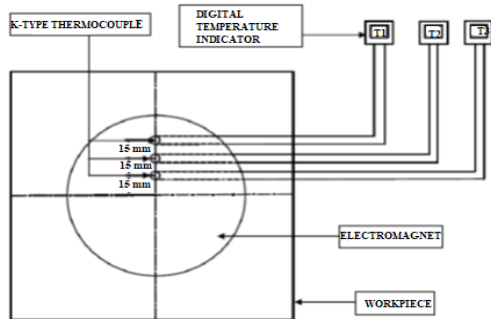


Figure 1. Method of insertion of k-type thermocouple probe

Three 100 g samples of magnetic abrasive particles were created by mixing silicon carbide in a fixed proportion i.e. 20g, 25g, 30g in iron powder. The particles size of silicon carbide were 400 mesh and iron were 300 mesh. After this, working gap is filled with magnetic abrasive particles in required proportions. Flexible magnetic abrasive brush was formed when DC supply was fed and FMAB acted as multipoint cutting tool to erode the surface of aluminium 6060.

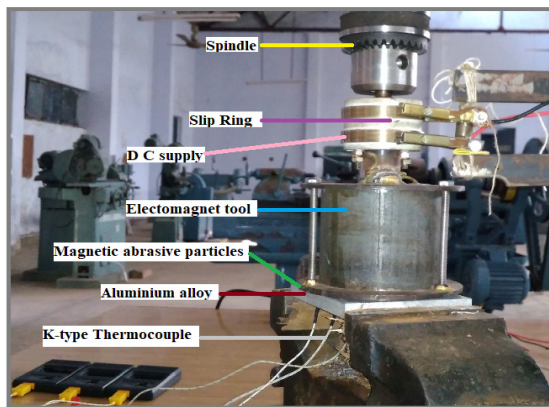


Figure 2. Magnetic abrasive finishing experimental set-up

Table 1 - Selected process parameters range

Sr no	Process parameter	Units	Range
1	Working gap (P1)	mm	1.0-2.0
2	Abrasive weight (P2)	g	20-30
3	Voltage (P3)	V	10-18
4	Rotational speed (P4)	rpm	100-300

Before performing the main L_9 OA experiments, pilot experiments were conducted to examine the performance of the MAF set-up and to define the process parameters range. The selected process parameters are listed in table (1) and their range were selected as per MAF set-up performance and constrained. While performing pilot experiment, it is seen that raise in temperature became constant approximately around 20 minutes. Hence, the main L_9 OA experiments were conducted for 20 minutes to micro-finish the aluminium 6060. During micro-finishing,

maximum 9° C raise in temperature is recorded for experiment-3 and lowest 3° C is recorded for experiments 1 and 8, as shown in table (2). After successful completion of experiments, final surface roughness and hardness of micro-finished surface were measured. The 'change in roughness (ΔRa)', 'raise in temperature (ΔT)' and 'change in hardness (ΔH)' of micro-finished aluminium 6060 were selected as performance responses of MAF process for multi-objective optimization, listed in table (2).

3. GREY RELATIONAL ANALYSIS (GRA)

Grey relational analysis (GRA) is a normalization technique introduced by Professor Deng in 1982 for solving multi-objective response by translating the multiple experimental data into on a single response measure called grey relational grade [21]. GRA produces GRG, which is further analysed for predicting the most optimal solution for the desired performance of any system or process.

GRA method consists of the following steps:

- 1) Conduction of experiments at settings of parameters according to Taguchi orthogonal array [22].
- 2) Normalization of experimental results.
- 3) Determination of grey relational code (GRC).
- 4) Calculation of grey relational grade (GRG) and their corresponding rank.
- 5) Selection of optimal process parameters. Multiple outcome of experiment was investigated using GRA. GRA approach allows conversion of multiple responses such as material removal, cutting force and surface roughness into a single grey relational grade (GRG) [9].

3.1 Data Normalization

GRA starts with normalizing experimental data (Table 2) retrieved via micro-finishing on aluminium 6060 using MAF process. Normalization of experimental data is done in a range between 0 and 1 by applying machining characteristic i.e. 'lower is the best' using equation (1) to 'change in roughness', 'raise in temperature' and 'change in hardness'. Where $X_i(k)$ is comparability sequence and $Xi^*(k)$ sequence afterward data pre-processing. Table (3) illustrates the normalized sequence aimed at all the responses founded on their corresponding performance characteristics.

$$X_i(k) = \frac{\max Y_i(k) - Y_i}{\max Y_i(k) - \min Y_i(k)} \quad (1)$$

3.2 Grey Relational Coefficient (GRC)

After defining deviation sequence, GRC is determined by using the equation (3) where ξ is defined as an identification coefficient. The GRC for all the sequences of 'change in roughness', 'raise in temperature' and 'change in hardness' are given in table (4). In this case, all the process parameters were given an equivalent preference by considering $\xi=0.5$, while $\Delta \max$ and $\Delta \min$ shows the maximum and minimum absolute variance.

$$\xi_i(k) = \frac{\Delta \min + \theta \Delta \max}{\Delta 0_i + \theta \Delta \max} \quad (3)$$

Table 2 – Surface Temperature Experimental Results

Experiment no.	Process parameters				Responses		
	P ₁ (mm)	P ₂ (g)	P ₃ (V)	P ₄ (rpm)	ΔRa (μm)	ΔT (°C)	ΔH (HV)
1	1.0	20	10	100	0.15	3.0	3.3
2	1.0	25	14	200	0.19	5.0	4.3
3	1.0	30	18	300	0.23	9.0	5.2
4	1.5	20	14	300	0.17	4.0	3.8
5	1.5	25	18	100	0.21	7.0	4.6
6	1.5	30	10	200	0.18	5.0	4.1
7	2.0	20	18	200	0.19	5.0	3.7
8	2.0	25	10	300	0.16	3.0	3.1
9	2.0	30	14	100	0.17	4.0	4.5

Table 3- Data normalization and deviation sequence of experimental responses

Experiment no.	Data Normalization			Deviation Sequence		
	ΔRa	ΔT	ΔH	ΔRa	ΔT	ΔH
	Xi(1)	Xi(2)	Xi(3)	Δoi(1)	Δoi(2)	Δoi(2)
1	1	1	0.9047	0	0	0.0958
2	0.5	0.6667	0.4285	0.5	0.3333	0.5719
3	0	0	0	1	1	1
4	0.75	0.8333	0.6666	0.25	0.1667	0.3333
5	0.25	0.3333	0.2857	0.75	0.6667	0.7146
6	0.625	0.6666	0.5238	0.375	0.3333	0.4769
7	0.5	0.6666	0.7142	0.5	0.3333	0.2854
8	0.875	1	1	0.125	0	0
9	0.75	0.8333	0.3333	0.25	0.1667	0.6667

3.3 Grey Relational Grade (GRG)

At last, GRG (γ_i) is calculated using the equation (4) to evaluate the multiple performance characteristics. GRG for each experiment is intended by collecting the mean values of the GRCs for ‘change in roughness’, ‘raise in temperature’ and ‘change in hardness’. The rank of each experiment was tabularized grounded on the highest GRG, as listed in table 4. The higher value of GRG is extremely desired for favourable parametric setting during multi-attribute optimization.

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \tag{4}$$

Table 4- Grey Relational Coefficients

Experiment no	Grey relational coefficient			Grey relational grade	Rank
	ΔRa ξ _i (1)	ΔT, ξ _i (2)	ΔH, ξ _i (3)		
1	1	1	0.84	0.7100	1
2	0.5	0.6	0.4667	0.3917	7
3	0.3333	0.3333	0.3333	0.25	9
4	0.6667	0.75	0.6	0.5047	3
5	0.4	0.4281	0.4175	0.3184	8
6	0.5719	0.6	0.5125	0.4205	6
7	0.5	0.6	0.6364	0.4340	5
8	0.8	1	1	0.7000	2
9	0.6667	0.75	0.4281	0.4613	4

3.4 GRG for process parameters level

Table (4) shows that experiment no. 1 has the best multiple performance characteristic because this combination of machining process parameters has highest grey

relational grade (GRG) value. Since the experiments are orthogonally designed, the GRG for various levels can be sorted out by calculating the mean of GRG for process parameters at same levels. This can be computed for every process parameter at same level [23].

Here, GRG value for parameter A (working gap, P₁) at 1st level 1 (1 mm) can be determine by the mean value of corresponding GRG values of experiment no. 1-3. The calculated mean GRG for other process parameters for various levels is given in table (5). Calculating the mean of parameters for different levels gives the best optimal setting on the basis of desired performance responses. Table (5) shows that for parameter A (working gap, P₁) the optimal results for ‘change in roughness’, ‘raise in temperature’ and ‘change in hardness’ are achieved at 3rd level (2 mm). In the same way optimal results for other parameters are also calculated.

Table 5- Mean GRG of Process Parameter

S NO	Process parameters	GRG		
		Level 1	Level 2	Level 3
A	P1 (Working gap)	0.4505	0.4117	0.5318
B	P2(Abrasive weight)	0.5494	0.4672	0.2236
C	P3 (Voltage)	0.6103	0.4523	0.3313
D	P4 (Rotational speed)	0.4937	0.4155	0.4847

For distinguishing the optimal results for each process parameters, the calculated mean GRG value at different levels are plotted, as shown in figure (3). Primarily, greater GRG value represents the optimal setting of process parameters. Figure (3) shows the most optimal process parameter’s value based on the highest GRG which are **A3B1C1D1**. The predicted Grey relational grade (GRG) of the optimal process parameters level for the experiment can be calculated using equation (5):

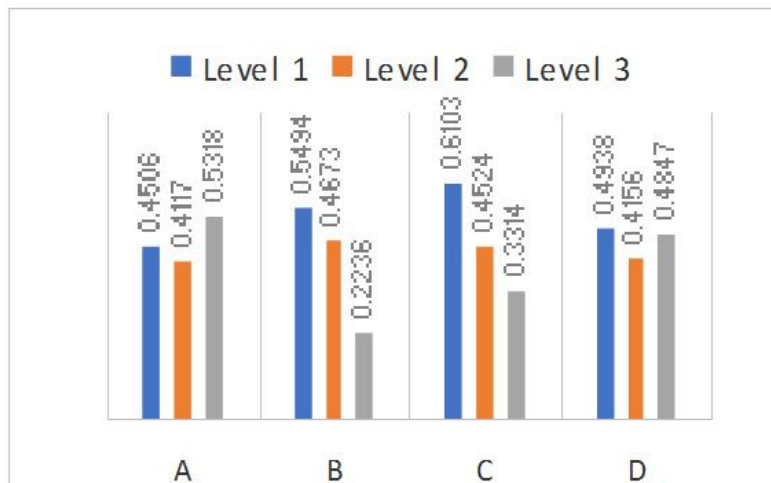


Figure 3. Optimal process parameters setting by GRA

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^n (\gamma_i - \gamma_m) \quad (5)$$

Where, γ_m and γ_i represent total mean of GRG and GRG mean at an optimal level, respectively and n is the total number of process parameters. The predicted GRG is calculated as follows:

$$\begin{aligned} \hat{\gamma} &= 0.46469 + (0.5318 - 0.46469) + (0.549419 - 0.46469) + \\ & (0.610302 - 0.46469) + (0.493798 - 0.46469) \\ \hat{\gamma} &= 0.8013 \end{aligned}$$

4. REGRESSION PREDICTIVE MODEL

Regression is a sophisticated technique to develop a predictive empirical model for predicting the behaviour of process parameters and grey relational grades associated with each experiment responses [24]. Present modelling is done using MINITAB 18 statistical software. The linear GRG regression model is given by equation (6). Here working gap (P_1), abrasive weight (P_2), voltage (P_3) and rotational speed (P_4) are the process parameters.

$$\begin{aligned} GRG &= 1.270 + 0.0812P_1 - 0.01720P_2 - \\ & -0.03486P_3 - 0.000045P_4 \end{aligned} \quad (6)$$

4.1 Model validation and ANOVA results

Analysis of variance (ANOVA) is a mathematical way to determine precision and adequacy of regression modelling. The adequacy of a regression model is examined by coefficient of determination (R^2), as it indicates the accuracy of fit for the regression model. In the present case, determination coefficient (R^2) and adjusted determination coefficient (adj. R^2) are 87.61% and 75.21% respectively, which depicts high significance of the regression model. ANOVA is used for predicting the individual percentage contribution of the process parameters with respect to GRG value. Table (6) shows that voltage with 59.75% value is the most important value followed by abrasive weight (22.73%), working gap (5.07%) and negligible contribution of rotational speed (0.06%).

ANOVA predicted the significance of each process parameters with respect to GRG. It is founded that voltage and abrasive weight are the most significant

process parameters influencing the GRG. Working gap and rotational speed has an insignificant influence on the GRG as shown in Table (6). Here, the effect of rotational speed on GRG is almost negligible, so it can be treated as idle process parameter in GRG predictive model. So, by idling the rotational speed there would be no substantial effect on the GRG value of multi-objective predictive model.

5. OPTIMIZATION USING SIMULATED ANNEALING

In this study, simulated annealing (SA) algorithm is used to develop a meta-heuristic SA-GRG predictive model, for better prediction of the optimal set of machining parameters [25]. SA is a meta-heuristic algorithm competent to find approximate global optima without stuck in local optima. SA algorithm is adapted from the physics of annealing of solid materials. SA had substantiated a connection for solving realistic problems. SA is implemented using the optimization tool box in MATLAB 2014. Objective function derived using GRG regression model is further used to optimize the GRG response using SA. Objective function is imported in optimization tool box and the initial conditions are provided. Its starts with defining initial starting point, an upper bound and lower bound of the objective function, chosen from the different processing conditions given in table (2). The next step is to define stopping criteria and annealing parameters. Finally, simulated annealing acceptance criteria is provided to find the target solution of the GRG. All the important SA criteria and parameters are listed in table (7). Figure (4) shows convergence plot of the best function value of 0.6632 SA-GRG at 100 iterations for experiment 1.

```
Objective function y=GRG(x)
y=(1.270+0.0812*x(1)-
0.01720*x(2)-0.03486*x(3)+0.000045*x(4));
end
```

SA algorithm starts with an initial possible solution and stepwise explores the solution domain for the optimal solution. At each iteration a new solution in the neighbourhood of the current solution is generated and evaluated. A move to new solution is then made under the following conditions:

- (a) If the new objective function value is less than the old, the new point is always accepted.
- (b) Otherwise, the new point is accepted at random with a probability depending on the difference in objective function values and on the current temperature.

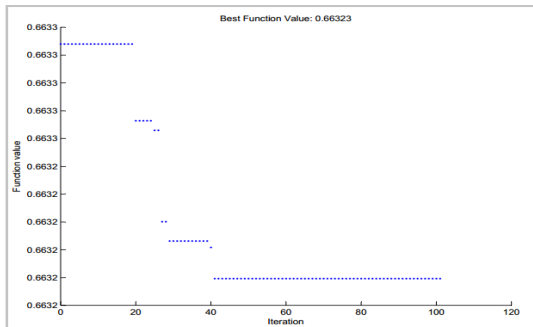


Fig (4). Best GRG function value via simulated annealing

The acceptance probability is:

$$\frac{1}{1 + \exp\left(\frac{\Delta}{\max(T)}\right)} \quad (7)$$

where, Δ = new objective – old objective, and T is the current temperature. The probability of acceptance is between 0 and $\frac{1}{2}$ for the positive value of both Δ and T. Larger Δ leads to smaller acceptance probability. Also, smaller temperature leads to smaller acceptance probability.

5.1 Simulated Annealing-Grey Relational Grade

The meta-heuristic SA-GRG predictive model simulated experimental results with an error between -9.2639% to +7.3321%, which is an adequate prediction rate. SA-GRG global optimal solution for all nine experiments was obtained, shown in table (8). SA-GRG is highest for experiment-1 i.e. 0.6632, which is the best optimal condition for ‘change in roughness’, ‘raise in temperature’ and ‘change in hardness’ for obtaining best performance for micro-finishing of aluminium 6060 through MAF process. Least SA-GRG value is obtained for experiment-3 i.e. 0.2316, which is the worst optimal condition for micro-finishing. Table (8) shows the percentage error between the GRG and SA-GRG for all the nine-experiments.

Table 6 - Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	4	0.171094	87.61%	0.171094	0.042774	7.07	0.042
P ₁	1	0.009901	5.07%	0.009901	0.009901	1.64	0.270
P ₂	1	0.044383	22.73%	0.044383	0.044383	7.33	0.054
P ₃	1	0.116686	59.75%	0.116686	0.116686	19.28	0.012
P ₄	1	0.000124	0.06%	0.000124	0.000124	0.02	0.893
Error	4	0.024204	12.39%	0.024204	0.006051		
Total	8	0.195298	100.00%				
S	R-sq	R-sq(adj)	PRESS	R-sq(pred)			
0.0777880	87.61%	75.21%	0.201300	0.00%			

Table 7- Simulated annealing parametric criteria

Stopping criteria	Annealing parameters			Acceptance criteria
Maximum iteration: 100	Annealing function: <i>Boltzmann annealing</i>	Temperature update function: <i>Exponential temperature</i>	Initial temperature: 500	Acceptance Probability function: <i>Simulated annealing</i>

Table 8- SA-Grey Relational Grade

S.No	P ₁	P ₂	P ₃	P ₄	GRG	SA-GRG	%Error
1	1.0	20	10	100	0.7100	0.6632	6.5915
2	1.0	25	14	200	0.3916	0.4267	-8.9523
3	1.0	30	18	300	0.2500	0.2316	7.3321
4	1.5	20	14	300	0.5041	0.5336	-5.8467
5	1.5	25	18	100	0.3100	0.3388	-9.2639
6	1.5	30	10	200	0.4209	0.4456	-5.8768
7	2.0	20	18	200	0.4340	0.4699	-8.2538
8	2.0	25	10	300	0.7000	0.6538	6.5942
9	2.0	30	14	100	0.4613	0.4328	6.1692

Table 9 - Comparative results

Method	Optimal Parametric Setting				GRG	% Improvement in GRG
	Working Gap	Abrasive Weight	Voltage	Rotational Speed		
Taguchi-GRA	2 mm	20 g	10 V	100 rpm	0.8013	
Taguchi-SA-GRA (predicted)	2 mm	20 g	10 V	100 rpm	0.8218	2.5%
Taguchi-SA-GRA (optimized)	2.5 mm	15 g	6 V	50 rpm	0.9194	12.84%

5.2 SA-GRG for process parameters

The optimal parametric setting for Taguchi-based Grey Relation Analysis (A3B1C1D1) were simulated using a meta-heuristic simulated annealing. The predicted output (SA-GRG) after simulation was observed to be 0.8218. In order to obtain the optimal parametric setting via simulated annealing model, one process parameter was varied into multiple level whereas the others remained constant at the predicted optimum level. The process parameter A (working gap, P_1) level was varied from 1.5 mm to 2.5 mm, while the others were kept constant at the predicted optimal level (B1C1D1).

For parameter B (abrasive weight, P_2), the level was varied from 15g to 25g, while the others were kept constant at the predicted optimum level (A3C1D1). Next parameter C (voltage, P_3) level was varied from 6V to 14V, while the others kept constant at the predicted optimum value (A3B1D1). The simulation results for factor A, B and C upon GRG are depicted in Figure 5, 6 and 7, respectively. The ANOVA results show that process parameter D (rotational speed, P_4) is insignificant, so it is kept constant as per SA-GRG results.

5.3 Verification tests

The verification test has been done to recheck the optimal parametric setting predicted by L_9 OA of Taguchi-based SA-GRA with the experimental results. Simulation based on the predicted process parameters via Taguchi-based SA-GRA was conducted. Final predicted SA-GRA value was found to be 0.9194. Table (9) shows the experimental results that were obtained by using the optimum process limits predicted via by L_9 OA of Taguchi- GRA module and L_9 OA of Taguchi-based SA-GRA module. The predicted GRG of process parameters via L_9 OA of Taguchi-based SA-GRA module has been improved by 12.84% which (Table 9) shows the satisfactorily performance of aforementioned optimization module. The highest GRG results indicated the desired values of the process responses.

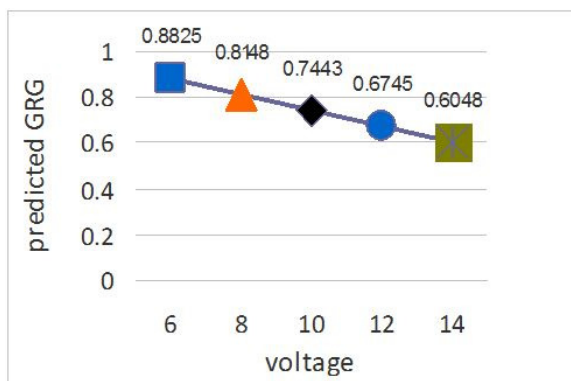


Figure 5. Simulation Result for Multiple Levels of voltage

Hence, it is found that ‘change in roughness (ΔRa)’, ‘raise in temperature (ΔT)’ and ‘change in hardness (ΔH)’ can be simultaneously optimized using a L_9 OA of Taguchi-based SA-GRA module. Moreover, the robust optimization can be executed through the assistance via simulated annealing model, predicting the values outside the specified level of process parameter.

6. CONCLUSIONS

Taguchi based hybrid meta-heuristic SA-GRA multi-objective optimization is done to enhance the performance of the magnetic abrasive finishing process. ‘Change in roughness (ΔRa)’, ‘raise in temperature (ΔT)’ and ‘change in hardness (ΔH)’ are the response that affects the micro-finished surface of aluminium 6060. The proposed optimization module is effective in evolving a strong, adjustable and flexible mass production systems GRA coupled simulated annealing model can ingeniously take care of multi-objective variables into its fundamental grading overcoming the constraint of prevailing Taguchi based optimization approaches. And for future research, this developed methodology can be well used for multi-objective optimization to enhance the machining performance of advanced machining process such as AJM, EDM, ECM, UAMAF etc. The major findings of multi-objective optimization are as follows,

1. Taguchi based hybrid meta-heuristic SA-GRA gives the improve optimal solution to produce the desired surface quality by reducing the impact of ‘change in surface roughness (ΔRa)’, ‘raise in temperature (ΔT)’ and ‘change in hardness (ΔH)’ on the micro-finished aluminium 6060 using MAF process.
2. ANOVA performed on the GRG revealed the percentage contribution of each process parameters. Voltage contributed most with 59.75%, followed by abrasive weight with 22.73% and least by working gap with 5.07%. Rotational speed with 0.06% which is almost negligible to contribute in affecting the GRG.
3. The simulation via meta-heuristic SA-GRA predicted that working gap (2.5mm), abrasive weight (15 g), voltage (6 V) and rotational speed (50 rpm) produces the highest GRG to maximize the performance of micro-finishing of aluminium 6060.
4. The predicted GRG of process parameters via L_9 OA of Taguchi-based hybrid meta-heuristic SA-GRA is improved by 12.84%, which shows a satisfactorily performance of above-mentioned optimization module.

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**ИСТРАЖИВАЊЕ ВИШЕЦИЉНЕ БАЗИРАНЕ
НА GRA МЕТОДУ ОПТИМИЗАЦИЈЕ
МАГНЕТСКЕ АБРАЗИВНЕ ЗАВРШНЕ ОБРАДЕ
ПРИМЕНОМ СИМУЛАЦИЈЕ ЖАРЕЊА**

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Процес магнетске абразивне завршне обраде (MAF) је напредан супер-процес завршне обраде који се врши од микро до нано нивоа. У раду је развијен хибридни модул Тагучијевог греј релационе анализе и симулације жарења с вишециљном оптимизацијом завршне микро-обраде алуминијума 6060 применом MAF процеса. Сматра се да се перформанса као што су промена храпавости, повећање температуре и промена тврдоће минимизира њихов утицај на завршну микро-обработку алуминијума 6060. Наведене перформансе су коришћене за израчунавање греј релационог коефицијента за сваку перформансу посебно, које су потом преведене у појединачне променљиве, тј. вредност греј релационог градијента. Метатеуристички алгоритам за симулацију жарења је коришћен за предикцију најпожељнијих параметара процеса: радни размак (2мм),

тежина абразива (15г), напон (6V) и брзина ротације (50rpm). Овај скуп параметара је одабран на основу

највеће вредности GRA предвиђене на основу Тагучијеве SA-GRA методе.