Parametric Optimization of Magnetic Abrasive Finishing Process Using Genetic Algorithm and Particle Swarm Optimization

Gopal Kumar Saxenaa, Anjaneyulu Kamepalli, Venkatesh Gudipadu, Satish Kumar Injeti, and Ramalingaswamy Cheruku

***Abstract*—Magnetic Abrasive Finishing (MAF) is advanced finishing techniques which can generate surface finishes at the nanoscale for both magnetic and non-magnetic materials.By enhancing or optimizing the important MAF process parameters, the material's surface finish may be greatly enhanced. The current paper looks into the experimental studies of Hastelloy C- 276 for surface finish improvement ($\%\Delta R_a$), material removal (MR) and forces (F_n & F_t) as well as the parametric optimization of MAF process. The optimum results obtained after the application of Particle swarm optimization (PSO) and Genetic algorithm (GA) were compared with each other for improving the finishing of Hastelloy C- 276 using the MAF process. The experimentation was carried out using MATLAB software. Using GA and PSO algorithms, the regression equation was utilized to determine the optimal influencing factors. Particle swarm optimization was found to be the best optimization method and to have produced the best optimal outcomes when these optimum results were compared.**

***Index Terms*— Optimization, Hastelloy C 276, Genetic algorithm, Particle swarm optimization, Surface finish improvement**

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I. INTRODUCTION

Fine finishing of advanced materials is essential because of rapid improvements in aerospace and medical implants [1]. However, the finishing of advanced materials using traditional methods (grinding, lapping, and honing, etc.) is a challenging task [2], [3]. Magnetic abrasive finishing (MAF) process is alternative to get a nano-scale finish because the MAF setup can easily fabricate on the conventional lathe and milling machines [4]. MAF process is becoming more popular because of the flexibility of flexible magnetic abrasive brush (FMAB) and getting nano level finish of materials [5]. MAF process involves the finishing of flat surfaces using a milling machine. In the MAF process, the FMAB is formed between the electromagnet is continuously rotating electromagnet and fixed work piece. Hence, due to the relative motion between FMAB and work surface material removal takes place in terms of microchips. Kanish et al. studied experimentally the finishing of SS 316L using the MAF process. The authors conducted experimentation using orthogonal arrays L_{27} and also explains the relation of each parameter on change in the surface finish (R_a) and material removal (MRR) [6]. Authors also reported the most influencing process parameters are increased in voltage and rational speed, and abrasive size gives a positive effect on change in surface roughness and material removal, whereas an increase in working gap and feed gives a negative effect. Any process that wants to improve product quality, lower machining costs, and boost machining efficiency must optimize its process variables [7]. To increase the efficiency of the MAF process, it is crucial to optimize the process parameters and choose the best process parameters [8]. According to the examination of the literature, some researchers optimized the MAF process parameters using orthogonal arrays, and others were claimed to have used Grey relational analysis to optimize various processes (such as EDM, drilling, wire EDM, etc.) for a superior surface quality [9]. While a small number of researchers concentrated on utilizing a genetic algorithm to optimize various operations (such as turning, scheduling, welding, etc.). Some studies employed JA to optimize the variables for a distinct process (surface grinding, welding, electrode deposition, etc.) [10], [11]. Hastelloy C-276 finishing and MAF process parameter optimization are the attention of a very small number of researchers. To evaluate the impact of various process parameters on surface finish improvement (Ra), material removal (MR), and forces (Fn & Ft), no targeted optimization of processes parameters of the MAF process was utilized.

II. EXPERIMENTAL DETAILS

The experiment is run on a vertical milling machine using a MAF process that was created in the lab, as illustrated in Fig.1. The work piece is secured to the work surface, and an arbour is used to attach the electromagnet. SiC abrasives with a mesh size of 60 and magnetic particles with a mesh size of 220 were utilized on a work piece with dimensions of 10 × 10 × 0.6 cm. The flexible magnetic abrasive brush (FMAB), which is used to finely polish both metallic and non-metallic surfaces, is made up of both abrasive and magnetic particles. The experimental information is displayed in Table 1.

TABLE I
DETAILS OF EXPERIMENT

Work materials	: Hastelloy C- 276
Workpiece size	: 100mm×100mm×6mm
Abrasives used	: Silicon carbide (SiC)
Abrasive size	: SiC (60&220 mesh)
Magnetic particles & size	: Iron powder (300 mesh)
Magnetic flux	: 1-1.5 Tesla
Run time	: 5 min
Dimmer stat	: 10 A–230 V

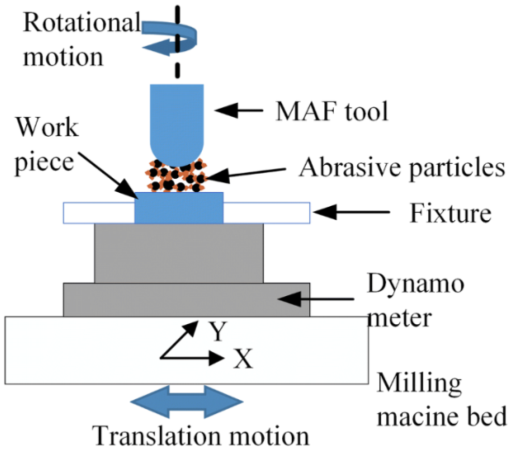

Fig. 1. 1. MAF set up on a vertical milling machine

A. Design of experiments

L27full factorial orthogonal array was used for the investigations' three-level and four-factor designs. The benefit of employing a complete factorial design is that it provides a substantial regression model as well as insight into how process factors affect response percent (%ΔRa), material removal (MR), and forces (Fn & Ft). The coded variables and their ranges are displayed in Table 2.

TABLE II
PARAMETERS AND LEVELS

Coded variables	**1**	**2**	**3**
Sic weight% (%Wt.) (C1)	20	25	30
Voltage (V) (C2)	35	45	55
Speed of electron (rpm) (C3	500	750	1000
Working gap(mm) (C4)	2	2.5	3

B. Parametric optimization

The following elements are frequently necessary for parametric optimization, including empirical equations relating to tool life, force, performance, surface polish, etc. The most popular production process optimization criteria are used to minimize process costs while maximizing process profits and offer a practical solution to the issues of uncertainty, many inputs, and discrete data. These sorts of issues may be solved and the process' effectiveness and efficiency improved by using Grey's relationship analysis. Because the genetic algorithm may create a population of solutions for generations without being distinguished by the study of difficult research areas and the utilization of genetic resources, genetic algorithms are employed as an effective technique for optimizing many goals. In order to successfully apply GA to a given issue, the solution must be correctly designed (coded), operators, fitness functions, and restrictions must be removed, among other things. The behavior of flocks of birds or schools of fish serves as the inspiration for the evolutionary computing approach known as particle swarm optimization (PSO), which is utilized for optimization. The algorithm's efficiency and simplicity make it suitable for usage in a variety of sectors, including operations and the production process.

1) Genetic algorithm: Selection, crossover, and mutation are three crucial genetic operators used by the GA algorithm [12], [13]. They serve as the fundamental building blocks of strong genetic algorithms. They are the main conduits for reproduction simulation and natural selection. Mutations and hybridization happen as a result of genetic processes. The GA method is described in detail below in Fig.2.

1. You must select a type of code that reflects the MAF process's most important parameters.

2. The length of the chromosome, population size, selector, crossover operator, crossover probability, mutation probability, and adaptive parameters are just a few examples of the factors that need to be properly chosen.

3. Random numbers within the range of each process should be used to start the GA process.

4. Choose the maximum number of iterations or the permitted algebra Set t= 0

5. Decoding binary to decimal conversion process variables

6. The fitness function for each string must be built using a regression equation in order to forecast the goal function, such as surface quality improvement.

7. Take the optimal solutions for the following generation when t > t max (i.e., the objective function achieves the maximum value).

8. Reproduce the new population

9. There is a chance that the two randomly chosen chains will cross at the chosen intersection.

10. Mutations can happen because the entire population chain is susceptible to them

11. Decoding the new overall chain in accordance with steps 5 and 6. To mark the conclusion of each iteration, the iteration value is increased by t = t + 1, and step 7 is repeated.

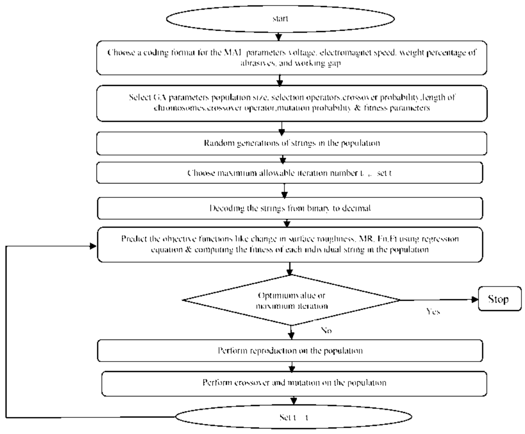

Fig. 2. Genetic algorithm flow chart

2) Particle swarm optimization: Particle Swarm Optimization (PSO) is a metaheuristic optimization algorithm that was inspired by the social behavior of bird flocking or fish schooling. In 1995 Kennedy and Eberhart proposed this algorithm. PSO is commonly used to solve optimization problems where the objective function is not known in advance or is difficult to evaluate analytically. In PSO, a population of candidate solutions, called particles, move through the search space to find the optimal solution. Each particle represents a potential solution to the problem and is associated with a position and a velocity. The position represents a point in the search space, while the velocity determines the direction and speed of movement. The particles in the swarm collaborate and communicate with each other to guide their search. At each iteration, the particles update their velocity and position based on their own experience (local best) and the experience of the swarm (global best). The updating process is influenced by the best positions found by individual particles and the best positions found by the swarm as a whole. Fig. 3 shows process involved in particle swarm optimization technique.

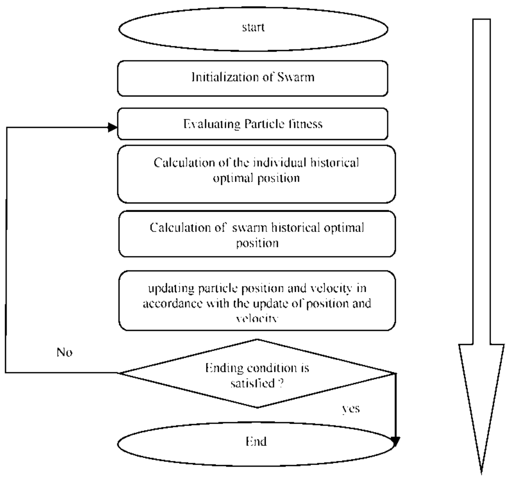

Fig. 3. Flowchart of the particle swarm optimization algorithm

An Intuition of Particle Swarm Optimization

To get the global optimum there is movement towards a promising area. Traveling velocity of each particle is adjusted dynamically. Each particle keeps track of : It's best result for him/her, known as personal best or **pbest** and best value of any particle is the global best or **gbest**. Position of each particle modified according to: Its Current Position , Its Current Velocity, The Distance Between Pbest & Its Current Position and The Distance Between Gbest & Its Current Position. Lets us assume a few parameters first. f: Objective function, Vi: Velocity of the particle or agent, A: Population of agents, W: Inertia weight, C1: cognitive constant, U1, U2: random numbers , C2: social constant, Xi: Position of the particle or agent, P_b: Personal Best, g_b: global Best. The actual algorithm goes as : Assemble a "population" of particles that are evenly scattered over X, Determine each particle's location while taking the objective function into account, If a particle's current position is superior than its prior best position, update its position, Locate the best particle based on the particle's last best locations, Update the speed of the particles by using equation V_i^{t+1}= W.V_i^t+ $c_1U_1^t(P_{b1}^t - P_i^t)$ +$c_2U_2^t(g_b^t - P_i^t)$, Place the particles in their new locations P_i^{t+1} = P_i^t+ V_i^{t+1}, Return to step 2 until the stopping requirements are met.

III. RESULTS AND DISCUSSIONS

The surface finish improvementis calculated using the below equation. $\%\Delta R_a = \frac{Final\ R_a - Initial\ R_a}{Final\ R_a} \times 100$ Material removal (MR (mg)) = (Weight before experimentation - Weight after experimentation)

Dynamometer is used to measure the forces & Talysurf is used to measure the roughness.

A. Regression equations

With the help of experimental datas Regression equations [14] are being generated using minitab software. Our objective is to maximize change in surface roughness ($\% \triangle R_a$) & material removal (MR) and minimize the forces (F_N & F_T).

Maximize

$\% \triangle R_a$= 73.7 – 3.606C1 + 0.244C2 – 0.0822C3 – 0.91C4 + 0.0700C1*C1 – 0.00991C2*C2 – 0.000010C3*C3 + 0.31C4*C4 + 0.00959C1*C2 + 0.001519C1*C3 – 0.281C1*C4 + 0.001666C2*C3 + 0.0000C2*C4 + 0.00470C3*C4 (1)

Maximize

MR = 20.4 – 0.596C1 + 0.081C2 + 0.00319C3 – 4.83C4 + 0.01225C1*C1 + 0.00181C2*C2 + 0.000000C3*C3 + 0.878C4*C4 + 0.00145C1*C2 + 0.000007C1*C3 + 0.0085C1*C4 – 0.000174C2*C3 – 0.0045C2*C4 – 0.00015C3*C4 (2)

Minimize

F_N = 50.8 – 1.660C1 + 0.574C2 – 0.0024C3 – 12.31C4 + 0.0341C1*C1 + 0.00330C2*C2 + 0.000004C3*C3 + 2.49C4*C4 + 0.00405C1*C2 + 0.000019C1*C3 – 0.024C1*C4 – 0.000488C2*C3 – 0.08221C2*C4 + 0.00255C3*C4 (3)

Minimize

F_T= -1.54 + 0.296C1 + 0.275C2 + 0.00041C3 – 1.02C4 – 0.00245C1*C1 – 0.00078C2*C2 – 0.000005C3*C3 + 0.770C4*C4 – 0.00166C1*C2 + 0.000166C1*C3 – 0.0600C1*C4 – 0.000098C2*C3 + 0.0130C2*C4 – 0.001060C3*C4 (4)

B. Optimization of maf process parameters

The following are the basic assumptions for the optimization of both PSO and GA .

Assomptions

- Population size was considered as 400 for genetic algorithms and 50 for PSO.

• Maximum number of iterations kept for GA is 200 and for PSO it is 400.

• Number of variables is kept 4 , lower bond is [20 35 500 2] [2] & upper bond is [30 55 1000 3] [3] for both GA and PSO.

• For PSO inertia weights Wmax & Wmin are kept 0.9 & 0.4 and acceleration factors c1 and c2 both are kept 2.05

• The random numbers are considered between 0 to 1.

• Generations time is the default it depends on how effectively the algorithm is working

• The search space is continuous, and the movement of the solution within the search space moves randomly.

1) Genetic algorithm: The GA was applied using MATLAB R2021a. It is observed that optimum values for %ΔR_a ,MR , Fn and Ft obtained at optimum input parameters % Wt. (30),Voltage (55V) , RPM (1000) , Working gap (2 mm) are shown in Table 3

TABLE III
GA RESULTS

Δ Ra (%)	MR	F_n	F_t
64.273799	12.01405218	34.63559273	16.907958

Pareto front obtained for the maximization and minimization objective functions are :

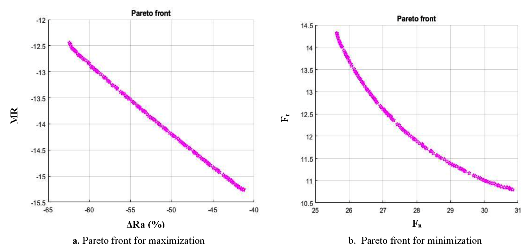

Fig. 4. Pareto fronts

Fig. 4a and Fig. 4b are representing the pareto front for maximization & minimization. In a GA, the Pareto front is the collection of non-dominated solutions that cannot be improved for any one goal or objective without degrading performance for a another goal. Here dotted line (in Fig.4a) and dotted curve (in Fig.4b) represents the pareto fronts for maximization and minimization and the values presents here will give the optimal results for at least one of the objective function.

2) Particle swarm optimization: The PSO was applied using MATLAB R2021a. It is observed that optimum values for %$\Delta R_{a,}$ MR , Fn and Ft obtained at optimum input parameters % Wt. (30),Voltage (55V) , RPM (1000) , Working gap (2 mm) are shown in Table 4.

TABLE IV
PSO RESULTS

Δ Ra(%)	MR	F_n	F_t
62.1525	15.0152	25.7247	10.8968

PSO convergence graph for different outputs are :

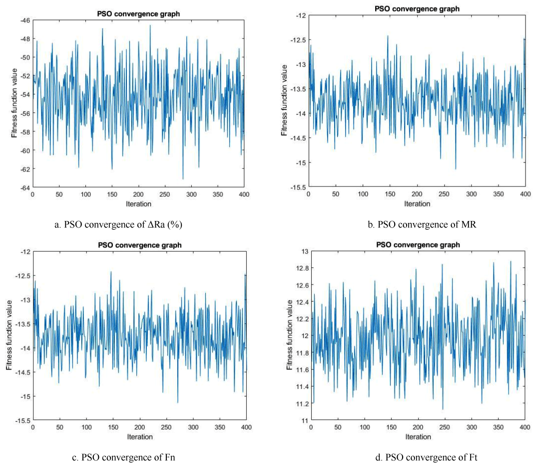

Fig. 5. PSO convergence characteristicsfor various functions

Fig. 5a, Fig. 5b, Fig. 5c and Fig. 5d are representing PSO convergence graph obtained for percentage change in surface roughness , Material removal and Forces are representing how the values of objective functions are changing as the iterations progress (here number of iterations kept are 400). The graph starts with an initial population of particles, and as the iterations proceed, the particles moves towards the optimal solutions.

IV. COMPARISION OF RESULTS

Comparison of results obtained using GA and PSO with experimental values at optimum input parameters % Wt. (30),Voltage (55V) , RPM

TABLE V
COMPARING RESULTS

Objective	Actual	Predicted value using GA	Predicted value using PSO	Comparision (%Error) for GA	Comparision (%Error) for PSO
$\%\Delta R_a$	61.5384	64.2738	62.1525	4.445	0.9978
MR	13.6824	12.0140	15.015	12.1933	9.740
F_n	27.6525	34.6355	25.7247	25.2526	6.9715
F_t	11.7835	16.079	10.8968	43.4879	7.5249

(1000) , Working gap (2 mm) are shown in Table 5.

Plotting the results of Actual , GA and PSO on bar graph. Fig.10 showing how different output parameters are close to the actual value. X-axis representing the output parameters and y-axis representing their values.

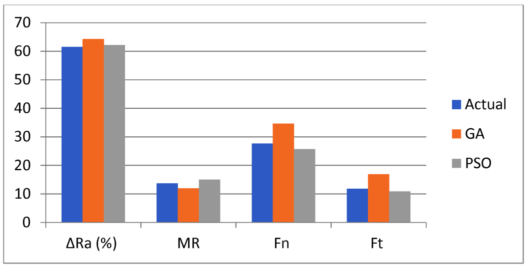

Fig. 6. Comparing results

V. CONCLUSION

Conclusions are listed below based on experimental investigations and optimization methods used for the MAF process**.**

- Metals and non-metals can both be finished using the magnetic abrasive finishing (MAF) method.
- MAF process improved the Surface roughness of Hastelloy material approximately by 61.5%.
- Based on PSO and GA the global optimum process parameters obtained are 30% Wt ratio of Sic, speed of electromagnet is 1000 rpm, voltage is 55V and working gap is 2mm.
- For GA corresponding to optimum input parameters output parameters such as change in surface finish improvement, MR and forces(Fn & Ft) are 64.273799, 12.0140, 34.6355 & 16.9079.
- For PSO corresponding to optimum input parameters output parameters such as change in surface finish improvement, MR and forces(Fn & Ft) are and 62.1525, 15.015, 25.7247 & 10.8968.
- The particle swarm optimization technique gave better result compared to genetic algorithm and ouputs obtained using PSO is close to experimental values.

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