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Advanced Machining Performance Study on Hardened Steel EN 31: A Particle Swarm Optimization Approach

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ABSTRACT

Electrochemical machining (ECM) has inaugurated itself as one of the major other possible way to conventional methods for machining hard materials and complicated outlines not having the properties like residual stresses and tool wear. Studies on Material Removal Rate (MRR) and Surface Roughness (Ra) are of extremely important in ECM, since it is one of the factors to be determined in the process decisions. Owing to the complexity of ECM it is very difficult to determine optimal cutting parameters for improving cutting performance. Hence, optimization of operating parameters is an important step in machining, particularly for unconventional machining processes like ECM. Machining parameters provided by the machine tool builder cannot meet the operator's requirements. Since for an arbitrary desired machining time for a particular job, they do not provide the optimal conditions. So the aim of present work is to investigate the MRR and Ra of EN19 alloy steel in the form of cylindrical (16mm Diameter and 32mm Height) dimensions copper electrode and solution of Sodium Chloride (Na Cl) in water as electrolyte by using computational approach. To solve this task, multiple regression model and Particle Swarm Optimization (PSO) model are developed as efficient approaches to determine the optimal machining parameters in ECM. Current (c), Voltage (V), Electrolyte Concentration (E) and Feed Rate (F) are considered as machining parameters and MRR and Ra are the output responses. This multi response has been modified as a single objective by a Grey Relational Analysis (GRA). Grey grade has been calculated for representing the multi-objective model. The predicted grade has been found and then the percentage deviation between the experimental grade and predicted grade has been calculated for multiple regression linear model & PSO model. Then optimizing to find best setting of process variables for higher MRR and lower Ra. Based on the testing results of the PSO the operating parameters are optimized. The designs are based on Response Surface Methodology (RSM), with the aid of MINITAB software. The optimum value has been determined which is suitable for both MRR and Ra.

KEY WORDS: ECM, GRA, RSM, ANOVA and Material.

1. INTRODUCTION

ECM is known to be a nontraditional process of machining utilized to machine tremendously hard materials which seems to be tough to get machined cleanly utilizing conventional methods which was known right the Faraday work, who established that if two conductive poles are located in a electrolyte bath that is conductive and current energizes it so that metal may be depilated from the pole that is positive (the anode) and plated onto the pole that is negative (the cathode). Thus, ECM is involved in removing a work piece material that is conductive electrically via anodic dissolution. No mechanical or thermal energy is involved. ECM was utilized much in the manufacturing of semiconductor devices and this process to find its application in Automotive, Aircrafts, Petroleum, Aerospace, Textile, Medical and Electronic industries. Hocheng (2004) also suggested a method to predict the work piece machine profile whereas it was brought up as a function of time and the changing gap opening. Bhattacharyya (2006), have examined the influence of vibration of tool on performance of machine similar to MRR and accuracy in electrochemical micro-machining of copper. Few authors were engaged on Electrochemical Discharge Machine (ECDM) [3–5] and targeted on the betterment of machine performance. Munda (2006), have examined the electrochemical micromachining through RSM approach taking MRR and radial over cut as objective measures and developed mathematics models. Every objective has been handled individually and analyzed referring parameters of machining. Parameters of machining optimum, setting rely on the operator's experience do not fulfill the demands of both greater efficiency and quality. Lots of researchers have till now were rigorous over process betterment in ECM and to the highest of the authors knowledge no attempt has been done for the progress of multi-objective models in correlating numerous machining parameters on the predominant electrochemical machining criteria. Considering that, we made an attempt in bringing up multi-objective models for learning the parameters effect of machining over machining performance criteria like MRR and Ra.

Past studies: EDM is one among the money-making processes of machining utilized for accurate and greater work piece precision geometry. EDM is identified to be highly reliable on conducting the research on performances to be achieved by it. Few areas of research in EDM are depicted in Fig. 1.

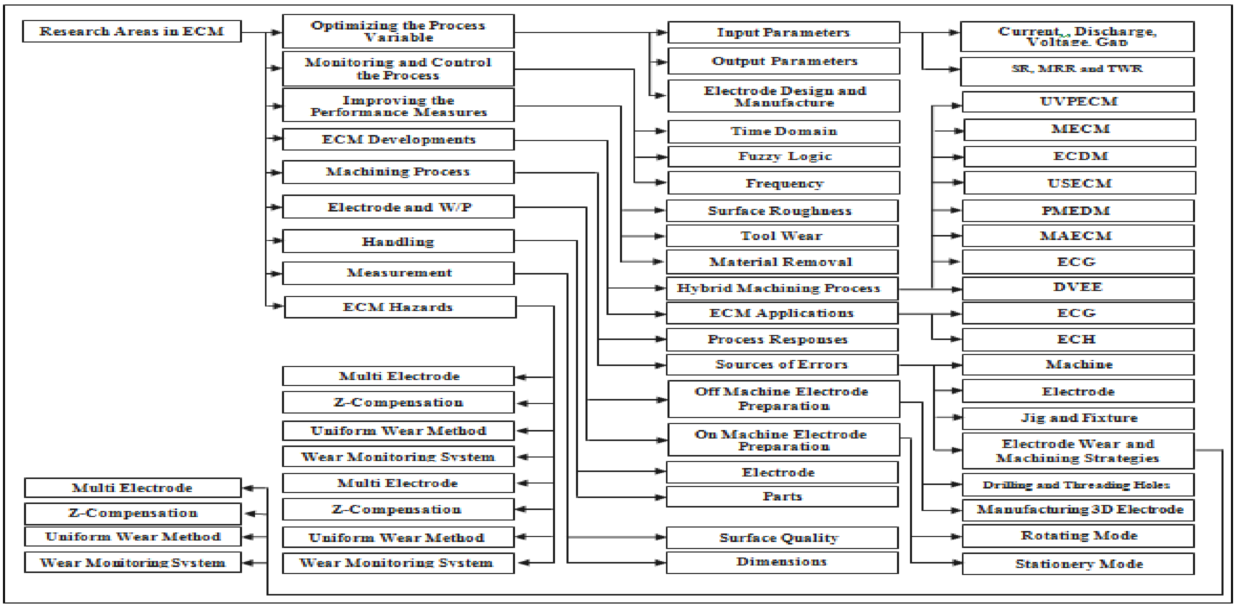

Fig.1.Classification of ECM research areas

Fig. 2 shows theoretical model available in literature for simulating the input and output model.

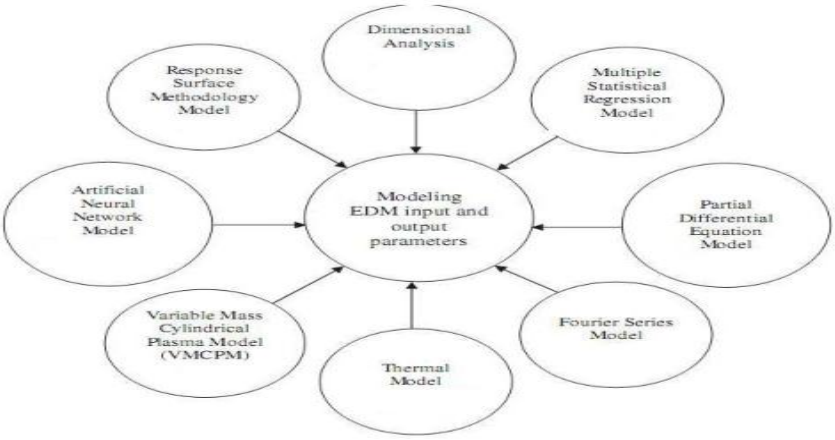

Fig.2.Theoretical model available of ECM research areas

2. EXPERIMENTAL DETAILS

Numerous experiments have been conducted in the idea of investigating the performance and study the influences of numerous machining parameters of ECM process on Hardened Steel EN 31 in the outline of cylindrical blank of test pieces (16mm Diameter and 32mm Height) dimensions. These researches were performed in the idea of investigating the effect of Current, Voltage, Feed Rate on MRR and SR and Electrolyte Concentration.

Experimental setup is explained in Fig. 3 and details are in Table 1. The setup holds three major sub-systems along with tool and work piece material: a) Machining Cell, b) Control Panel, c) Electrolyte Circulation.

Machining Cell: Assembly of electro-mechanical is a sturdy structure, connected with components that are machined to precision level, the tool that is servo motorized moving vertical up/down, an electrolyte dispensing arrangement. All the uncovered components and parts were involved for effective choice of material and coating/plating for protection towards corrosion.

Control Panel: Supply of power is an ideal incorporation of current at high range, power electronics and precision programmable micro-controller-based technologies. Since the machine operates at very low voltage, without any chances of any electrical shocks during operation.

Electrolyte Circulation: The electrolyte is taken off via a tank, insulated using a coating of resistance to corrosion using a pump that is corrosion resistant and is supplied to the work piece. The reservoir contributes isolated compartments for settling and siphoning.

Table.1.The experimental details

Conditions	Descriptions
Machine	MTEATECH ECM machine
Test Specimen	Hardened Steel EN 31 (C=0.916, Mn = 0.354, Si = 0.203, S = 0.050, P = 0.053, Cr = 0.990, Ni = 0.029, Mo = 0.005, Hardness = 205BHN)

Tool	Copper Electrode of Diameter 10mm
Tool Polarity	Positive
Dielectric Fluid	Kerosene
Flushing Type	Internal
Depth of Cut	1mm
Electrode Polarity	Positive
Dielectric Flushing	Flushing
Supply	AC
Weight Measuring Instrument	Digital Balance (FX-3000)
SR Measuring Instrument	Portable SR Tester SJ201
Technical Data	
Tool Area - 30 mm^2	
Cross Head Stroke - 150 mm.	
Job Holder - 100 mm Opening X 50 mm Depth X 100 mm Width.	
Tool Feed Motor - DC Servo Type	
Electrical Out Put Rating - 0-300 Amps, DC at any Voltage from 0 - 20 V.	
Efficiency - Better than 80% at Partial & Full Load Condition.	
Power Factor - Better than 85.	
Protections - Over Load, Short Circuit, Single Phasing.	
Operation Modes - Manual / Automatic.	
Timer - 0 - 99.9 min.	
Tool Feed - 0.2 to 2 mm / min.	

Fig.3.Experimental setup of ECM machining

Work Material: The work materials selected for the study was Hardened Steel EN 31 in cylindrical blank form of test pieces (16mm Diameter and 32mm Height) dimensions and have been fabricated utilizing suitable optimization method. The material is selected due to its growing choice of applications in the area of manufacturing tools in tool industries also used highly in aeronautical and automobile industries because of their greater strength to weight ratio, mechanical and physical properties compared to monolithic material. Table-1 shows the Hardened Steel EN 31material's major mechanical and physical properties. Table–2 shows the chemical composition of Hardened Steel EN 31material.

Table.2.Physical and mechanical properties of Hardened Steel EN 31

Material	Density (gms/cm^3)	Thermal Conductivity (W/mK)	Hardness (BHN)	Electrical Resistivity (x° C-cm)	Specific Capacity (J/g°C)
Hardened Steel EN 31	7.81	46.6	205	0.0000218	0.475

Table.3.Chemical composition of Hardened Steel EN31

Work Material	Hardened Steel EN 31
Mn (%)	0.580
C (%)	1.070
Si (%)	0.320
S (%)	0.030
P (%)	0.040
Cr (%)	1.120
Ni (%)	0.029
Mo (%)	0.005
Fe	Balance
V	-

Tool Material: Copper is frequently utilized as the electrode material. Graphite, Brass and copper-tungsten too frequently utilized as machining them is easy and conductive without corroding. The cylindrical tool electrode comprises of tool holder, flexible pipes, copper tool and 10 mm diameter plastic spur gear. In this experiment copper is taken as electrode material as cathode. Tool is designed to cut the cavity on Hardened EN31 steel in the similar profile.

Experimental procedure:

Machining Processes: The job which is targeted for being machined is held tightly in the vice with corrosion resistant machining chamber. A window permits the operator for viewing the machining process. The tool is made to move close to job using the aid of press buttons present on the control panel and table lifting arrangement, maintaining specific gap. Progress of the tool is maneuvered vertically by the servo motor and is administered by a micro-controller dependent programmable drive. In ECM, generally a cathode tool is produced from the material that is non-reacting like copper. Parameters of the process like Current, Voltage, Flow Rate and Gap, are set. Initialization of the process happens in the occurrence of an electrolyte flow which gets circulated using the assistance of special pump filling the gap between anode (Job) and cathode (Tool). Electrolyte flow is attuned using a valve for flow control. Machining is obtained on sinking the tool tending to form its replica. While operation, a complicated control panel handles any damage to the machine along the overload and protections over short circuits. After the desired time interval, a hooter gives an indication of achievement of the time/ process. Tiny are of machining with provided power supply can be machined within 30 min. to one hour. The specimen is prepared as a cylindrical blank of 16mm diameter and 32mm height and is produced out of hardened steel which is machined by ECM. The electrolyte composition is 10% NaCl with water. The tool is placed on the tool holder and its alignment is checked with the assistance of dial gauge. Count of runs was decided to be 31 with different parameter combinations as depicted in Table 4.

Table.4.Different variables used in the experiment and their levels

Items	-2	-1	0	1	2
Parameters					
Current (Amps)	100	130	160	190	220
Voltage (Volts)	5	7	9	11	13
Electrolyte	5	8	11	14	17
Feed Rate	0.1	0.2	0.3	0.4	0.5

Measurement Procedure: Roughness measurement was done using a portable roughness tester SJ201. This instrument (Surtronic 3^+) is a handy instrument that is self-contained too for measuring texture of surface. Evaluations of parameter are microprocessor dependent. Outcomes of measurement are exhibited on an LCD screen and pass output to an optional printer or another computer for additional investigation. Non-rechargeable alkaline battery (9V) powers the instrument. It is equipped with a diamond stylus having a tip radius 5µm. The measuring stroke forever gets initialized from the tremendous external position. At the closing point of measurement the pickup turn back to the position alert for the consecutive measurement. The selection of cut-off length determines the traverse length. Usually as a default, the traverse length is five times the cut-off length though the magnification factor can be changed. The profilometer calibrated to a cut-off length of 0.8mm, filter 2CR, and traverse speed 1mm/sec and 4mm traverse length. Along transverse direction Roughness measurements, over the work pieces were recurring four times and its average of four measurements of parameter values of surface roughness was recorded.

MRR is estimated by determining the time of machining using the formula. The values were tabulated in the Table 2 and Table 3.

$$\mathrm{MRR(mg/min)} = \frac{\text{(Initial weight-Final weight)}}{\text{(Machining time)}}$$

Machining process observations depend on second order central composite rotatable design. A total of four machining parameters (Current, Voltage, Flow Rate and Gap) were chosen. Machining outcomes later to ECM process have been determined depending on two machining performances, MRR and SR. ECM process observation is depicted in Table 5.

Table.5.Process variables and their corresponding responses

Current (A)	**Voltage (V)**	**Electrolyte Concn.**	**Feed Rate**	**MRR (g/min)**	**SR (µm)**
130	11	14	0.2	0.017	3.20
130	11	8	0.2	0.034	3.20
190	7	8	0.2	0.029	1.90
160	5	11	0.3	0.056	1.50
190	7	8	0.4	0.032	2.90
160	9	11	0.3	0.034	3.50

160	9	11	0.3	0.042	3.50
130	7	8	0.2	0.030	2.90
190	11	14	0.2	0.035	3.00
160	9	11	0.3	0.035	3.50
220	9	11	0.3	0.031	3.20
130	7	14	0.4	0.032	2.60
160	9	11	0.1	0.019	3.30
160	9	5	0.3	0.028	3.38
190	11	8	0.2	0.035	3.10
160	9	11	0.3	0.025	3.50
130	11	8	0.4	0.028	3.10
160	9	11	0.5	0.017	3.40
190	11	8	0.4	0.034	4.10
130	7	14	0.2	0.029	3.30
190	11	14	0.4	0.056	3.70
130	7	8	0.4	0.032	2.60
160	9	11	0.3	0.034	3.50
160	9	11	0.3	0.042	3.50
160	9	17	0.3	0.030	3.30
130	11	14	0.4	0.035	2.50
160	13	11	0.3	0.035	2.70
190	7	14	0.4	0.031	2.90
160	9	11	0.3	0.032	3.40
100	9	11	0.3	0.019	3.00
190	7	14	0.2	0.028	2.60

Multi Response Model Using Grey Relational Analysis: Association among numerous factors expressed in the earlier section is uncertain called "grey", implying poor, unfinished and tentative information and that analysis on standard procedure with respect to statistics might be unacceptable or reliable without large data sets. In this work, GRA was utilized for converting the multi-response optimization model into a single response grey relational grade. Instead of using experimental values straight away in multiple regression model and PSO model, grades are utilized for studying about multi-response characteristics. Subsequent steps are to be followed while applying grey relational analysis:

i). Normalizing the outcomes of experiments of MRR and SR in avoiding the influence of adopting dissimilar units to reduce the variability.

$Z = Y- MIN/ MAX –MIN$ (1)

$Z = MAX- Y/ MAX- MIN$ (2)

ii). Performing the grey relational producing and estimating the grey coefficient for the normalized values yield.

$R = \Delta_{min} +€\Delta_{max}/\Delta_{oj} + €\Delta_{max}$ (3)

iii). Manipulative the grey relational grade on averaging the grey relational coefficient yield.

$S = 1/k\sum r_{ij}$ (4)

Where sis the grey relational grade for the jth experiment and k is the count of performance characteristics. Equation (1) is utilized in normalizing the experimental value when the target of the innovative value is having the characteristic of 'higher the better'. Here MRR is normalized using the above equation. When the 'lower the better' is a characteristic of the innovative sequence, then the innovative sequence is normalized using Eq. (2), i.e., SR is normalized using this equation. Using Eq. (3), we estimate the grey relational coefficient for MRR and SR as depicted in Table 6.

Table.6.Grey relational coefficients and the grey relational grade

Normalized Value For MRR	Normalized Value For SR	GRC Value for MRR	GRC Value for SR	Grade	Normalized Value For MRR	Normalized Value For SR	GRC Value for MRR	GRC Value for SR	Grade
0	0.3461	0.3333	0.4333	0.3833	0.2820	0.3846	0.4105	0.4482	0.4294
0.4358	0.3461	0.4698	0.4333	0.4516	0	0.2692	0.3333	0.4062	0.3698
0.3076	0.8461	0.4193	0.7646	0.5920	0.4358	0	0.4698	0.3333	0.4016
1	1	1	1	1	0.3076	0.3076	0.4193	0.4193	0.4193
0.3846	0.4615	0.4482	0.4814	0.4648	1	0.1538	1	0.3714	0.6857
0.4358	0.2307	0.4698	0.3939	0.4319	0.3846	0.5769	0.4482	0.5416	0.4949

0.6410	0.2307	0.5820	0.3939	0.4880	0.4358	0.2307	0.4698	0.3939	0.4319
0.3333	0.4615	0.4285	0.4814	0.4550	0.6410	0.2307	0.5420	0.3939	0.4680
0.4615	0.4230	0.4814	0.4642	0.4728	0.3333	0.3076	0.4285	0.4193	0.4239
0.4615	0.2307	0.4814	0.3939	0.4377	0.4615	0.6153	0.4814	0.5651	0.5233
0.3589	0.3461	0.4381	0.4333	0.4357	0.4615	0.5384	0.4814	0.5199	0.5007
0.3846	0.5769	0.4482	0.5416	0.4949	0.3589	0.4615	0.4381	0.4814	0.4598
0.0512	0.3076	0.3451	0.4193	0.3822	0.3846	0.2692	0.4482	0.4062	0.4272
0.2820	0.2769	0.4105	0.4087	0.4096	0.0512	0.4230	0.3451	0.4642	0.4047
0.4615	0.3846	0.4814	0.4482	0.4648	0.2820	0.5769	0.4105	0.5416	0.4761
0.2015	0.2307	0.3861	0.3939	0.3900					

Model development: In the idea of predicting the behavior of the grey relational grade, two approaches were brought up in associating the relationship among parameters of process and responses of output using multiple regression and PSO models. The process parameters, Current (c), Voltage (V), Flow Rate (F) and Gap (G) are considered as independent variables and the grey grade as a dependent variable.

Multiple Regression Models: Multiple regression techniques utilized in analyzing data from unexpected experiments, such as might arise from observation of uncontrolled phenomena or historical data. Regression methods too have been utilized much in designed experiments where something has "gone wrong". Wide-ranging idea of multiple regressions is identified for learning much concerning the relationship among numerous independent or predictor variables and a dependent or criterion variable. Subsequent two models were brought up in analyzing the process variable in ECM process.

(i) Model I: Linear Model Excluding Interaction Terms

(ii) Model II: Particle Swarm Optimization Model

Model I Linear Model Excluding Interaction Terms: This model is a linear multiple regression model without considering interaction terms. A multiple regression model using independent variables C, V, E and F and dependent variable grade can be represented as:

Grade = b0 + b1 C + b2 V + b3 F + b4 G

Where b_0, b_1, b_2, b_3 and b_4 are the regression coefficients to be determined. Regression model brought up utilizing MINITAB software based on these equations.

The regression equation is

G = 0.518 + 0.000594C - 0.0217V + 0.0026 E + 0.089F

The predicted values are calculated through the regression Eq. 4. The percentage deviations are computed for both data's and the outcomes are mentioned below.

Model II Particle Swarm Optimization Model: This model is a PSO model without considering as nonlinear terms. The input variables are Current (C), Voltage (V), Electrolyte Concentration (E) and Feed Rate (F). The total number of inputs nodes is four. It is built to relate the parameters of process and responses of output. The output layer is considered as grey relational grade. To define the figure of hidden layers and quantity of nodes in each hidden layer are to be established and also the transfer functions of each processing element are identified.

These are the nonlinear equations in finding the Predicted Grade of Differential evolution model:

The Predicted Grade equation:

G= 0.51953 + 0.00783 C -0.07106 V -0.13150 E + 2.28484 F -0.00002 C*C+0.00384 V*V+0.00719 E*E -0.01483 F*F+0.00030 C*V -0.00020 C*E -0.01043 C*F -0.00100 V*E -0.07758V*F+0.00724 E*F

The Table 6 depicts the deviation of percentage and the results obtained from PSO.

Particle swarm optimization: In computer science, PSO is a method of computing which optimizes an issue on iteratively annoying for improving a candidate solution regarding to a provided measure of quality. An issue gets optimized by PSO on having a count of candidate solutions, here dubbed particles and shifting these particles approximately in the search-space as per the straightforward mathematical formulae towards the position and velocity of particle. Each particle's movement is subjective by its local best familiar position and too guided on the way to the well identified positions in the search-space, that are reorganized as ideal positions were identified by added particles which is anticipated for moving the swarm on the way to the greatest solutions.

PSO is a population dependent stochastic optimization technique brought up by Dr. Eberhart and Dr. Kennedy in 1995, enthused by bird flocking or fish schooling social behavior. PSO contribute to numerous similarities with evolutionary computation techniques namely Genetic Algorithms (GA) whereas the system gets started with random solutions population and investigates optima by on future generations. However, unlike GA, PSO does not have any evolution operators like crossover and mutation. In PSO, the potential solutions, named particles, fly via the space of problem on adopting the particles that are currently optimum.

Every particle follows its coordinates in the issue space that are connected with the greatest solution (fitness) it has obtained so far. (The fitness value is also stored) which is called p_{best}. An additional "best" value which is tracked by the particle swarm optimizer is the most excellent value, achieved so far by some particle among the particle neighbors and this location is called lbest. On taking a particle population as its topological neighbors, the suitable value is a global best and is reffered g_{best}.

The PSO concept comprise of, at every time step, altering every particle's velocity (accelerating) toward its p_{best} and l_{best} locations (local version of PSO). Acceleration is weighted by a random term, with disconnected random numbers being produced for acceleration pointing p_{best} and l_{best} locations.

In past quite a few years, PSO was productively functional in numerous research and areas of application. It also demonstrates that PSO holds optimum outcomes in a quicker, cheaper way assessed with various methods.
Some other reason that PSO is striking is that some adjustable parameters exists. One version, among minor variations, functions fine in a greater choice of applications. Particle swarm optimization was utilized for moving toward that could be utilized across a greater choice of applications, together for particular applications targeting on a definite requirement.

From the above mentioned case, there exists two key steps which could be learnt on application of PSO to the issues of optimization: the solution representation and the fitness function. One among the PSO advantages is that PSO obtain real numbers as particles which is alike GA demanding modification to binary encoding, or particular genetic operators have been utilized. For example, on trying to identify the solution for f(x) = x1^2 + x2^2+x3^2, the particle can be set as (x1, x2, x3), and fitness function is f(x). Then standard procedure could be utilized in finding the optimum. The searching is a replicate process, and the stop criteria known to be that the maximum iteration number is reached or the minimum error circumstance is fulfilled.

Few parameters were only identified for getting tuned in PSO with a parameters list and their distinctive values. Count of particles: the distinctive range is 20 - 40. In point of fact for much of the issues 10 particles is highly sufficient in getting better results. For few hard or extraordinary problems, one can attempt 100 or 200 particles as well.

Range of particles: It is also identified by the issue to be optimized, which could be specified at various choices for dissimilar particle dimension.

V_{max} it determines the maximum change one particle can take during one iteration. Usually we contribute the choice of the particle as the Vmax for example, the particle (x1, x2, x3).

X1 belongs [-10, 10], then Vmax = 20Learning factors: c1 and c2 typically equal to 2. On the other hand, other settings have been put in various papers. But typically c1 equals to c2 and ranges from [0 and 4]

The stop condition: the maximum count of iterations the PSO execute and the least requirement of error. For example, for ANN training in earlier section, we can put the least requirement of error is one mis-classified pattern. The maximum count of iterations is set to 2000. This condition of stopping relies on the issue of optimization. Global version vs. local version: we brought in two versions of PSO global and local version. Global version is earlier but could converge to local optimum for few problems. Local version is comparatively slower but not much easy for being trapped into local optimum. One could utilize global version for getting faster result and utilize local version. Some factor is inertia weight, which is brought in by Shi and Eberhart (1998). PSO development is in progress still and there exists still much of unfamiliar areas in PSO research namely the validation mathematically the particle swarm theory.

As mentioned before, PSO simulates the bird flocking behavior. In case the upcoming scenario: in an area a group of birds are arbitrarily searches food with availability of only one piece of food there. Every bird do not know the place of food. But they recognize the distance for it in every iteration hence identifying the ideal strategy for finding the food? The efficient one is to adopt the bird that is closest to the food.

PSO recognized from the scenario and utilized in solving the problems of optimization. In PSO, every single solution is a "bird" in the search space calling it "particle". Every particle holds fitness values that are evaluated by the fitness function for being optimized, and possess velocities that direct the particles flying whereas they fly via the problem space on following the existing optimum particles. PSO gets commenced with a group of random particles (solutions) and then searches for optima on updating generations. In all iteration, every particle gets updated by following two "best" values. The foremost one is the most excellent solution (fitness) it has accomplished till now. (The fitness value is also stored). Calling the value p_{best}. An additional "best" value which is monitored by the particle swarm optimizer is the greatest value, achieved so far by any particle in the population. Global best is the best value and called g_{best}. On participation of a particle in its population as its topological neighbors, local best is known to the best value. Later on finding the two best values, the particle keeps changing its velocity and positions with subsequent equation (a) and (b)

$$V [] = v[] + c1 * rand() * (p_{best}[] - present[]) + c2 * rand() * (g_{bes}t[] - present[]) \quad (a)$$

$$present [] = persent[] + v[] \quad (b)$$

Where v [] is the particle velocity, present [] is the current particle (solution), p_{best} [] and g_{best}[] are defined as stated before, rand () is a random number between (0,1). c_1, c_2 are learning factors. Usually $c_1 = c_2 = 2$. Particles' velocities on every dimension are clamped to an utmost velocity V_{max}. If the accelerations sum would lead to the velocity on that dimension for exceeding V_{max}, that is a parameter particular by the user.

From the procedure, we could learn that PSO shares numerous familiar points with GA. Both algorithms commence with a collection of a erratically produced population, both having values of fitness for evaluating the population. On the other hand, PSO does not possess genetic operators like crossover and mutation. Particles keep updating themselves with the internal velocity with memory that is significant to the algorithm.

Assessed with GAs, the information allotment mechanism in PSO is appreciably dissimilar. In GAs, chromosomes distribute information among one another. So the entire population goes like a single group towards an optimal area. In PSO, only g_{best} (or p_{best}) contribute the information to others. It is a one -way information sharing mechanism. The evolution only looks for the best solution. Assessed with GA, every particles move forward in converging to the apt solution speedily even in the local version in the majority scenarios.

Optimization process: These are the nonlinear equations in finding the fitness values in optimization process.

$MRR=-0.058007+0.000253C+0.011500V+0.008014E-0.250000F-0.000003C^2-0.001187V^2-0.000375E^2+0.400000F^2+0.000044CV+0.000017CE+0.000417CF+0.000167VE+0.006250VF-0.007917EF$

SR=2.0411-0.0254C+1.3904V+0.3726E-10.5101F-0.0001C2-0.0865V2-0.0040E2-3.3512F2+0.0031CV+0.0003CE+0.1000CF-0.0229VE+0.1875VF-0.4167EF

Table.7.Better output responses

Model	Current (A)	Voltage (V)	Electrolyte Concentration (%)	Feed Rate (mm)	SR (µm)	MRR (mg/m)	% of Deviation
LR	187.807	10.485	11.9992	0.5	2.77556	0.061335	13.74
PSO	187.807	10.485	11.9992	0.5	2.77556	0.061335	03.28

```
Program Sequence
clear all
clc
close all
global lb ub Fx pop newpop rands
[sol, fval] = swarm2(@objfns, 10, lb, ub)
lb=[100,5,5,0.1];
ub=[220,13,17,0.5];
[sol, fval] = swarm1(@objfnm, 10, lb, ub)
C=sol(1);
V=sol(2);
E=sol(3);
F=sol(4);
MRR=-0.058007+ 0.000253*C+0.011500*V+0.008014*E-0.250000*F-0.000003*C.^2-0.001187*V.^2-
0.000375*E.^2+0.400000*F.^2+0.000044*C.*V+0.000017*C.*E+
0.000417*C.*F+0.000167*V.*E+0.006250*V.*F-0.007917*E.*F ;
SR=-2.0411-0.0254*C+1.3904*V+0.3726*E-10.5101*F-0.0001*C.^2-0.0865*V.^2-0.0040*E.^2-
3.3512*F.^2+0.0031*C.*V+0.0003*C.*E+0.1000*C.*F -0.0229*V.*E+0.1875*V.*F-0.4167*E.*F;
fprintf(' \n\n')
fprintf(' Current = %g',C),fprintf(' A \n\n')
fprintf(' Voltage = %g',V),fprintf(' V \n\n')
fprintf(' Electrolytic Concenteration = %g',E),fprintf(' percent \n\n')
fprintf(' Feed Rate = %g',F),fprintf(' mm \n\n')
fprintf(' Material Removal Rate = %g',MRR),fprintf(' gm/min \n\n')
fprintf(' Surface Roughness = %g',SR),fprintf(' micro-m \n\n')
figure(1)
figure(1)
plot(1./Fx,'k')
plot(Fx,'k')
xlabel('Iterations')
ylabel('Fitness Value')
```

3. CONCLUSION

A practical technique to optimize cutting parameters for ECM dependant on multiple regression models and PSO Model are accessed in this work. Current, Voltage, Electrolytic Concentration and Feed Rate have been considered as machining parameters. MRR and SR have been obtained as responses from the ECM process. MRR and SR are associated for having a solitary objective as grey relational grade by GRA application. Linear regression model and PSO MODEL were brought up for mapping the association among machining parameters and output responses. The average percentage deviation the linear regression model is 13.74 and PSO is 3.28. PSO model gives the better prediction depending on the deviation of percentage in machining data sets and the same was utilized in finding the optimal parameters of machining in ECM has been noted very clearly. Lastly the optimal conditions for MRR, Current = 187.807A, Voltage = 10.485V Electrolytic Concentration = 11.9992%, Feed Rate = 0.5mm and maximum MRR = 0.061335gm/min and minimum SR = 2.77556e-016 micro-m, for maximizing MRR and minimizing SR simultaneously among the 31 experimental data. Highly influencing factor obtained by the response table is the current for the ECM process. The developed model was weighed against experimentally and exhibit low values of error. For integrating the PSO with Meta heuristics and Intelligent Techniques for finding the optimal parameters of machining as future scope of this work has also been proposed.

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