International Journal of Latest Trends in Engineering and Technology
Vol.(8)Issue(4-1), pp.305-315
DOI: http://dx.doi.org/10.21172/1.841.49
e-ISSN:2278-621X

GENETIC ALGORITHM PARAMETERS OPTIMIZATION FOR ELECTROCHEMICAL MACHINING USING RESPONSE SURFACE METHODOLOGY

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Abstract-In this paper, an attempt has been made for the judgment of the optimum parameters of GA for the optimization of Material Removal Rate (MRR) and the Surface Roughness (SR) simultaneously in Electro Chemical Machining (ECM) using Response Surface Methodology (RSM). Performance of GA can be achieved by optimization of its various parameters, i.e. creation function, crossover fraction, mutation function, population size etc. Fitness functions has been developed in GA for maximizing the MRR and minimization of SR. Combinational parameters of GA have been obtained by 5 levels central composite design approach of Response Surface Methodology (RSM) The optimization of the process parameter is primarily based on the working parameter used by the operator which is not possible that every time operator work on the optimum parameters. Due to this aspect GA optimization tool is required for effective utilization of the process. The main aim of this paper is to get the optimum GA parameters for maximizing the Material removal rate (MRR) and minimizing surface roughness (SR) for the Electro Chemical Machining (ECM) simultaneously.
Keywords-Electro Chemical Machining(ECM), Genetic algorithm , Regression model, Response surface methodology, Material Removal Rate(MRR), Surface Roughness (SR).

1. INTRODUCTION

Electrochemical machining (ECM) is one of the most broadly used nontraditional machining processes, which is used to machine extremely hard materials. ECM is a method of removing metal by electrochemical process.ECM has characterized as reverse electroplating and working on the principles of Faraday (1833).Faraday's law states that the mass of a metal distorted by the electrode is proportional to the quantity of electrical charges transferred to that electrode. A potential difference is maintained between electrodes as a result the ions existing in the electrolyte transfer toward the electrode. The desired amount of metal is removed because of ions movement towards the tool. In ECM the removal of metal is controlled by the anodic dissolution in the electrolyte. In ECM work piece act as anode and tool act as cathode. The electrolyte should be placed narrow in the gap of about 0.5 mm. The anode and cathode should be placed deep into the electrolyte. A genetic algorithm is used for optimizing the process parameters of the ECM machine. A genetic algorithm is a population based approach which is very effective in solving very hard problems like optimization of process parameters of various machines .GA is global , robust and anyone can apply it in such a situation where a little or a priori knowledge about the process and how to control it . Genetic algorithm normally starts with a preliminary population of chromosomes, which are randomly produced and based on several algorithms, other policies and Socratics.

Bhattacharyya et al (2005) highlighted various electrochemical micro-machining parameters like machining voltage, frequency, pulse period and electrolyte concentration and their influences on the Material Removal Rate (MRR), surface finish and accuracy in infinitesimal field. His study shows that 3V machining voltage, 20 g/l electrolyte concentration and 55 Hz frequency are optimal values of Electro chemical machining that can augment the accurateness with the uppermost possible amount of material removed (MRR). N. K. Jain et al (2007**)** concentrates his work on the optimization of tool feed rate, applied voltage, and electrolyte flow velocity with the purpose to minimize the geometrical inaccuracy subjected to choking, passivity constraint and temperatures. Via single objective real-coded genetic algorithms for obtaining the optimization process parameter of ECM machine after those optimum results were verified graphically and theoretically. His work shows that the optimum process parameters can extensively progress the process recital and progression economics by dropping operating, maintenance cost and tooling cost and manufacturing components of higher precision also try to extend

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tool life, machining cost and machining time by using suitable evolutionary algorithms. Dilip Datta et al (2010) applied a multi-objective GA to electrochemical machining for obtaining the optimum diverse process parameters by taking a tentative dataset for sculpting the problem through regression equation after that applied the genetic algorithm to linear model and an exponential model for obtaining the maximum MRR and minimizing the surface roughness (SR) simultaneously. Chinnamuthu Senthilkumar et al (2012) developed a second order polynomial arithmetical models for linking the interactive and higher-order of diverse machining parameters in the machining standard I,E. MRR and SR by using response surface methodology. They test models by ANOVA test. After that Non-dominated Sorting Genetic Algorithm-II (NSGA-II) was applied to get the optimized process parameter for exploit material removal rate and diminish surface roughness. Optimized value attained through NSGA-II, is 5.020 μm and the consequent MRR is 0.831 gm/min and the pertinent constraints were , electrolyte flow rate, electrolyte concentration applied voltage and tool feed rate are 5 lit/min, 16 gm/lit, 15 volts and 1.0 mm/min correspondingly. Biswesh R. Acharya et al (2013) used a central composite design for response surface methodology to study the effect of 4 different constraints (current , flow rate of electrolyte, voltage , and inter-electro gap) on Material Removal rate (MRR) and Surface roughness (SR) of the hardened steel material on ECM machine and also they develop empirical equation for MRR and SR and tested for statistical study on four parameters of ECM machine. After that they use a non-dominated sorted genetic algorithm to find out the optimal process parameter that simultaneously maximizes MRR and minimize SR and the validation of optimum result can be done by doing electrochemical machining for the corresponding input parameters. A Giribabu et al (2014) used L27 orthogonal array and genetic algorithms for optimizing the machining parameters for electrochemical machining of Al/B4C composites in that they considered four main parameters applied voltage (electrical constraint),tool feed rate(electrode constraint), electrolyte concentration (electrolyte constraint) and reinforcement content (work piece property) as input machining constraints and also developed a regression models for Material removal Rate, Surface roughness and Radial Over Cut and then use that regression equation in genetic algorithms for getting the optimum machinating parameters to maximize Material removal rate(MRR), minimize Surface roughness(SR) and minimize Radial Over Cut (ROC) simultaneously. M. Sankar et al (2014) used response surface methodology (RSM) relevance to optimize the machining constraints with multiple response method in electrochemical machining (ECM) of a 7075Al/B4C metal matrix compound and after obtaining the optimum parameter the result was compared with ANOVA . The result what they obtain through after applied the response surface methodology (RSM) demonstrate that feed rate and voltage are the most considerable constraint which affect multiple machining responses concurrently and the responses in ECM can be improved successfully through this loom. The optimum results given by the experiment are as follows 8V voltage and 0.3mm/min feed rate and 217A current are most appropriate and momentous to achieve utmost surface finish with NaNO3 electrolyte solution. V. Sathiyamoorthy et al (2015) attempted to diminish the formation of spikes in the work piece of high carbon and high chromium die tool steel using nano particles of copper floating in plain NaNO3 electrolyte. They used Design expert 7.0 software to developed the mathematical models for getting the response like MRR and SR and after that multi-objective genetic algorithm in MATLAB was used for the best probable combination for accomplishing the maximum MRR and minimum SR. After comparing the result from design expert 7.0 to the optimum results obtained by using multi-objective genetic algorithm (MOGA) the conclusion come that the distinction from the predicted performance is less than 4% which verify the composite popularity of the developed models. Abhishek Tiwari et al (2015) done the optimization of ECM for EN 19 tool steel by using Non- dominated sorting Genetic Algorithm-II (NSGA-II) for maximizing the MRR and minimizing the SR. They prepared a mathematical model for correlating the input and output parameters and ANOVA test was done on that to show the concentrate- ion and feed rate was most dominating criteria for MRR and SR respectively. They also represent the optimal machine parameter for ECM machine through Non-dominated Sorting Genetic Algorithm-II (NSGA-II).

1.1 Problem statement

ECM is widely used in various industries. Quality and productivity of a product are highly considered. There are diverse parameters which affect the quality of the product and productivity .The MRR and SR are the prime response factors for higher productivity and good quality respectively. Improper combinational process parameters leads in productivity reduction and for the poor quality. So, we need to optimize the process parameters for maximizing the MRR and minimize the SR . Previously, research work has been done on optimizing the machine parameter for maximizing the MRR and minimizing the SR by using various mathematical and computational models. The ranges of the selected input parameters and regression equation used in this study are taken from (Rao and Padmanabhan, 2013).With the help of these regression equations the fitness function is created in GA for getting the values of MRR and SR.

$$MRR = -0.166 + 0.0272X1 + 0.424X2 + 0.00776X3 - 0.0284X4 \tag{1}$$

$$SR = 5.04 + 0.0153X1 - 0.648X2 - 0.0292X3 + 0.0551X4 \tag{2}$$

And there limits are as follow

Applied voltage	$12 \le X1 \le 20$	(3)
Feed rate	$0.2 \le X2 \le 1$	(4)
Electrolyte concentration	$10 \le X3 \le 30$	(5)
Percentage of reinforcement	$2.5 \le X4 \le 7.5$	(6)

2. METHODOLOGY

In GA every generation of the population goes throughout various progressions like encoding, Fitness function valuation selection, crossover and transformation. Genetic Algorithms work on the principles of natural genetics to evolve solutions of the problems .A Script fitness function is created in GA according to our requirement. When we execute this fitness function each set of the population represent a solution of the problem. Crossover & Mutation are used for producing new offsprings which are known as Reproduction operators. In this two Mutation function (Uniform and Adaptive feasible) and three crossover functions (Scattered, Single point and two points) are used for optimization. GA represents a novel programming pattern that attempts to copy the course of natural evolution, to resolve computing and optimization problems of computers. In GA, a population of chromosomes, which are generally twine of bits, is arbitrarily selected. This population further altered into a new population by a variety of natural selection based on the utilize of the operators encouraged by the natural genetic operatives.

The natural selection is fully based on the output of the function which is called fitness function. Only the best fit chromosomes are survived and permissible to further reproduce the new offsprings or we can say these are used in the next population. After exchanging the properties of two parents with each other and as a result of which two children created or making arbitrary changes to single parent by mutation. By replacing the present population with the children to structure the new generation. The algorithm end when the generation of a new population had completed.

The complete work is separated into two parts: first part is finds the maximum MRR and minimum SR simultaneously uses GA and the second part optimize the parameters of GA using Design expert. In this approx. 156 experiments were obtained by using 5 level central composite design approaches for Response surface methodology in design expert software are shown in Table 1.

Table1: Various Parameters Combination Of Ga By Using Design Expert

Std	Run	Factor1 A:Population size	Factor2 B:Crossover fraction	Factor3 C:Creation function	Factor4 D:Mutation function	Factor5 E:Crossover function	Response1 MRR	Response2 SR
16	1	20	0.9	Feasible population	Uniform	Scattered	0.68323	3.889
63	2	45	0.7	Uniform	Uniform	Single point	0.7174	3.894
2	3	70	0.4	Uniform	Uniform	Scattered	0.7242	3.8588
106	4	70	0.4	Uniform	Uniform	Two point	0.7328	3.8708
55	5	20	0.9	Uniform	Uniform	Single point	0.7222	3.9126
9	6	45	0.7	Uniform	Uniform	Scattered	0.6938	3.892
116	7	45	0.7	Uniform	Uniform	Two point	0.7348	3.8688
95	8	70	0.9	Feasible population	Adaptive feasible	Single point	0.743	3.8448
13	9	45	0.7	Uniform	Uniform	Scattered	0.746	3.8282
86	10	45	1.0	Uniform	Adaptive feasible	Single point	0.7288	3.882
77	11	45	0.7	Feasible population	Uniform	Single point	0.7318	3.7984
35	12	45	0.7	Uniform	Adaptive feasible	Scattered	0.7424	3.8487
1	13	20	0.4	Uniform	Uniform	Scattered	0.7122	3.9632
145	14	70	0.4	Feasible population	Adaptive feasible	Two point	0.746	3.8405
30	15	70	0.9	Uniform	Adaptive feasible	Scattered	0.7458	3.8408
141	16	45	0.7	Uniform	Adaptive feasible	Two point	0.747	3.8386
132	17	70	0.4	Uniform	Adaptive feasible	Two point	0.7446	3.8474
20	18	45	0.3	Feasible population	Uniform	Scattered	0.7366	3.875
53	19	20	0.4	Uniform	Uniform	Single point	0.73	3.94

150	20	45	0.3	Feasible population	Adaptive feasible	Two point	0.746	3.838
71	21	80	0.7	Feasible population	Uniform	Single point	0.7284	3.8637
140	22	45	0.7	Uniform	Adaptive feasible	Two point	0.7484	3.8394
130	23	45	0.7	Feasible population	Uniform	Two point	0.7542	3.895
112	24	45	1.0	Uniform	Uniform	Two point	0.7352	3.8824
135	25	10	0.7	Uniform	Adaptive feasible	Two point	0.741	3.9342
69	26	70	0.9	Feasible population	Uniform	Single point	0.7308	3.868
143	27	45	0.7	Uniform	Adaptive feasible	Two point	0.748	3.838
111	28	45	0.3	Uniform	Uniform	Two point	0.7356	3.8514
7	29	45	0.3	Uniform	Uniform	Scattered	0.71662	3.8642
120	30	20	0.9	Feasible population	Uniform	Two point	0.6884	3.9634
37	31	45	0.7	Uniform	Adaptive feasible	Scattered	0.746	3.838
23	32	45	0.7	Feasible population	Uniform	Scattered	0.7342	4.1
61	33	45	0.7	Uniform	Uniform	Single point	0.7456	3.894
5	34	10	0.7	Uniform	Uniform	Scattered	0.67392	4.0304
113	35	45	0.7	Uniform	Uniform	Two point	0.7158	3.894
139	36	45	0.7	Uniform	Adaptive feasible	Two point	0.7476	3.8394
134	37	70	0.9	Uniform	Adaptive feasible	Two point	0.7438	3.8412
94	38	20	0.9	Feasible population	Adaptive feasible	Single point	0.7428	3.8478
19	39	80	0.7	Feasible population	Uniform	Scattered	0.7326	3.864
65	40	45	0.7	Uniform	Uniform	Single point	0.7352	3.8672
40	41	20	0.4	Feasible population	Adaptive feasible	Scattered	0.746	3.9245
102	42	45	0.7	Feasible population	Adaptive feasible	Single point	0.7404	3.8496
41	43	70	0.4	Feasible population	Adaptive feasible	Scattered	0.746	3.837
22	44	45	0.7	Feasible population	Uniform	Scattered	0.7358	3.91
154	45	45	0.7	Feasible population	Adaptive feasible	Two point	0.7458	3.84
122	46	10	0.7	Feasible population	Uniform	Two point	0.6798	3.9522
131	47	20	0.4	Uniform	Adaptive feasible	Two point	0.7423	3.9536
78	48	45	0.7	Feasible population	Uniform	Single point	0.7304	3.8318
96	49	10	0.7	Feasible population	Adaptive feasible	Single point	0.7034	4.0048
127	50	45	0.7	Feasible population	Uniform	Two point	0.7368	3.8592
64	51	45	0.7	Uniform	Uniform	Single point	0.7356	3.861
97	52	80	0.7	Feasible population	Adaptive feasible	Single point	0.7446	3.8385
149	53	80	0.7	Feasible population	Adaptive feasible	Two point		

							0.746	3.837
83	54	10	0.7	Uniform	Adaptive feasible	Single point	0.7204	3.9242
89	55	45	0.7	Uniform	Adaptive feasible	Single point	0.7464	3.8384
151	56	45	1.0	Feasible population	Adaptive feasible	Two point	0.723	3.8856
87	57	45	0.7	Uniform	Adaptive feasible	Single point	0.746	3.837
59	58	45	0.3	Uniform	Uniform	Single point	0.7352	3.8608
155	59	45	0.7	Feasible population	Adaptive feasible	Two point	0.74836	3.8424
124	60	45	0.3	Feasible population	Uniform	Two point	0.7334	3.9002
17	61	70	0.9	Feasible population	Uniform	Scattered	0.7106	3.8986
68	62	20	0.9	Feasible population	Uniform	Single point	0.7175	4.0256
25	63	45	0.7	Feasible population	Uniform	Scattered	0.7162	3.8922
104	64	45	0.7	Feasible population	Adaptive feasible	Single point	0.746	3.8378
82	65	70	0.9	Uniform	Adaptive feasible	Single point	0.743	3.846
138	66	45	1.0	Uniform	Adaptive feasible	Two point	0.7254	3.8794
100	67	45	0.7	Feasible population	Adaptive feasible	Single point	0.746	3.828
107	68	20	0.9	Uniform	Uniform	Two point	0.7232	3.9248
156	69	45	0.7	Feasible population	Adaptive feasible	Two point	0.7447	3.8466
4	70	70	0.9	Uniform	Uniform	Scattered	0.7144	3.8382
91	71	45	0.7	Uniform	Adaptive feasible	Single point	0.746	3.838
52	72	45	0.7	Feasible population	Adaptive feasible	Scattered	0.7458	3.837
98	73	45	0.3	Feasible population	Adaptive feasible	Single point	0.745	3.84
128	74	45	0.7	Feasible population	Uniform	Two point	0.7306	3.8824
42	75	20	0.9	Feasible population	Adaptive feasible	Scattered	0.7452	3.8392
75	76	45	0.7	Feasible population	Uniform	Single point	0.7272	3.8796
14	77	20	0.4	Feasible population	Uniform	Scattered	0.7094	4.0256
125	78	45	1.0	Feasible population	Uniform	Two point	0.7268	3.8854
85	79	45	0.3	Uniform	Adaptive feasible	Single point	0.7414	3.8532
18	80	10	0.7	Feasible population	Uniform	Scattered	0.6748	4.076
92	81	20	0.4	Feasible population	Adaptive feasible	Single point	0.7338	3.8906
70	82	10	0.7	Feasible population	Uniform	Single point	0.6902	3.9662
117	83	45	0.7	Uniform	Uniform	Two point	0.706	3.9266
50	84	45	0.7	Feasible population	Adaptive feasible	Scattered	0.748	3.838

60	85	45	1.0	Uniform	Uniform	Single point	0.7145	3.889
24	86	45	0.7	Feasible population	Uniform	Scattered	0.709	3.9078
47	87	45	1.0	Feasible population	Adaptive feasible	Scattered	0.7038	3.93
6	88	80	0.7	Uniform	Uniform	Scattered	0.7271	3.8661
66	89	20	0.4	Feasible population	Uniform	Single point	0.6978	3.9388
73	90	45	1.0	Feasible population	Uniform	Single point	0.725	3.884
48	91	45	0.7	Feasible population	Adaptive feasible	Scattered	0.746	3.837
51	92	45	0.7	Feasible population	Adaptive feasible	Scattered	0.746	3.8492
147	93	70	0.9	Feasible population	Adaptive feasible	Two point	0.746	3.838
115	94	45	0.7	Uniform	Uniform	Two point	0.737	3.8654
101	95	45	0.7	Feasible population	Adaptive feasible	Single point	0.746	3.837
76	96	45	0.7	Feasible population	Uniform	Single point	0.734	3.914
118	97	20	0.4	Feasible population	Uniform	Two point	0.729	3.904
142	98	45	0.7	Uniform	Adaptive feasible	Two point	0.7474	3.838
46	99	45	0.3	Feasible population	Adaptive feasible	Scattered	0.7455	3.838
27	100	20	0.4	Uniform	Adaptive feasible	Scattered	0.7438	3.92
153	101	45	0.7	Feasible population	Adaptive feasible	Two point	0.746	3.831
10	102	45	0.7	Uniform	Uniform	Scattered	0.6966	3.8746
8	103	45	1.0	Uniform	Uniform	Scattered	0.7058	3.8858
81	104	20	0.9	Uniform	Adaptive feasible	Single point	0.7414	3.8532
67	105	70	0.4	Feasible population	Uniform	Single point	0.73942	3.8574
57	106	10	0.7	Uniform	Uniform	Single point	0.6708	3.9548
121	107	70	0.9	Feasible population	Uniform	Two point	0.7428	3.8512
28	108	70	0.4	Uniform	Adaptive feasible	Scattered	0.748	3.842
74	109	45	0.7	Feasible population	Uniform	Single point	0.7312	3.8808
29	110	20	0.9	Uniform	Adaptive feasible	Scattered	0.7358	3.8582
33	111	45	0.3	Uniform	Adaptive feasible	Scattered	0.746	3.838
108	112	70	0.9	Uniform	Uniform	Two point	0.7234	3.8918
103	113	45	0.7	Feasible population	Adaptive feasible	Single point	0.744	3.831
114	114	45	0.7	Uniform	Uniform	Two point	0.748	3.868
26	115	45	0.7	Feasible population	Uniform	Scattered	0.7312	3.8854
109	116	10	0.7	Uniform	Uniform	Two point	0.6886	4.0832
126	117	45	0.7	Feasible population	Uniform	Two point	0.7334	3.8668
105	118	20	0.4	Uniform	Uniform	Two point	0.7386	3.8882

72	119	45	0.3	Feasible population	Uniform	Single point	0.7176	3.8958
144	120	20	0.4	Feasible population	Adaptive feasible	Two point	0.7496	3.8406
90	121	45	0.7	Uniform	Adaptive feasible	Single point	0.7452	3.8378
36	122	45	0.7	Uniform	Adaptive feasible	Scattered	0.746	3.8392
110	123	80	0.7	Uniform	Uniform	Two point	0.7363	3.8726
31	124	10	0.7	Uniform	Adaptive feasible	Scattered	0.715	3.96
12	125	45	0.7	Uniform	Uniform	Scattered	0.7242	3.8571
32	126	80	0.7	Uniform	Adaptive feasible	Scattered	0.7452	3.841
137	127	45	0.3	Uniform	Adaptive feasible	Two point	0.7458	3.8388
49	128	45	0.7	Feasible population	Adaptive feasible	Scattered	0.746	3.837
148	129	10	0.7	Feasible population	Adaptive feasible	Two point	0.6882	3.9378
38	130	45	0.7	Uniform	Adaptive feasible	Scattered	0.746	3.837
21	131	45	1.0	Feasible population	Uniform	Scattered	0.7142	3.893
39	132	45	0.7	Uniform	Adaptive feasible	Scattered	0.746	3.8382
11	133	45	0.7	Uniform	Uniform	Scattered	0.726	3.8842
44	134	10	0.7	Feasible population	Adaptive feasible	Scattered	0.7296	3.9048
80	135	70	0.4	Uniform	Adaptive feasible	Single point	0.746	3.837
152	136	45	0.7	Feasible population	Adaptive feasible	Two point	0.7496	3.8478
99	137	45	1.0	Feasible population	Adaptive feasible	Single point	0.746	3.838
34	138	45	1.0	Uniform	Adaptive feasible	Scattered	0.7138	3.8182
136	139	80	0.7	Uniform	Adaptive feasible	Two point	0.7477	3.8403
146	140	20	0.9	Feasible population	Adaptive feasible	Two point	0.7354	3.8702
43	141	70	0.9	Feasible population	Adaptive feasible	Scattered	0.7426	3.8434
54	142	70	0.4	Uniform	Uniform	Single point	0.7278	3.8792
93	143	70	0.4	Feasible population	Adaptive feasible	Single point	0.746	3.838
123	144	80	0.7	Feasible population	Uniform	Two point	0.7398	3.8612
84	145	80	0.7	Uniform	Adaptive feasible	Single point	0.7447	3.8402
56	146	70	0.9	Uniform	Uniform	Single point	0.7294	3.8898
133	147	20	0.9	Uniform	Adaptive feasible	Two point	0.7466	3.8548
15	148	70	0.4	Feasible population	Uniform	Scattered	0.738	3.856
45	149	80	0.7	Feasible population	Adaptive feasible	Scattered	0.7451	3.8404
3	150	20	0.9	Uniform	Uniform	Scattered	0.69	3.91
58	151	80	0.7	Uniform	Uniform	Single point	0.729	3.8718

79	152	20	0.4	Uniform	Adaptive feasible	Single point	0.7422	3.865
129	153	45	0.7	Feasible population	Uniform	Two point	0.7314	3.8696
88	154	45	0.7	Uniform	Adaptive feasible	Single point	0.746	3.837
119	155	70	0.4	Feasible population	Uniform	Two point	0.731	3.872
62	156	45	0.7	Uniform	Uniform	Single point	0.734	3.94

3. RESULT AND DISCUSSIONS

In this work optimization of parameters of multi-objective genetic algorithm for maximizing the MRR and minimize the SR in ECM machine like population size, crossover, mutation, creation function etc. 5 level Central Composite Design (CCD) of Response Surface Methodology (RSM) of Design Expert software have been considered for optimizing the different multi-objective GA constraints for maximizing the Material Removal Rate(MRR) and minimizing Surface roughness of ECM machine. Table 2 shows the parameters of GA with their range and levels ,which are taken into consideration in this work. 156 experiments have been provided by the design expert through the combination of various parameters which are to be performed for the optimization. Each combinational set is run five times and the average of these taken as the final result. Hence total 156*5=780 outcomes were used for the optimization of GA constraints. Design summary is shown below in table 3. In which 2 factors (A and B) are numeric and other 3 factors (C, D and E) are definite.

Table 2: Genetic Algorithm Parameters With Range And Levels

S no.	Parameters	Range
1	Population size (A)	20 – 70 (5 Levels)
2	Crossover fraction(B)	0.4 - 0.9 (5 Levels)
3	Creation function(C)	Level 1(Uniform),Level 2(Feasible population)
4	Mutation function(D)	Level 1(Uniform),Level 2(Adaptive feasible)
5	Crossover function(E)	Level 1(Scattered), Level 2(Single point), Level 3(Double point)

Table 3: Design Review

Type of study	Response Surface	**Experiments**		156
Initial Design	Central Composite	**Blocks**	No Blocks	
Design Model	Quadratic			

Response	**Name**	**Units**	**Obs**	**Minimum**	**Maximum**	**Model**
Y1	MRR	g	156	0.67	0.75	Quadratic
Y2	SR	micrometer	156	3.80	4.10	Quadratic

Factor	**Name**	**Units**	**Type**	**Low Actual**	**High Actual**	**Low Coded**	**High Coded**		
A	Population size			Numeric	20.00	70.00	-1.000	1.000	
B	Crossover Fraction		Numeric	0.40	0.90	-1.000	1.000		
C	Creation function		Categorical	Uniform	Feasible population		**Levels:**	2	
D	Mutation function		Categorical	Uniform	Adaptive feasible			**Levels:**	2
E	Crossover function		Categorical	Scattered	Two point		**Levels:**	3	

A. ANOVA for the Response Surface Quadratic Model

ANOVA test have been conducted for the optmisation of the MRR and SR as shown in table 4 and 5.The model used for optimizing process parameters of GA is quadratic in nature. The F-test and probability test have been performed for checking the significance. The F-ratio is the fraction between groups means square values to within group mean square values. The P-values have been compared with each coefficient to check its significance. If P- value is less than 0.05 for a planned model, then it is significant at the 5% level of significance. It is to be noted that Lack of fit is not significant in both cases.

TABLE 4: ANOVA for Response Surface Quadratic Model of MRR

Source	Sum of Squares	Degree of freedom	Mean Square	F Value	Prob > F	
Model	035	22	1.604 x10^{-003}	13.69	< 0.0001	significant
A	9.069x10^{-003}	1	9.069 x10^{-003}	77.38	< 0.0001	
B	1.795 x10^{-003}	1	1.795 x10^{-003}	15.32	0.0001	
C	9.901 x10^{-008}	1	9.901 x10^{-008}	8.448 x10^{-004}	0.9769	
D	0.014	1	0.014	121.89	< 0.0001	
E	1.395 x10^{-003}	2	6.974 x10^{-004}	5.95	0.0033	
A^2	4.714 x10^{-003}	1	4.714 x10^{-003}	40.23	< 0.0001	
B^2	3.333 x10^{-004}	1	3.333 x10^{-004}	2.84	0.0941	
AB	4.951 x10^{-005}	1	4.951 x10^{-005}	0.42	0.5168	
AC	4.175 x10^{-004}	1	4.175 x10^{-004}	3.56	0.0613	
AD	1.382 x10^{-003}	1	1.382 x10^{-003}	11.80	0.0008	
AE	1.043 x10^{-005}	2	5.216 x10^{-006}	0.045	0.9565	
BC	4.436 x10^{-007}	1	4.436 x10^{-007}	3.785 x10^{-003}	0.9510	
BD	2.387 x10^{-007}	1	2.387 x10^{-007}	2.036 x10^{-003}	0.9641	
BE	7.797 x10^{-004}	2	3.898 x10^{-004}	3.33	0.0389	
CD	7.387 x10^{-005}	1	7.387 x10^{-005}	0.63	0.4286	
CE	2.498 x10^{-004}	2	1.249 x10^{-004}	1.07	0.3475	
DE	9.799 x10^{-004}	2	4.899 x10^{-004}	4.18	0.0173	
Residual	0.016	133	1.172 x10^{-004}			
Lack of Fit	0.011	85	1.300 x10^{-004}	1.38	0.1146	not significant
Pure Error	4.534 x10^{-003}	48	9.446 x10^{-005}			
Cor Total	0.051	155				

F-value of 13.69 of this model mean that the model is significant and there is only a 0.01% chance that a "Model F-Value" this large could occur due to noise.Values of "Prob > F" is less than 0.0500 specify model terms are considerablely. A, B, D, E, A^2, AD, BE, DE are significant model expressions.Values greater than 0.1000 specify that the model provisions are not significant.

Table 5: Anova For Response Surface Quadratic Model Of Sr

Source	Sum of Squares	Degree of freedom	Mean Square	F Value	Prob > F	
Model	0.26	22	0.012	10.82	< 0.0001	significant
A	0.12	1	0.12	107.74	< 0.0001	
B	1.432 x10^{-004}	1	1.432 x10^{-004}	0.13	0.7197	
C	6.972 x10^{-004}	1	6.972 x10^{-004}	0.63	0.4290	
D	0.073	1	0.073	65.57	< 0.0001	
E	2.071 x10^{-003}	2	1.036 x10^{-003}	0.93	0.3952	
A^2	0.047	1	0.047	42.60	< 0.0001	
B^2	1.741 x10^{-005}	1	1.741 x10^{-005}	0.016	0.9004	
AB	2.715 x10^{-003}	1	2.715 x10^{-003}	2.45	0.1198	
AC	1.723 x10^{-004}	1	1.723 x10^{-004}	0.16	0.6939	
AD	6.082 x10^{-003}	1	6.082 x10^{-003}	5.49	0.0206	
AE	1.494 x10^{-003}	2	7.470 x10^{-004}	0.67	0.5112	
BC	2.536 x10^{-004}	1	2.536 x10^{-004}	0.23	0.6331	
BD	1.148 x10^{-004}	1	1.148 x10^{-004}	0.10	0.7480	

BE	1.766×10^{-003}	2	8.832×10^{-004}	0.80	0.4527	
CD	8.252×10^{-004}	1	8.252×10^{-004}	0.75	0.3896	
CE	6.124×10^{-003}	2	3.062×10^{-003}	2.76	0.0666	
DE	1.556×10^{-003}	2	7.782×10^{-004}	0.70	0.4971	
Residual	0.15	133	1.108×10^{-003}			
Lack of Fit	0.096	85	1.124×10^{-003}	1.04	0.4467	not significant
Pure Error	0.052	48	1.079×10^{-003}			
Cor Total	0.41	155				

The Model F-value of 10.82 implies the model is significant. A, D, A^2, AD are significant model terms.

B. Optimum GA Parameters Predicted by RSM

Optimum parameters have been obtained using Central Composite Design (CCD) of Response Surface Methodology (RSM) of Design Expert software. Total of 156 experiments have been carried out for the optmisation of the MRR and SR simultaneously for ECM machine. Criteria for optimization and Optimum parameter selection for MRR and SR have been shown in table 6 and table 7.Through the various experiments the optimum parameters have been found to be population size: 59, Crossover Fraction: 0.4,creation function: Feasible population, mutation: Adaptive feasible, creation function: Two point and selection: tournament.

Table 6: Criteria For Optimization

Name	Goal	Lower	Upper	Importance
Population size	is in range	20	70	3
Crossover Fraction	is in range	0.4	0.9	3
Creation function	is in range	Uniform	Feasible population	3
Mutation function	is in range	Uniform	Adaptive feasible	3
Crossover function	is in range	Scattered	Two point	3
MRR	maximize	0.6708	0.7542	3
SR	minimize	3.7984	4.1	3

Table 7: Optimum Parameter Selection For MRR And SR

NO.	**Population size**	**Crossover Fraction**	**Creation function**	**Mutation function**	**Crossover function**	**MRR**	**SR**	**Desirability**	
1	59	0.4	Feasible p.	Adaptive feasible	Two point	0.749454	3.81884	0.938	Selected
2	66	0.4	Feasible p.	Adaptive feasible	Scattered	0.7542	3.83659	0.935	
3	58	0.4	Uniform	Adaptive feasible	Scattered	0.750998	3.82765	0.932	
4	57	0.4	Uniform	Adaptive feasible	Scattered	0.751071	3.82792	0.932	
5	57	0.4	Uniform	Adaptive feasible	Scattered	0.751121	3.82812	0.932	
6	55	0.4	Uniform	Adaptive feasible	Two point	0.75164	3.83767	0.918	
7	59	0.5	Feasible p.	Adaptive feasible	Single point	0.746955	3.82579	0.911	
8	54	0.6	Uniform	Adaptive feasible	Single point	0.748442	3.83572	0.903	
9	54	0.6	Uniform	Adaptive feasible	Single point	0.748438	3.83571	0.903	
10	70	0.4	Feasible p.	Uniform	Two point	0.741799	3.8443	0.850	

4. CONCLUSION

In this research paper, parametric optmisation for Genetic Algorithm for the maximization of the MRR and minimizationof the SR have been done. The efficiency and effectiveness of GA is primarily depends on its various parameters like population size, crossover fraction, creation function, mutation, crossover function etc. For the optimization of these GA parameters a 5 level numeric factor Central Composite Design (CCD) of Response surface methodology (RSM). Total 156 experiments are performed by varying its various GA parameters in MATLAB environment for the optimal result. The optimum values for maximizing the MRR and minimizing the SR simultaneously are Population size: 59, Crossover Fraction: 0.4, Creation function: Feasible population, Mutation: Adaptive feasible, Creation function: Two point.

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