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Research Article

ECM PARAMETERS FOR GENERATING SURFACE HAVING LOW COEFFICIENT OF FRICTION IN LUBRICATED CONDITION BY USING GENETIC ALGORITHM

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A B S T R A C T

Coefficient of friction in service is strongly influenced by surface roughness parameters. The objective of this work is to maximize the surface roughness parameters S_{ku} and minimize S_q, S_{HTp}, S_{sk} to lower the coefficient of friction in lubricated case. Multi objective genetic algorithm is used to find the Pareto front consisting of a number of non dominated solutions. The number of solutions found is large. Agglomerative hierarchical clustering method is used to obtain 3,4 and 5 clusters. Two linkage methods- centroid and complete are used to generate clusters with population 45 and 100. The Pareto optimal points closest to the cluster centroids are obtained. Complete linkage, population 45, cross over:0.8 represents the population well. The cluster1 and cluster 2 (complete linkage, population 45, cross over:0.8) which have low values of S_q and S_{htp} can be further analyzed to select a high value of S_{ku} and a low value of S_{sk}.

INTRODUCTION

The ability to machine very complex features in hard and difficult to machine materials with negligible tool wear, reasonable accuracy and acceptable surface finish has made electrochemical machining (ECM) an important non-traditional machining process. Many process parameters both controllable and uncontrollable determine the material removal rate, accuracy and surface texture. [1-6]. Statistical design has been used extensively to model the effect of different process parameters of ECM on output parameters such as surface roughness, material removal rate (MRR), overcut [5,7-10] etc. Maximizing one output parameter usually affects another desirable output parameter. A variety of approaches such as goal programming [11], Particle swarm optimization [12-14], Desirability Approach [15, 16], Genetic algorithm has been employed to find a set of optimal solutions involving conflicting objective functions [7-9, 17]. In this paper a set of non-dominated solutions i.e. Pareto front is obtained using multi objective genetic algorithm. However, choosing a representative solution from a set of non-dominated solution is not easy. Clustering solutions in Pareto front has been used by many authors [18-20]. One common method of choosing the representative solution is to select the non dominated solution which is nearest to the cluster centroid [20].

Functional performance of engineering components in service is strongly influenced by surface roughness.

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A single surface texture parameter is not sufficient to reflect true quality of the product [21]. Combination of parameters is necessary to characterize the functional property of a surface. For example friction and wear has been reported to be influenced by surface roughness parameters such as (R_a, R_q), (R_t,R_z), R_{sk}, R_{ku}, R_{DelA},W_a [21]. Wear is reported [22] to be larger when the initial values of the amplitude parameters S_k, S_q and S_{Htp} as well as rms. slope S_{Dq} are high. It is reported [23] that in case of dry wear test, coefficient of friction is low when roughness is high. In lubricated case, when roughness is low, then coefficient of friction is low. It is reported [23] that increase in parameter R_{ku} led to decrease in friction in lubricated case and increase in friction for dry tests. Friction also observed to be lower when the parameter R_{sk} tends to be more negative in lubricated tests.

Based on the above reports it is decided to locate optimal process parameters for ECM namely applied potential, inter-electrode gap and machining time for low coefficient of friction for lubricated condition.

Objective

The objective function for lubricated case- Minimize S_q ,S_{HTp}, S_{sk} and Maximize S_{ku}

METHODOLOGY

The first step is to develop mathematical models to predict the effect of process variables on surface roughness parameters- S_q, S_{sk}, S_{ku}, S_{HTp}. To use the models to calculate the values of roughness parameters at any point in the allowable design space.

The second step is to use these models to generate optimum levels of process parameters (Pareto front) for minimum coefficient of friction for lubricated condition using multi objective genetic algorithm in MATLAB environment.

The third step is to use clustering methods for obtaining representative solutions from the large number of solutions in the Pareto front.

Experiment Details

The experimental work and mathematical models used in this work are reported in ref.16. The essential details are presented here.

The matrix selected for conducting the experiments is eighteen points face centered composite design. The actual and coded values of the different variables are listed in Table-1. The design matrix is shown in Table-2.

Table 1 ECM process Variables and Their Levels

Variables	Symbol	Low level		Medium level		High level	
		Actual	Coded	Actual	Coded	Actual	Coded
VOLTAGE(volt)	V	15	-1	20	0	25	+1
TIME(min)	T	2	-1	3	0	4	+1
GAP(mm)	G	0.64	-1	0.96	0	1.28	+1

Table 2 Design matrix of three process parameter for surface roughness

SL NO	Voltage	Machining time	Inter electrode gap
1	-1	-1	-1
2	1	-1	-1
3	-1	1	-1
4	1	1	-1
5	-1	-1	1
6	1	-1	1
7	-1	1	1
8	1	1	1
9	-1	0	0
10	1	0	0
11	0	-1	0
12	0	1	0
13	0	0	-1
14	0	0	1
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0

ECM machine model ECMAC - II, manufactured by MetaTech Industries, Pune, is used with a round shaped tool made of copper. Electrolyte used is a mixture of NaCl and $NaNO_3$ solution (125 grams of NaCl and 250 grams of $NaNO_3$ / litre of tap water). Work piece material selected is SG Iron 450/12 grade received courtesy M/s. Hindustan Malleables & Forging Ltd., Dhanbad, India. The chemical composition of the material is given in Table 3.The material has pearlitic matrix. Hardness (Brinell)-196.

Table 3 Chemical Composition of SG Iron 450 grades. [45]

C	Si	Mn	P	S	Cr	Mo	Cu	Mg	Ti
3.365	2.393	0.238	0.072	< 0.150	0.0072	< 0.010	0.37	0.085	0.032
Zn	Fe	Others(Bi,Ce,Co,La,W,V,Ta,Sn,B,As,Zr,Sb,etc..)							
0.027	90.75	2.6608							

Developing the Models

To analyze the effects of the process variables on the surface roughness parameters such as S_q, S_{sk}, S_{ku}, S_{Htp}, the following second order polynomial is used.

$$Y = Bo + B1T + B2V + B3G + B11T^2 + B22V^2 + B33G^2 + B12TV + B13TG + B23VG \quad \ldots\ldots. (1)$$

Where, B's are the regression coefficients. V, T, G are the controllable process parameters in coded form. To check the adequacy of the statistical regression models analysis of variance are carried out. F-ratios of the models developed are calculated and are compared with the corresponding tabulated values for 95% level of confidence. The goodness of fit of the models are tested by calculating R^2, $R^2_{(adjusted)}$ & $R^2_{(predicted)}$. Design Expert [24] is used to develop the models. The coefficients of the models developed and the model statistics for the models are given in Table-4. All the models are statistically adequate. To validate the models further one set of experiment are carried out at levels different than those of design matrix (table 5).

Table 4 The Coefficients for surface roughness parameter

Co-efficient	S_q	S_{ku}	S_{sk}	S_{HTp}
B_0	11.55988	2.75464	-0.31755	20.0088
B_1	2.562	0.165	0.16968	6.042
B_2	0.932	-0.227	-0.21158	1.198
B_3	-2.017	0.045	-0.038599	-4.892
B_{12}	2.4775	-0.11125	0.080125	5.3025
B_{13}	0.05	-0.04125	0.013675	0.7525
B_{23}	0.355	-0.39125	-0.229375	2.1225
B_{11}	3.067738095	-0.306786	0.005351905	8.357380952
B_{22}	-0.382261905	0.573214	0.182851905	-3.742619048
B_{33}	-2.997261905	-0.336786	0.280946905	-3.192619048
F ratio	0.052	0.075	0.068	0.16
σ^2	8.32	0.021	0.051	24.28
R^2	0.8819079	0.9573	0.921507	0.921485
R^2(adj)	0.7490542	0.9092	0.833203	0.833155
R^2(pred)	0.7613867	0.8242	0.819541	0.783204

Table 5 Validation run

Process parameter	Coded	Actual	Responses	From experiment	From model
VOLTAGE (v)	-0.6	17	S_q	10	10.4460
			S_{ku}	2.79	2.8144
TIME (min)	-0.5	2.5	S_{sk}	-0.207	-0.2006
GAP (mm)	0.28125	1.05	S_{HTp}	17	17.3945

For locating optimum levels of process parameters for minimum coefficient of friction for lubricated condition genetic algorithm, a multi objective optimization technique is used. The four objective functions for lubricated case S_q, S_{ku}, S_{sk}, S_{HTp} are constructed using the coefficients given in table 4.

Table 6 Upper and lower limit of surface parameters In the design space

Surface Roughness Parameter	Lower Limit	Upper Limit
S_q	5.35	20.434
S_{ku}	1.8267	3.747
S_{sk}	-0.6612	0.675
S_{HTp}	4.795	37.687

Matlab [25] is used to generate the Pareto front. The following parameters are selected for finding the Pareto front. Population size two sets are used: 45 and 100; Selection function: tournament; two Cross over functions: 0.8 and 0.6; Mutation function: constraint dependent; Migration: 0.2; Distance measure function: distance crowding; Pareto front population: 0.35. For each population 5 sets of results are obtained based on random distribution. So for population of 45, 80 sets of results are obtained and for population of 100, 175 sets of results are obtained. For choosing representative solutions from the large set of Pareto optimization result clustering method is applied. Minitab 18 [26] is used to generate the clusters. In this paper a standard agglomerative hierarchical clustering technique with centroid method and complete linkage method are used. The numbers of clusters considered are 3, 4 and 5. The Pareto optimal point closest to the cluster centroid is obtained and given in tables 7-15.

RESULTS AND DISCUSSIONS

Table 7 3 clusters with centroid linkage (population 45, cross over function 0.8)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	15	2.8396	0.397144	0.84417
Cluster2	49	14.6352	0.498108	1.05384
Cluster3	16	1.6856	0.291102	0.56894

Pareto optimal point closest to cluster centroid.

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	-0.97526	0.938669	0.870361	6.470658	2.19516	-0.60856	9.456993
Cluster 2	0.128561	-0.75225	0.711175	7.647237	3.34388	0.197843	11.23132
Cluster 3	0.08798	0.971285	-0.10921	12.71175	3.11053	-0.29697	18.95483

Table 8 4 clusters with centroid linkage (population 45, cross over function 0.8)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	14	2.0761	0.354904	0.77007
Cluster2	49	14.6352	0.498108	1.05384
Cluster3	16	1.6856	0.291102	0.56894
Cluster4	1	0.0000	0.000000	0.00000

Pareto optimal point closest to cluster centroid

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	-0.97526	0.938669	0.870361	6.470658	2.19516	-0.60856	9.456993
Cluster 2	0.128561	-0.75225	0.711175	7.647237	3.34388	0.197843	11.23132
Cluster 3	0.08798	0.971285	-0.10921	12.71175	3.11053	-0.29697	18.95483
Cluster 4	-0.9266	-0.03025	0.999725	6.791637	2.10105	-0.2249	12.85199

Table 9 5 clusters with centroid linkage (population 45, cross over function 0.8)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	13	1.4375	0.311919	0.58616
Cluster2	49	14.6352	0.498108	1.05384
Cluster3	16	1.6856	0.291102	0.56894
Cluster4	1	0.0000	0.000000	0.00000
Cluster5	1	0.0000	0.000000	0.00000

Pareto optimal point closest to cluster centroid

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	-0.97526	0.938669	0.870361	6.470658	2.19516	-0.60856	9.456993
Cluster 2	0.128561	-0.75225	0.711175	7.647237	3.34388	0.197843	11.23132
Cluster 3	0.08798	0.971285	-0.10921	12.71175	3.11053	-0.29697	18.95483
Cluster 4	-0.16134	0.668552	0.998909	6.634894	2.29074	-0.32676	11.03159
Cluster 5	-0.9266	-0.03025	0.999725	6.791637	2.10105	-0.2249	12.85199

Table 10 3 clusters with complete linkage (population 45, cross over function 0.8)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	17	5.1753	0.505113	1.14605
Cluster2	47	12.5516	0.470265	0.92923
Cluster3	16	1.6856	0.291102	0.56894

Pareto optimal point closest to cluster centroid.

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	-0.99804	0.76007	0.998912	5.880925	1.98035	-0.54353	9.818269
Cluster 2	0.224842	-0.92998	0.775492	6.961643	3.61368	0.365856	9.216878
Cluster 3	0.08798	0.971285	-0.10921	12.71175	3.11053	-0.29697	18.95483

Table 11 4 clusters with complete linkage (population 45, cross over function 0.8)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	17	5.17527	0.505113	1.14605
Cluster2	29	2.64841	0.277244	0.66926
Cluster3	16	1.68564	0.291102	0.56894
Cluster4	18	3.59998	0.412999	0.83383

Pareto optimal point closest to cluster centroid

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	-0.99804	0.76007	0.998912	5.880925	1.98035	-0.54353	9.818269
Cluster 2	0.224842	-0.92998	0.775492	6.961643	3.61368	0.365856	9.216878
Cluster 3	0.08798	0.971285	-0.10921	12.71175	3.11053	-0.29697	18.95483
Cluster 4	0.38848	-0.65294	0.376625	10.35341	3.25261	0.028677	17.18728

Table 12 5 clusters with complete linkage (population 45, cross over function 0.8)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	14	2.07610	0.354904	0.770072
Cluster2	29	2.64841	0.277244	0.669260
Cluster3	16	1.68564	0.291102	0.568937
Cluster4	18	3.59998	0.412999	0.833832
Cluster5	3	0.28264	0.297511	0.394576

Pareto optimal point closest to cluster centroid

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	-0.97526	0.938669	0.870361	6.470658	2.19516	-0.60856	9.456993
Cluster 2	0.224842	-0.92998	0.775492	6.961643	3.61368	0.365856	9.216878
Cluster 3	0.08798	0.971285	-0.10921	12.71175	3.11053	-0.29697	18.95483
Cluster 4	0.38848	-0.65294	0.376625	10.35341	3.25261	0.028677	17.18728
Cluster 5	-0.60973	-0.15337	0.55063	9.151852	2.54744	-0.29607	15.56235

Table 13 3 clusters with complete linkage (population 100, cross over function 0.8)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	43	15.0277	0.554071	1.17082
Cluster2	103	23.7100	0.455306	0.82329
Cluster3	29	2.4490	0.256935	0.75590

Pareto optimal point closest to cluster centroid.

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	-0.51223	0.932189	0.800339	7.116287	2.47455	-0.50733	9.754073
Cluster 2	0.251945	-0.8292	0.600708	8.384413	3.47648	0.204483	12.35301
Cluster 3	-0.02138	0.963365	-0.17742	12.20159	3.11469	-0.30201	17.86244

Table 14 4 clusters with complete linkage (population 100, cross over function 0.8)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	33	5.1650	0.370557	0.617876
Cluster2	103	23.7100	0.455306	0.823288
Cluster3	29	2.4490	0.256935	0.755899
Cluster4	10	0.8512	0.262023	0.492615

Pareto optimal point closest to cluster centroid

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	-0.74002	0.936349	0.748625	7.196147	2.42517	-0.57331	9.89996
Cluster 2	0.251945	-0.8292	0.600708	8.384413	3.47648	0.204483	12.35301
Cluster 3	-0.02138	0.963365	-0.17742	12.20159	3.11469	-0.30201	17.86244
Cluster 4	-0.31038	-0.05957	0.942502	6.451072	2.46465	-0.1329	11.16594

Table 15 5 clusters with complete linkage (population 100, cross over function 0.8)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	33	5.16498	0.370557	0.617876
Cluster2	56	5.40757	0.280384	0.732989
Cluster3	47	6.95932	0.362647	0.653771
Cluster4	29	2.44896	0.256935	0.755899
Cluster5	10	0.85120	0.262023	0.492615

Pareto optimal point closest to cluster centroid

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	-0.74002	0.936349	0.748625	7.196147	2.42517	-0.57331	9.89996
Cluster 2	0.034209	-0.86372	0.897901	5.986445	3.45794	0.375203	7.652399
Cluster 3	0.349626	-0.77345	0.158849	10.77425	3.36783	0.023694	17.46678
Cluster 4	-0.02138	0.963365	-0.17742	12.20159	3.11469	-0.30201	17.86244
Cluster 5	-0.31038	-0.05957	0.942502	6.451072	2.46465	-0.1329	11.16594

Table 16 3 cluster with complete linkage (population 45, cross over function 0.6)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	52	21.3794	0.605172	1.08828
Cluster2	16	1.2379	0.264513	0.48224
Cluster3	12	1.2896	0.298715	0.61214

Pareto optimal point closest to cluster centroid

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	0.409319	-0.99062	0.662845	7.946185	3.73084	0.361523	11.03765
Cluster 2	-0.9981	0.990087	0.753339	7.1653	2.31339	-0.642	10.1014
Cluster 3	0.058386	0.992969	-0.11689	12.56536	3.13239	-0.2979	18.47358

Table 17 4 clusters with complete linkage (population 45, cross over function 0.6)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	42	14.4299	0.553949	1.05341
Cluster2	16	1.2379	0.264513	0.48224
Cluster3	10	0.6733	0.236734	0.40009
Cluster4	12	1.2896	0.298715	0.61214

Pareto optimal point closest to cluster centroid

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	0.161251	-0.98672	0.995853	5.044897	3.66168	0.551765	5.528087
Cluster 2	-0.9981	0.990087	0.753339	7.1653	2.31339	-0.642	10.1014
Cluster 3	0.562784	-0.83927	-0.06411	11.88601	3.37332	0.038957	20.29753
Cluster 4	0.058386	0.992969	-0.11689	12.56536	3.13239	-0.2979	18.47358

Table18 5 clusters with complete linkage (population 45, cross over function 0.6)

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	34	7.12923	0.433715	0.736863
Cluster2	16	1.23787	0.264513	0.482236
Cluster3	10	0.67327	0.236734	0.400092
Cluster4	12	1.28959	0.298715	0.612142
Cluster5	8	2.53296	0.541778	0.739072

Pareto optimal point closest to cluster centroid

Cluster	V	T	G	Sq	Sku	Ssk	Shtp
Cluster1	0.409319	-0.99062	0.662845	7.946185	3.73084	0.361523	11.03765
Cluster 2	-0.9981	0.990087	0.753339	7.1653	2.31339	-0.642	10.1014
Cluster 3	0.562784	-0.83927	-0.06411	11.88601	3.37332	0.038957	20.29753
Cluster 4	0.058386	0.992969	-0.11689	12.56536	3.13239	-0.2979	18.47358
Cluster 5	-0.27052	0.251129	0.500069	9.412603	2.56899	-0.38981	15.61056

When the centroid and complete linkage are compared two interesting trends are observed Table (9 &12). The cluster 1 and 3 are same. Second cluster in centroid case which contains 49 elements are shown as two clusters (29 elements and 18 elements) in complete linkage. Centroid linkage (table 9) has two clusters having 1 element each. The Pareto optimal point closest to the centroids for clusters 4 &5 (table 9) are quite close. Where as in case of complete linkage the Pareto optimal point closest to the centroids are well dispersed (table 12). When population is increased to 100 little change in Pareto optimal points closest to the centroids are observed when compared to the results obtained with population of 45 (table 12 &15). Effect of changing the cross over function from 0.8 to 0.6 is studied also (table 12 & 18). The trends observed are similar. If S_{ku} and S_{sk} are considered then it is observed that is Ssk is in the range -0.6 to -0.6 then S_{ku} is in the range 2.2-2.3. If S_{ku} is in the range 3.37-3.6 the S_{sk} is in the range .03-0.36. S_q and S_{htp} show similar trends. As S_q decreases S_{htp} decreases. It seems the case: complete linkage, population 45, cross over:0.8 (Table 12) represents the population well. The cluster1 and cluster 2 (complete linkage, population 45, cross over:0.8) which have low values of S_q and S_{htp} can be further analyzed to select a high value of S_{ku} and a low value of S_{sk}.

CONCLUSIONS

The objective of this work is to minimize the surface roughness parameters S_q, S_{HTp} , S_{sk} and maximize S_{ku} to lower the coefficient of friction in lubricated case. Multi objective genetic algorithm is used to find the Pareto front consisting of a number of non dominated solutions. The number of solutions found is large. Agglomerative hierarchical clustering method is used to obtain a number of clusters. Representative solutions are selected by choosing the non dominated solution which is nearest to the cluster centroid. Complete linkage, population 45, cross over:0.8 represents the population well. The cluster1 and cluster 2 (complete linkage, population 45, cross over:0.8) which have low values of S_q and S_{htp} can be further analyzed to select a high value of S_{ku} and a low value of S_{sk}.

Roughness Parameters

All parameters with S is 3D extension of R roughness profile parameter: for example S_q is the 3D extension of R_q

R_{DelA} : Average Slope of the Profile.

R_t : Maximum Height of Profile.

S_a: Arithmetic Mean Deviation of the Surface, µm

S_{Dq} : Root mean square gradient of the surface

S_{Htp}: Surface section height difference (20% - 80%)

S_{ku}: Kurtosis of the Topography Height Distribution.

S_q: Root-Mean-Square (RMS) Deviation of the Surface,µm

S_p: Surface section height difference (20% - 80%)

S_{sk}: Skewness of the Topography Height Distribution.

S_z: Ten Point Height of the Surface,µm.

W_a : Mean Value of the Waviness of the Unfiltered Profile.

Experimental Variables

T : Time of machining (minutes)

V : Applied potential(volts)
G : Inter electrode gap(mm)

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