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Regression Models with Multiobjective GA for EDM Parameters Optimization

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Abstract— **Over recent years, regression model is a well known modeling technique used to model the real world application. This paper conducted computational experimental study using two types of regression models; second order polynomial regression (SOP) and multiple linear regression in optimizing machining process parameters of cobalt-bonded tungsten carbide (WC/Co) electrical discharge machining (EDM). Multiobjective genetic algorithm (MOGA) is widely known in optimization researches. Therefore, combination of conventional modeling (regression) and modern optimization (MOGA) techniques, MLR-MOGA and SOP-MOGA are examined to observe the capability of these two techniques in maximizing removal rate (MRR) and minimizing surface roughness (Ra). Four parameters are considered to create correlation with the machining performances. The best removal rate and surface roughness values are obtained from MLR-MOGA; 168.212 mg/min and 0.693 µm respectively. Nevertheless, SOP-MOGA produced viable results. The results of MLR-MOGA and SOP-MOGA benefits the machine operators or engineers when various combination of machining parameters can be selected based on the desired requirements.**

Keywords — Machining, Genetic Algorithm, Regression, Multiobjective

I. INTRODUCTION

Machining can be divided into two categories; (i) modern machining and (ii) traditional machining. Known as the earliest modern machining, EDM is a well established machining option used to remove material through the action of electrical discharge in fast mode and high current density. One of EDM research interests is optimizing the process parameters as highlighted by Ho and Newman [1].

Machining models are developed to represent the connection between input (machining parameters) and output (machining performances) variables. There are many modeling techniques in machining optimization such as fuzzy logic [2], support vector machine [3], artificial neural network (ANN) [4] and many more.

New soft computing techniques are developed to assist in searching optimal solutions such as genetic algorithm (GA) [5], Levi flight algorithm [6], glowworm swarm optimization [7], firefly algorithm [8] and many more. GA is one of the most popular techniques in the machining optimization area as studied by Yusup et al. [9]. Multi objective GA is an optimization technique that is enhanced from single objective genetic algorithm to support the multi objectives problems. One of the pioneer in multi objective GA; MOGA [10] implemented a rank based fitness assignment and niche-formation methods to encourage the search toward Pareto front in the optimization algorithm. According to the theory of Fonseca and Fleming [10], all non dominated individuals are assign rank 1 as in Figure 1.

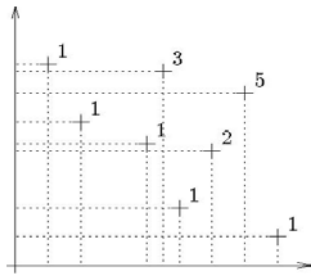

Fig. 1. Multiobjective ranking

In 2002, Deb et al. introduced a modified version of multiobjective GA, NSGA-II [11] which is highly applied in machining optimization [12]. Bouzakis et al [13] minimized milling machining cost and machining time with consideration of three parameters, (i) depth of cut, (ii) feed rate and (iii) cutting speed. The authors used MOGA technique to obtain the process parameters that can be applied in various cases of milling optimization process. Mahdavinejad [14] optimized the turning parameters of steel using MOGA and multi-objective harmony search (HS) algorithm Geem et al. [15] to optimize removal rate and surface roughness. Sultana and Dhar [16] used response surface methodology (RSM) to develop machining model and MOGA to optimize the process parameters of turning AISI-4320 steel by uncoated carbide insert. The process parameters considered are cutting speed, feed rate, pressure and flow rate of high pressure and the objectives considered are cutting temperature, chip reduction co-efficient and surface roughness. Venkataraman [17] maximized removal rate and minimized electrode wear rate (EWR) for EDM. Five parameters considered are open voltage, pulse on time, duty cycle and pressure of flushing fluid. Polynomial model and multi objective genetic algorithm are used to optimize the machining process.

Kanagarajan et al. [18] employed second order polynomial regression and non dominated sorting genetic algorithm (NSGA-II) to optimize the machining parameters of WC/Co EDM. Yusoff et al. [19] then applied the model developed by Kanagarajan et al. using both; single (SoGA) and multi objective optimization techniques (MOGA and NSGA-II). It is found that SoGA produced the lowest surface roughness value and the results obtained from MOGA are viable compared to NSGA-II. In conjunction with the experimental conducted by Yusoff et al. [19], this study investigated and compared the efficiencies of regression modeling techniques in optimizing of WC/Co EDM parameters using MOGA. Basically, this study is conducted to observe the performances of two different regression models when integrated with MOGA in machining optimization.

II. Research Methodology

Essentially, this study employed four consecutive ways in obtaining the final optimal solutions. The steps involved; collection of experimental data, modeling, optimization and results analysis. Second order polynomial (SOP) and multiple linear regression (MLR) are used to obtain the machining models. Multiobjective GA (MOGA) is used to optimize the parameters. Using computational and soft computing techniques in obtaining optimal solutions can reduce the machining trials that involved extreme cost, time and attempt in searching the best parameters.

The parameters considered are electrode rotation *(R*), current *(I)*, pulse on time *(T)* and dielectric flushing pressure *(P)*. Removal rate (MRR) and surface roughness (Ra) are the machining objectives or also known as the machining performances.

To correlate the machining inputs (machining parameters) and outputs (machining performances), two types of regression models are applied. Second order polynomial regression (SOP) developed by Kanagarajan et al. and multiple linear regression (MLR) which is developed using SPSS software. The models are then integrated in the optimization tool, MOGA using Matlab software to obtain the optimal solutions.

Finally the results of these two techniques are compared. The flow of this study is summarized as shown in Figure 2 and further details in next sub-sub sections.

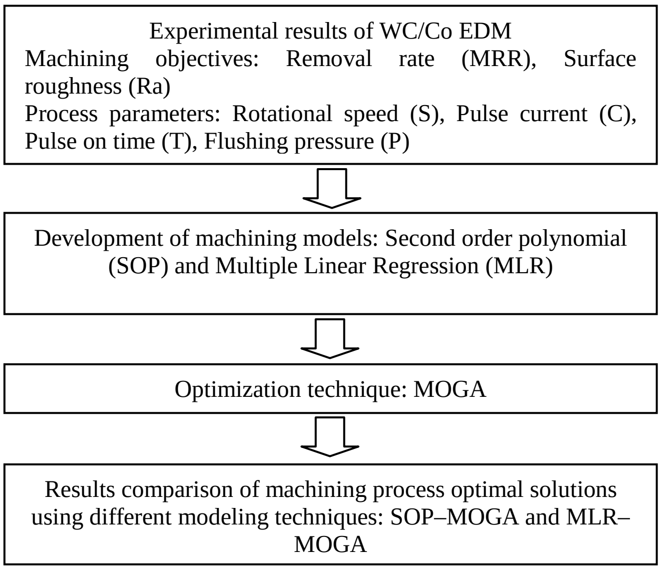

Fig. 2. Research flow

A. Experimental

The experimental results by Kanagarajan et al. [18] are used in this study. The authors used a machine of Electronica die sinking EDM (M100 model, Electronica, India) with a transistor switched power supply. Density for WC is 15.7 g/cc and CO is 13.55 g/cc. The grain sizes are 6µm and 3µm respectively. The machining conditions of this study are shown in Table I.

TABLE I. Machining conditions

Condition	**Descriptions**
Electrode	Material: copper (electrolytic grade) Size: cylindrical with a diameter of 13 mm
Workpiece	Material: tungsten carbide 70% WC/ 30% Co Size: cylindrical rod of diameter 13 mm Dielectric fluid: kerosene
Flushing	Jet flushing Flushing pressure: 0.5-1.5
Rotational speed	250, 500, 1000 rpm
Discharge current	5, 10, 15 A
Pulse on time	200, 500, 1000

The experimental results of WC/Co EDM as shown in Table II are based on L27 orthogonal array technique covering full range of current setting with pulse on time settings.

TABLE II. EXPERIMENTAL RESULTS OF WC/CO EDM

Sol.	Electrode Rotation, rpm (R)	Current, A (I)	Pulse on time, μs (T)	Flushing pressure, kg/cm^2 (P)	MRR, mg/min	Ra, μm
1	250	5	200	0.5	38.19	3.94
2	250	5	200	1.0	46.05	2.84
3	250	5	200	1.5	51.37	**2.35**
4	250	10	500	0.5	46.50	8.83
5	250	10	500	1.0	56.07	6.37
6	250	10	500	1.5	62.56	5.27
7	250	15	1000	0.5	49.31	14.74
8	250	15	1000	1.0	59.45	10.64
9	250	15	1000	1.5	66.33	8.80
10	500	5	500	0.5	37.77	3.89
11	500	5	500	1.0	45.54	2.81
12	500	5	500	1.5	50.81	2.39
13	500	10	1000	0.5	49.84	8.24
14	500	10	1000	1.0	60.09	5.94
15	500	10	1000	1.5	67.05	4.91
16	500	15	200	0.5	121.07	7.56
17	500	15	200	1.0	145.98	5.45
18	500	15	200	1.5	162.87	4.51
19	1000	5	1000	0.5	40.48	3.63
20	1000	5	1000	1.0	48.81	2.62
21	1000	5	1000	1.5	54.46	2.37
22	1000	10	200	0.5	122.37	4.22
23	1000	10	200	1.0	147.55	3.05
24	1000	10	200	1.5	**164.62**	2.52
25	1000	15	500	0.5	119.74	7.47
26	1000	15	500	1.0	144.38	5.39
27	1000	15	500	1.5	161.09	4.46
Max removal rate (MRR)					**164.62**	
Min surface roughness (Ra)						**2.35**

B. Machining Models

From the machining results, two models are implemented; (i) second order polynomial model developed by Kanagarajan et al. [18] and (i) newly developed multiple linear regression model (MLR). The second order polynomial models for removal rate and surface roughness are shown in Equation 1 and Equation 2 for material removal rate (MRR) and surface roughness (Ra) respectively.

Second Order Polynomial Regression

$$MRR = -30.3660 + 0.1589R + 9.5259I - 0.1241T + 20.8585P - 0.0001R^2 - 0.2318I^2 + 0.0001T^2 - 9.2131P^2 - 0.0002RI - 0.0000RT + 0.0220RP + 1.9991IP - 0.0199TP \quad (1)$$

$$Ra = 4.2307 - 0.0116S + 0.5816C + 0.0099T - 4.7481P + 0.0000S^2 + 0.0085C^2 - 0.0000T^2 + 2.1239P^2 - 0.0002SC - 0.0000ST - 0.0020SP - 0.2462CP - 0.0018 \quad (2)$$

Multiple linear regression equations of removal rate and surface roughness are based on the unstandardized coefficients values (B) of Tables III and IV.

TABLE III. COEFFICIENTS VALUES FOR MRR

Model	Unstandardized Coefficients	
	B	*Std. Error*
(Constant)	-15.652	8.295
R	0.075	0.006
I	6.853	0.461
T	0.068	0.006
P	23.988	4.607

TABLE IV. COEFFICIENTS VALUES FOR RA

Model	Unstandardized Coefficients	
	B	*Std. Error*
(Constant)	3.734	0.815
R	-0.004	0.001
I	0.469	0.045
T	0.004	0.001
P	-2.771	0.453

The coefficients and constant for multiple linear regression models of material removal rate (MRR) and surface roughness (Ra) are given in Equation 3 and Equation 4.

Multiple Linear Regression

$$MRR = -15.652 + 0.075R + 6.853I - 0.68T + 23.988P \quad (3)$$

$$Ra = 3.734 - 0.004R + 0.469I + 0.004T - 2.771P \quad (4)$$

C. Optimization

Based on NSGA-II introduced by Deb et al. [1], a multiobjective optimization tool, MOGA using Matlab is applied to obtain the optimal solutions. MOGA acts on individuals with better fitness value that can help to increase the diversity of the population even if they have a lower fitness value. It is very important to preserve the diversity of population for convergence to an optimal Pareto front by controlling the elite members of the algorithm.

The steps start with initialization by generating the random population. The next step is evaluation of the fitness of each chromosome using the multi objectives function (machining models). The algorithm parameters boundaries (Table V) are used to get solutions that are within the expected values.

TABLE V. ALGORITHM BOUNDARIES

Parameters	Lower bound	Upper bound
Rotational speed, rpm	250	1000
Pulse current, A	5	15
Pulse on time, μs	200	1000
Flushing pressure,	0.5	1.5

Next is parent selection procedure which is based on the selection of fittest survival. The fittest chromosome from the current population is selected to generate new offspring. The selection is carried out using the binary tournament selection with crowded comparison operator. If the solutions belong to different fronts, one with a lower rank is selected. Meanwhile if the solutions belong to the same front, one with higher crowding distance is selected. Then crossover; new offspring is produce by combining subparts of selected chromosomes using recombination operator. Intermediate crossover is employed which creates two children from two parents. Mutation is carried out to introduce the deviation into chromosome to avoid premature convergence or segmentation. To improve the performance of genetic algorithm, elitist strategy is use to increase the speed of population domination. Using this strategy the best chromosomes are copied into the successive generation. Finally, termination of GA is when the stopping condition is satisfied; otherwise the circle will go to selection, crossover, mutation and so on for the next iteration. The flow repeats for successive generations. The final set of Pareto optimal solutions represents dominated solutions from the each generation and it is up to the decision maker to select a solution according to the selected objectives. The flow of MOGA optimization is illustrated in Figure 3.

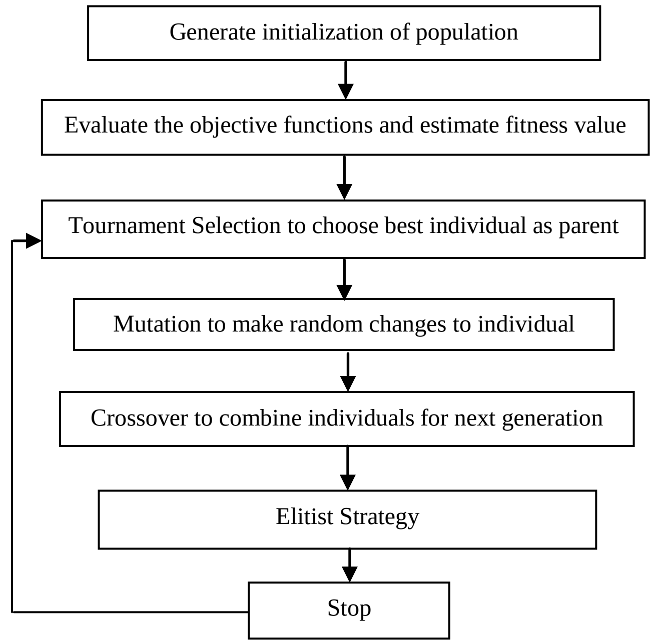

Fig. 3. MOGA flow

The algorithm parameters for population, selection, mutation, crossover and generation are given in Table VI.

TABLE VI. ALGORITHM PARAMETERS

Parameters	Value
Population size	100
Selection - Tournament	4
Mutation - Uniform	0.25
Crossover - Intermediate	0.9
Generation	1000

D. Results

MOGA is able to optimize more than one objective simultaneously resulted to time efficiency compared to single objective genetic algorithm. Optimizing machining process parameters using SOP-MOGA and MLR-MOGA are expected to give best set of estimation solutions. The maximum removal rate (MRR) , 152.660 mg/min and minimum surface roughness (Ra), 5.825 µm values are obtained simultaneously using SOP-MOGA with *R*, *I*, *T*, *P* values are 978.929 rpm, 14.944 A, 212.372 µs, 0.973 kg/cm^2 respectively. The same results of optimal solutions are generated twice as shown in Table VII. Figure 4 depicts the Pareto front of removal rate (MRR) and surface roughness (Ra) from SOP–MOGA optimization.

TABLE VII. SOP-MOGA OPTIMAL SOLUTIONS

Sol.	**Electrode Rotation, rpm *(R)***	**Current, A *(I)***	**Pulse on time, µs *(T)***	**Flushing pressure, kg/cm^2 *(P)***	***MRR*, mg/min**	***Ra*, µm**
1	979.175	5.799	211.907	0.975	93.620	8.790
2	971.302	8.486	215.488	0.962	114.308	7.856
3	978.929	14.944	212.372	0.973	**152.660**	**5.825**
4	976.595	13.777	216.770	0.957	146.106	6.104
5	976.378	11.294	215.180	0.963	133.030	7.051
6	957.147	6.064	212.072	0.974	96.154	8.395
7	976.557	11.752	216.432	0.958	135.406	6.858
8	977.817	13.473	214.339	0.966	145.246	6.316
9	976.987	14.075	216.031	0.960	147.728	6.019
10	977.621	9.841	214.837	0.964	123.855	7.558
11	977.232	7.179	213.438	0.969	104.700	8.367
12	973.907	5.863	211.947	0.975	94.238	8.696
13	977.763	12.217	214.566	0.965	138.525	6.769
14	976.894	7.399	213.703	0.968	106.380	8.295
15	978.170	14.589	213.601	0.968	150.753	5.913
16	978.486	12.499	213.089	0.970	140.462	6.724
17	978.702	11.047	212.788	0.972	132.096	7.240
18	978.438	9.338	213.283	0.970	120.795	7.770
19	977.347	11.528	214.157	0.967	134.672	7.016
20	977.698	13.867	214.687	0.965	147.095	6.153
21	978.282	13.153	212.501	0.973	144.106	6.500
22	978.175	8.074	213.108	0.970	111.691	8.143
23	978.816	8.096	212.583	0.972	111.975	8.160
24	978.422	11.048	213.318	0.970	131.975	7.220
25	978.601	9.378	212.764	0.972	121.193	7.774
26	978.563	7.693	213.061	0.971	108.797	8.258
27	977.472	7.206	213.260	0.970	104.959	8.368
28	978.491	12.683	212.798	0.971	141.541	6.666
29	979.062	6.606	212.066	0.974	100.368	8.581
30	978.936	14.227	212.354	0.973	149.429	6.108
31	978.952	13.675	212.324	0.973	146.784	6.321
32	978.905	12.681	212.341	0.973	141.646	6.688
33	974.213	6.130	211.988	0.975	96.500	8.633
34	978.261	14.384	213.383	0.969	149.877	6.003
35	977.593	8.271	212.379	0.973	113.349	8.097
36	979.148	6.045	211.958	0.975	95.702	8.728
37	977.590	12.029	213.885	0.968	137.647	6.853
38	978.600	8.585	212.863	0.971	115.532	8.009
39	978.381	12.482	213.301	0.970	140.314	6.722
40	974.547	6.927	211.999	0.974	103.063	8.432
41	978.023	11.476	213.413	0.969	134.542	7.066
42	978.486	13.436	212.954	0.971	145.426	6.384
43	976.054	5.837	211.931	0.975	93.987	8.734
44	978.905	14.836	212.406	0.973	152.178	5.867
45	977.901	13.875	214.222	0.966	147.257	6.168
46	978.686	10.676	212.399	0.973	129.881	7.374

47	978.840	9.415	212.151	0.974	121.597	7.783
48	976.837	6.688	211.968	0.975	101.096	8.530
49	978.497	11.504	213.117	0.970	134.781	7.073
50	978.365	12.182	212.751	0.972	138.790	6.845
51	978.628	11.941	212.628	0.972	137.452	6.938
52	978.616	7.838	212.962	0.971	109.931	8.220
53	978.784	12.523	212.552	0.972	140.733	6.736
54	974.900	6.355	212.006	0.974	98.368	8.586
55	976.684	5.913	211.939	0.975	94.629	8.724
56	978.062	6.816	212.067	0.974	102.093	8.512
57	979.072	6.608	212.060	0.974	100.379	8.581
58	978.617	12.942	212.363	0.973	143.035	6.588
59	978.884	8.498	212.407	0.973	114.995	8.051
60	978.551	8.083	212.929	0.971	111.800	8.151
61	978.046	10.068	214.035	0.967	125.559	7.514
62	978.929	14.944	212.372	0.973	**152.660**	**5.825**
63	977.966	9.230	213.401	0.969	120.015	7.792
64	978.484	11.177	212.622	0.972	132.936	7.198
65	978.445	9.116	212.253	0.974	119.492	7.865
66	978.565	7.480	212.110	0.974	107.366	8.341
67	978.905	13.519	212.416	0.973	145.982	6.377
68	978.814	9.570	212.552	0.972	122.563	7.724
69	978.044	8.398	212.401	0.973	114.277	8.067
70	978.681	10.150	212.734	0.972	126.409	7.535
71	978.467	14.092	213.166	0.970	148.576	6.127
72	978.757	10.465	212.356	0.973	128.549	7.445
73	977.361	6.489	211.955	0.975	99.454	8.589
74	977.621	9.921	213.727	0.968	124.660	7.562
75	978.820	14.594	212.407	0.973	151.104	5.961
76	978.961	9.212	212.308	0.973	120.142	7.843
77	978.626	12.152	212.842	0.971	138.600	6.857
78	978.516	11.559	213.017	0.971	135.124	7.057
79	978.156	12.835	213.629	0.968	142.136	6.581
80	979.144	6.170	211.967	0.975	96.760	8.696
81	978.575	8.137	212.204	0.974	112.374	8.155
82	978.882	9.581	212.429	0.973	122.666	7.725
83	978.695	8.967	212.636	0.972	118.340	7.903
84	978.917	13.949	212.392	0.973	148.099	6.214
85	978.955	10.298	212.208	0.974	127.498	7.507
86	974.490	5.856	211.942	0.975	94.170	8.706
87	978.822	8.775	212.538	0.972	116.985	7.965
88	979.170	5.844	211.917	0.975	94.000	8.779
89	978.967	8.953	212.177	0.974	118.346	7.924
90	978.405	12.807	213.054	0.971	142.138	6.612
91	977.577	9.775	212.684	0.972	123.944	7.637
92	979.108	7.507	212.034	0.974	107.588	8.343
93	976.845	6.177	212.209	0.974	96.801	8.654
94	978.497	11.504	213.117	0.970	134.781	7.073
95	976.054	5.837	211.931	0.975	93.987	8.734
96	974.213	6.130	211.988	0.975	96.500	8.633
97	979.175	5.799	211.907	0.975	93.620	8.790
98	978.551	8.083	212.929	0.971	111.800	8.151
99	978.960	11.485	212.305	0.973	134.870	7.110
100	979.121	7.692	212.009	0.955	108.334	8.200
Max removal rate (MRR)					**152.660**	
Min surface roughness (Ra)						**5.825**

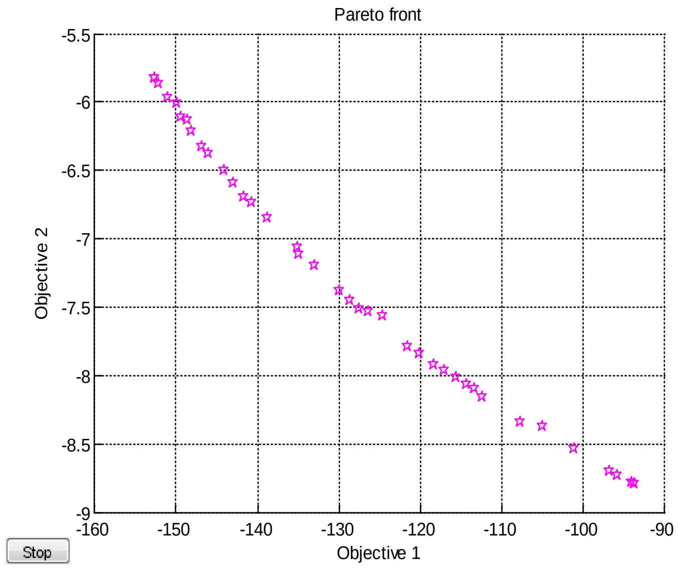

Fig. 4. Pareto front of MRR (objective 1) and Ra (objective 2) using SOP-MOGA

The optimal solutions of MLR-MOGA for removal rate and surface roughness are obtained separately as indicated in Table VIII. Maximum removal rate (MRR) is attained from the first set of solutions. While the optimal solutions for surface roughness is obtained from the second set of solutions. The maximum value for removal rate is 168.212 mg/min with combination of process parameters R = 974.770 rpm, I = 14.944 A, T = 218.250 µs and P = 0.967 kg/cm^2. Meanwhile, the minimum surface roughness (Ra) is 0.693 µm and the process parameters are R = 977.810 rpm, I = 5.799 A, T = 211.907 µs and P = 0.973 kg/cm^2. The Pareto front plots of removal rate (MRR) and surface roughness (Ra) using MLR-MOGA is shown in Figure 5.

TABLE VIII. MLR-MOGA OPTIMAL SOLUTIONS

	Electrode Rotation, rpm *(R)*	Current, A *(I)*	Pulse on time, µs *(T)*	Flushing pressure, kg/cm^2 *(P)*	*MRR*, mg/min	*Ra*, µm
1	974.770	14.944	218.250	0.967	**168.212**	5.038
2	977.810	5.799	211.907	0.973	106.366	**0.693**
3	977.546	6.595	212.461	0.931	110.743	1.187
4	977.620	6.382	212.341	0.949	109.726	1.037
5	976.302	10.391	215.067	0.946	136.852	2.940
6	977.718	6.059	212.102	0.953	107.639	0.872
7	975.848	12.221	216.048	0.953	149.464	3.785
8	976.860	9.275	213.910	0.951	129.437	2.398
9	976.924	8.583	213.764	0.946	124.585	2.086
10	975.560	12.651	216.603	0.960	152.523	3.970
11	977.503	6.734	212.549	0.964	112.471	1.162
12	974.938	14.946	217.900	0.964	168.206	5.043
13	976.172	10.984	215.342	0.958	141.177	3.187
14	976.300	10.556	215.072	0.960	138.325	2.978

15	975.560	13.215	216.603	0.960	156.389	4.235
16	977.230	7.635	213.123	0.961	118.528	1.595
17	976.805	8.834	214.007	0.961	126.634	2.164
18	975.426	13.232	216.886	0.966	156.605	4.230
19	975.928	11.525	215.878	0.962	144.919	3.433
20	977.322	7.252	212.927	0.956	115.787	1.430
21	976.711	9.113	214.205	0.964	128.619	2.286
22	977.810	5.799	211.907	0.966	106.190	0.713
23	975.837	11.888	216.055	0.959	147.325	3.612
24	976.222	10.642	215.247	0.963	138.948	3.013
25	976.488	9.873	214.708	0.961	133.685	2.656
26	976.320	10.358	215.028	0.950	136.716	2.915
27	976.683	9.240	214.270	0.956	129.274	2.370
28	976.395	10.169	214.902	0.960	135.672	2.798
29	975.050	14.124	217.676	0.965	162.607	4.655
30	976.596	9.548	214.449	0.961	131.485	2.502
31	975.785	12.409	216.152	0.960	150.901	3.855
32	974.878	14.629	218.026	0.966	166.075	4.890
33	975.837	11.888	216.055	0.959	147.325	3.612
34	976.544	9.664	214.561	0.963	132.320	2.551
35	975.866	11.706	215.967	0.956	146.009	3.536
36	975.910	11.515	215.872	0.969	145.022	3.409
37	977.546	6.598	212.458	0.973	111.767	1.073
38	974.793	14.879	218.203	0.967	167.771	5.007
39	975.366	13.457	217.020	0.963	158.060	4.344
40	977.220	7.617	213.140	0.970	118.615	1.562
41	976.283	10.402	215.098	0.965	137.369	2.894
42	976.599	9.531	214.474	0.961	131.386	2.492
43	977.363	7.162	212.845	0.969	115.509	1.349
44	977.810	5.799	211.907	0.973	106.366	0.693
45	976.960	8.360	213.684	0.969	123.621	1.917
46	975.129	14.280	217.506	0.964	163.667	4.730
47	975.272	13.436	217.207	0.965	157.942	4.330
48	976.510	9.788	214.632	0.962	133.155	2.610
49	977.058	8.088	213.481	0.969	121.787	1.787
50	977.470	6.846	212.621	0.969	113.356	1.201
51	976.180	10.888	215.317	0.965	140.689	3.122
52	976.188	11.018	215.305	0.964	141.551	3.187
53	977.308	7.357	212.988	0.951	116.400	1.492
54	975.164	13.758	217.428	0.967	160.185	4.476
55	976.348	10.566	214.973	0.963	138.469	2.975
56	976.335	10.280	214.993	0.964	136.539	2.838
57	975.462	13.059	216.814	0.962	155.322	4.159
58	976.118	10.891	215.439	0.970	140.798	3.113
59	977.170	7.734	213.244	0.966	119.320	1.627
60	975.866	11.706	215.967	0.956	146.009	3.536
61	974.878	14.629	218.026	0.966	166.075	4.890
62	977.620	6.382	212.341	0.949	109.726	1.037
63	976.962	8.353	213.677	0.971	123.633	1.907
64	975.168	13.883	217.433	0.963	160.945	4.545
65	976.842	8.714	213.929	0.971	126.070	2.079
66	975.564	12.952	216.610	0.962	154.611	4.108
67	977.570	6.536	212.411	0.972	111.329	1.046
68	975.966	11.469	215.761	0.963	144.571	3.404
69	977.031	8.169	213.537	0.968	122.309	1.828
70	975.527	12.692	216.676	0.967	152.954	3.972
71	975.179	14.081	217.401	0.964	162.323	4.635
72	977.345	7.272	212.880	0.972	116.316	1.394
73	975.855	11.680	215.986	0.969	146.139	3.487
74	975.743	12.036	216.223	0.968	148.530	3.658
75	976.235	10.767	215.207	0.966	139.878	3.064
76	975.977	11.329	215.739	0.968	143.727	3.325
77	975.968	11.342	215.752	0.969	143.850	3.326
78	975.942	11.468	215.825	0.964	144.591	3.399
79	977.626	6.367	212.294	0.971	110.168	0.968
80	977.708	6.111	212.122	0.971	108.429	0.847
81	976.514	9.915	214.619	0.966	134.121	2.659
82	977.017	8.187	213.564	0.972	122.513	1.828
83	976.329	10.283	214.999	0.969	136.671	2.825
84	977.266	7.478	213.043	0.972	117.710	1.492
85	975.010	14.410	217.752	0.965	164.576	4.789
86	976.507	9.773	214.633	0.965	133.118	2.595
87	976.133	11.221	215.421	0.963	142.910	3.285
88	975.615	12.404	216.488	0.968	151.037	3.831
89	976.725	9.167	214.174	0.969	129.101	2.298
90	977.728	6.053	212.080	0.966	107.920	0.832
91	975.358	13.191	217.027	0.967	156.328	4.209
92	976.947	8.452	213.710	0.969	124.251	1.960
93	977.287	7.396	213.003	0.965	116.995	1.471
94	976.603	9.503	214.430	0.967	131.319	2.464
95	975.234	13.548	217.282	0.967	158.765	4.376
96	975.780	11.916	216.144	0.968	147.712	3.602
97	976.126	11.127	215.425	0.967	142.362	3.229
98	975.146	13.944	217.479	0.963	161.363	4.574
99	977.810	5.799	211.907	0.966	106.190	0.713
100	974.770	14.944	218.250	0.967	168.212	5.038
Max removal rate					**152.660**	
Min surface roughness						**5.825**

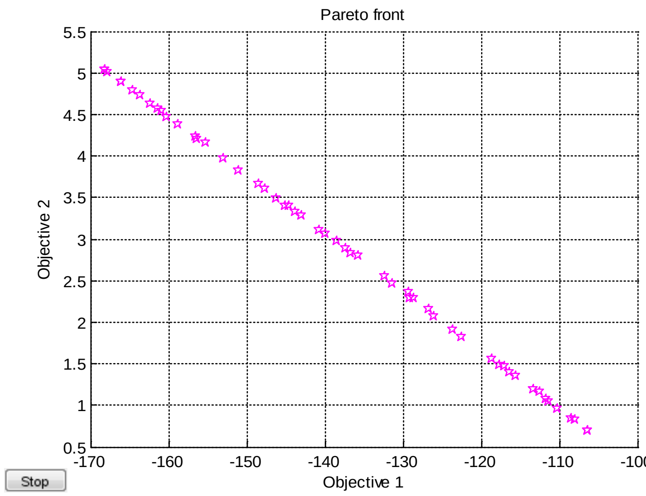

Fig. 5. Pareto front of MRR (objective 1) and Ra (objective 2) using MLR-MOGA

Table IX shows the maximum removal rate and minimum surface roughness obtained from SOP-MOGA and MLR-MOGA. T test were conducted to validate the differences between experimental with SOP-MOGA and MLR- MOGA optimization. If $p < 0.05$, it shows that the observed different within two methods are significant. Value of p for SOP-MOGA and MLR-MOGA are given in Table X, whereby p values of removal rate are 4.599E-05 and 8.016E-07 respectively. Therefore, both optimization techniques are statistically significant, however MLR-MOGA shows better confidence interval. The t test for validation of surface roughness value is shown in Table XI. The p values of SOP-MOGA and MLR-MOGA are 0.000517533 and 8.138E-05 respectively. The differences in surface roughness between experimental with SOP-MOGA and MLR-MOGA are also considered to be statistically significant. Though, p value of surface roughness is lower when using MLR-MOGA and provides better confidence level than SOP-MOGA.

TABLE IX. MLR-MOGA OPTIMAL SOLUTIONS

Model-Optimization	**Electrode Rotation, rpm *(R)***	**Current, A *(I)***	**Pulse on time, µs *(T)***	**Flushing pressure, kg/cm^2 *(P)***	***MRR,* mg/min**	***Ra,* µm**
SOP-MOGA	978.929	14.944	212.372	0.973	**152.660**	**5.825**
MLR-MOGA	974.770 977.810	14.944 5.799	218.250 211.907	0.967 0.973	**168.212** 106.366	5.038 **0.693**

TABLE X. RESULT COMPARISON OF MRR

MRR	**Experimental**	**SOP-MOGA**	**MLR-MOGA**
Mean	82.235185	123.26438	136.57759
Variance	2090.1961	350.06605	328.6352
Observations	27	100	100
Hypothesized Mean Difference		0	0
df		28	28
t Stat		-4.561184	-6.0492194
P(T<=t) one-tail		4.599E-05	8.016E-07
t Critical one-tail		1.7011309	1.7011309
P(T<=t) two-tail		9.197E-05	1.603E-06
t Critical two-tail		2.0484071	2.0484071

TABLE XI. RESULT COMPARISON OF RA

Ra	**Experimental**	**SOP-MOGA**	**MLR-MOGA**
Mean	5.378148148	7.5066018	2.8434038
Variance	8.826023362	0.8302611	1.5969289
Observations	27	100	100
Hypothesized Mean Difference		0	0
df		27	29
t Stat		-3.676352422	4.3288881
P(T<=t) one-tail		0.000517533	8.138E-05
t Critical one-tail		1.703288423	1.699127
P(T<=t) two-tail		0.001035066	0.0001628
t Critical two-tail		2.051830493	2.0452296

III. CONCLUSION

This paper presented comparative empirical results of using two types of regression models to integrate with multiobjective GA. Most researchers used second order polynomial regression [18, 20, 21, 22]. Lower level of regression model, multiple linear regression is used in this study to compare the efficiency of these two techniques when integrating it with multi objective optimization, as in this case, MOGA is used. Generally, SOP-MOGA and MLR-MOGA are relevant in optimizing machining process parameters. The results proved that the best removal rate (MRR) and surface roughness (Ra) are obtained from MLR-MOGA. However, SOP-MOGA is able to generate possible maximum removal rate (MRR) and minimum surface roughness (Ra) values simultaneously from same solution without neglecting any of the objectives. From the results of MLR-MOGA, operators and engineers can choose either to maximize removal rate (MRR) or minimize surface roughness (Ra).

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