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Modeling and Optimization of Electrical Discharge Machining of SiC Parameters, Using Neural Network and Non-dominating Sorting Genetic Algorithm (NSGA II)

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ABSTRACT

Silicon Carbide (SiC) machining by traditional methods with regards to its high hardness is not possible. Electro Discharge Machining, among non-traditional machining methods, is used for machining of SiC. The present work is aimed to optimize the surface roughness and material removal rate of electro discharge machining of SiC parameters simultaneously. As the output parameters are conflicting in nature, so there is no single combination of machining parameters, which provides the best machining performance. Artificial neural network (ANN) with back propagation algorithm is used to model the process. A multi-objective optimization method, non-dominating sorting genetic algorithm-II is used to optimize the process. Affects of three important input parameters of process viz., discharge current, pulse on time (T_{on}), pulse off time (T_{off}) on electric discharge machining of SiC are considered. Experiments have been conducted over a wide range of considered input parameters for training and verification of the model. Testing results demonstrate that the model is suitable for predicting the response parameters. A pareto-optimal set has been predicted in this work.

Keywords**:** *Electro Discharge Machining, Non-Dominating Sorting Algorithm, Neural Network, REFEL SiC*

1. Introduction

Electrical discharge machining (EDM) is one of the most extensively used non-conventional material removal process. Its unique feature of using thermal energy to machine electrically conductive parts regardless of hardness has been its distinctive advantage in the manufacture of mould, die, automotive, aerospace and surgical component [1]. The selection of appropriate parameters for maximum material removal rate and minimum surface roughness during the EDM process traditionally carried out by the operator's experience or conservative technological data provided by the EDM equipment manufacturers, which produced inconsistent machining performance.[2]

Some researchers carried out various investigations to improve the stock material removal rate and surface finishing in EDM process. Proper selection of machining parameters for the best process performance is still a challenging job.

Wang *et al.* [3] used genetic algorithm (GA) with artificial neural network (ANN) to find out optimal main output parameters such as material removal rate and surface roughness. They used ANN to model the process and Hunter Software to solve multi-objective optimization problem. Using ANN and GA, Su *et al.* [4] optimized EDM parameters, roughing and finishing machining stages. They utilized artificial neural network to establish the relationship between the process parameters and outputs. GA with properly defined objective functions was then adapted to the neural network to determine the optimal process parameters. They transformed material removal rate, tool wear and surface roughness into a single objective. Rao *et al.* [7] used ANN and GA to optimize the surface roughness of die sinking electric discharge machining (EDM) by considering the simultaneous affect of various input parameters. Genetic algorithm concept was used to optimize the weighting factors of the network.

Pal *et al.* [1] used non dominating sorting genetic algorithm-II to optimize the process. They conducted some experiments on C40 Steel to generate input and output data for training an ANN model. Material removal rate and tool wear were two objectives to be optimized. So they predicted a pareto-optimal set for outputs.

In this study material removal rate and surface roughness have been considered to produce a pareto-optimal set for EDM of REFEL SiC. Some related properties of this material are shown in **Table 1**.

2. Experimentations

In this study, Deckel CNC Spark, ISO frequency system, with gap control system was used to carry out the experiments. Copper electrode was selected to drill holes in the REFEL SiC blocks. For evaluating the EDM process the MRR and surface roughness (Ra) are mentioned with input machining parameters such as pulse on time (T_{on}), pulse off time (T_{off}), discharge current (I). Proper selection of the machining parameters can result a higher material removal rate and lower Ra. Using an orthogonal array L_{25} according Taguchi method decreased the number experiments effectively. Hence 25 sets of experiments have been conducted with five levels of each parameter (current, pulse on time and off time) to collect for training of the neural network model. Moreover five sets of experiments have been for testing the trained neural network. For each experiment, a new set of tool and work-piece has been used. For normal polarity the work-piece is connected to the negative terminal and the tool is connected to the positive terminal of the source, where as for reverse polarity it is just the opposite. Experiment has been performed with normal polarity. The current range is 0.1 - 5 A and the pulse on time and pulse off time ranges are 21 - 1125 µs.

3. Material Removal Rate (MRR)

Material removal rate and surface roughness have been used to evaluate machining performance. Material removal rate (MRR) is calculated from the difference of weight of work piece before and after experiment.

$$\mathrm{MRR} = \frac{\left(w_i - w_f\right)}{\rho_{\mathrm{SiC}} t} \quad \mathrm{mm^3/min} \tag{1}$$

where, w_i is the initial weight of workpiece in g; w_f the weight of workpiece after machining in *g*; *t* the machining time in minutes; ρ_{SiC} is the density of SiC (3.1×10^{-3} g/mm^3).

4. Surface Roughness

The surface roughness R_a is the arithmetic average of collected roughness data points and given by the sum of the absolute values of all the areas above and below the mean line (in integrally form). A mean line is found that is parallel to the general surface direction and divides the surface in such a way that the sum of the areas formed above the line is equal to the sum of the areas formed below the line. When sample points were taken, R_a is calculated as follows:

$$R_a = \frac{1}{n}\sum_{i=1}^{n}\left|y_i\right| \tag{2}$$

where y_i is the distance between the i^{th} sample point on the profile from the mean line, and n is the number of sample points.

5. Neural Network

Modeling of EDM with feed forward neural network is composed of two stages: training and testing of the network with experimental machining data. The scale of the input and output data is an important matter to consider, especially, when the operating ranges of process parameters are different. The scaling or normalization ensures that the ANN will be trained effectively. By searching in different network architectures using a MATLAB code, multilayer-perceptron (3-5-5-2) was chosen as the network architecture. The networks were trained using a back-propagation algorithm. The selected network architecture had the minimum value of the error. The error E indicates the difference between the actual and the desired output of the neural network, as follows:

$$E = \sum_{j=1}^{az}\left(y_j - a_j\right)^2 \rightarrow \min \tag{3}$$

where y_j is the desired output, a_j is the calculated output, *az* the number of testing data. Five sets of experiments allocated to test the network's error value. Pulse on-time, pulse off-time and the current are the inputs of neural network and material removal rate and surface roughness are the outputs of the neural network. **Figure 1** shows the

Table1. Some characteristics of REFEL SiC [5].

Density (gr/cm^3)	Hardness (HV)	Young modulus (E) (GN/m)	Thermal expansion 1×10^{-6}°C	Thermal conductivity (k) at 100°C (W/m·°C) at 1200°C		Specific heat (J/g°C)	Electrical resistance (Ω·cm)	Thermal shock (cal/cm·s) at 500°C
3.10	2500	413	4.3	83.6	38.9	670.710	0.42 (at 25°C) 0.016 (at 1200°C)	59

material removal rate comparison between experimental outputs and the corresponding values that are predicted by neural network. The average percentage of error for predicting MRR is 6.71%.

Figure 2 shows the surface roughness comparison between experimental outputs and the corresponding values that are predicted by neural network. The average percentage of error for predicting is 5.67% in this case.

6. NSGA II

A single objective optimization algorithm provides a single optimal solution. However, most of the multi-objective problems, in principle, give rise to a set of optimal solutions instead of a single optimal solution [1-9]. The set of solution is known as pareto-optimal solution. In the absence of any further information, none of these pareto-optimal solutions cannot be said to be better than the other. Suitability of one solution depends on a number of factors including user's choice and problem environment and etc. Hence, this demands finding the entire set of optimal solutions. In this study two objectives that we considered are MRR and Ra. It is observed that when MRR is increasing the Ra increases too. But our goals are maximizing of MRR and minimizing of Ra. A single optimal solution will not serve our purpose, as these objectives are conflicting in nature. Optimization of both the output parameters requires multi-objective optimization. Genetic algorithm works with a population of feasible solutions and, therefore, it can be used in multi-objective optimization problems to capture a number of solutions simultaneously. NSGA-II is fast and elitist multi objective GA, proposed by Dev *et al.* [6]. The flow chart of NSGA-II is shown in **Figure 3**.

7. Discussion

The objectives in this study, which are conflicting together, are MRR and surface roughness. In order to convert the first objective (MRR) for minimization, it is suitably modified. Two objective functions are given below:

$$\text{objective } 1 = 1/\text{MRR} \quad \text{and} \quad \text{objective } 2 = R_a \qquad (4)$$

The non-dominated solution set obtained over the entire optimization procedure is shown in **Figure 4**. This shows the formation of the pareto-optimal front leading to the final set of solutions.

Since none of the solutions in the pareto-optimal front is absolutely better than any other, any one of them is an acceptable solution. The choice of one solution over the other depends on the requirement of the process engineer. If the situation or environment can permit a surface roughness rate of 3 μm to maintain the accuracy of the

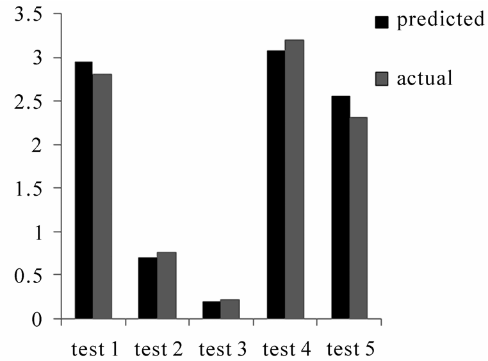

Figure 1. Comparison between experimental and neural network predicted outputs of material removal rate.

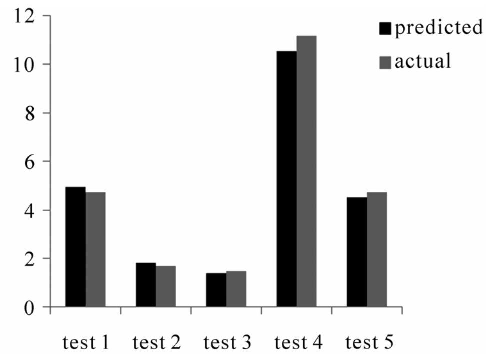

Figure 2. Comparison between experimental and neural network predicted outputs of surface roughness.

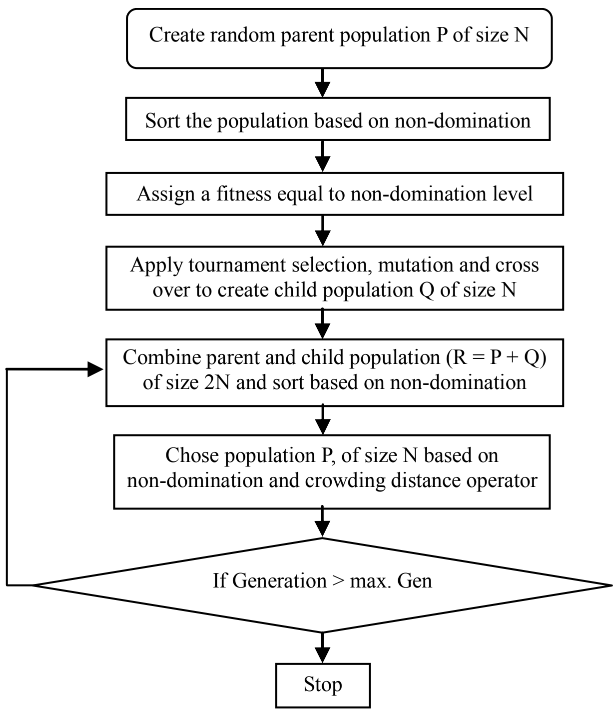

Figure 3. Flow chart of NSGA II.

Table 2. Optimal sets of parameters.

	Ti	To	I	MRR	Ra
1	858.9584	924.4639	4.8902	3.6446	8.4364
2	141.5017	496.6855	0.1	0.3466	0.886
3	174.6221	682.9052	1.0473	1.4528	1.1667
4	316.126	21	3.8979	1.9901	1.1703
5	206.7583	663.0539	4.1795	3.5945	5.5242
6	168.7212	536.2421	4.2317	3.5695	5.0381
7	429.4838	70.5361	4.5337	2.3535	1.4294
8	407.6555	101.8867	4.5579	2.4078	1.5658
9	431.1151	33.2454	4.5007	2.2597	1.2826
10	372.2205	1082.09	3.9459	2.5234	1.6222
11	299.4541	937.1161	3.2485	3.2904	3.5347
12	349.6336	21	4.2386	2.1084	1.1764
13	133.5872	406.38	3.9202	3.4407	4.251
14	180.275	545.7843	0.5586	0.676	0.9604
15	120.2597	409.5408	3.9015	3.4017	4.0785
16	942.8562	855.8315	4.5168	3.6315	6.7868
17	287.1614	1024.018	3.0806	2.8177	1.7393
18	284.3813	1032.874	3.0924	2.7484	1.7079
19	877.9769	938.2853	4.871	3.6442	7.9565
20	171.6979	605.3086	0.7507	0.9007	1.0196
21	194.7966	529.194	0.7099	0.8277	1.0017
22	403.2268	21.0838	4.4904	2.1987	1.2137
23	300.4237	948.3546	3.2485	3.2873	3.117
24	113.1908	369.4054	3.8439	3.2937	3.8086
25	917.4061	941.7156	4.8294	3.6407	7.5638
26	916.4971	891.0667	4.6921	3.6398	7.379
27	984.2048	816.5333	4.4308	3.6187	6.2749
28	303.9082	938.2599	3.2566	3.2897	3.3114
29	1046.005	805.3527	4.3747	3.5948	5.7939
30	870.1822	924.2211	4.8671	3.6445	8.21
31	281.8689	1032.299	3.0245	2.6488	1.6937
32	315.6009	21	3.9119	1.993	1.1704
33	181.5296	531.0391	0.6132	0.7553	0.9725
34	275.9709	1016.142	3.0625	2.9787	1.809
35	131.772	491.3254	4.1534	3.5081	4.5261
36	305.2944	948.2171	3.2467	3.2833	2.8871
37	861.9278	930.9182	4.8708	3.6445	8.1551

38	119.1833	477.8889	4.0229	3.4609	4.3141
39	376.0995	24.0189	4.3534	2.1632	1.1971
40	173.1123	685.8219	1.0394	1.4358	1.1631
41	284.2434	1035.765	3.0867	2.6966	1.6946
42	286.2831	1021.49	3.0881	2.8707	1.7557
43	148.4211	482.6119	0.1	0.3784	0.886
44	298.755	937.8997	3.1764	3.2873	3.0139
45	308.5639	948.8102	3.1985	3.2631	2.5244
46	366.4247	1078.362	3.9262	2.593	1.6522
47	996.3369	816.5368	4.4229	3.6152	6.1633
48	115.4423	368.0682	3.9275	3.3269	3.8915
49	168.5636	634.8079	0.9029	1.183	1.095
50	176.8979	645.9134	0.9506	1.2511	1.1102
51	172.9696	685.0409	1.0058	1.3451	1.1468
52	304.4127	946.2207	3.2116	3.2803	2.772
53	157.1823	527.6218	4.3731	3.5523	4.8573
54	925.4805	861.5791	4.5397	3.6341	6.9647
55	149.998	493.2173	4.2715	3.5425	4.7609
56	306.9045	981.8667	3.249	3.2036	2.1755
57	302.2196	938.9002	3.2589	3.2901	3.3997
58	908.0573	923.543	4.8141	3.6424	7.6703
59	927.5109	896.1882	4.6304	3.6355	7.13
60	113.3054	371.2426	4.1168	3.36	4.0045
61	163.5354	448.252	0.1	0.4499	0.8898
62	161.4533	546.5079	4.2317	3.5642	4.9386
63	175.078	447.2047	0.3503	0.5919	0.9336
64	190.6357	418.0032	0.4155	0.6059	0.9571
65	184.3604	585.3931	0.7912	0.9543	1.0309
66	968.7002	849.109	4.5269	3.6279	6.6203
67	138.972	500.3413	4.1505	3.5256	4.6216
68	179.8468	438.7951	0.2235	0.5309	0.9089
69	305.3556	971.6719	3.2454	3.2423	2.3567
70	285.3319	1012.133	3.0527	2.9273	1.7853
71	133.0257	431.1921	4.0818	3.4829	4.3986
72	959.5319	825.0148	4.421	3.6244	6.4444
73	183.5624	532.4206	0.6413	0.7817	0.9806
74	368.9871	1078.629	3.9218	2.5689	1.6401
75	1009.683	804.5483	4.4012	3.6083	6.0169

76	176.643	618.4106	0.9651	1.2652	1.1409
77	134.2186	431.9405	4.1533	3.4907	4.4421
78	961.3217	825.2114	4.4227	3.6242	6.4331
79	172.7149	683.4143	0.9945	1.3194	1.1413
80	301.2341	945.2716	3.1541	3.2729	2.6102
81	300.4964	945.9148	3.165	3.2768	2.6725
82	143.7192	487.6615	4.2564	3.5319	4.6777
83	174.965	613.1224	0.8278	1.03	1.05
84	159.3381	649.6514	0.8593	1.0943	1.0768
85	966.0411	847.5901	4.5269	3.6284	6.6415
86	305.7388	981.1644	3.2702	3.2229	2.2694
87	925.6356	861.3723	4.556	3.6351	7.005
88	276.5219	994.4977	2.9962	3.0797	1.8856
89	886.8913	930.2199	4.8374	3.6436	7.8378
90	182.7754	581.0766	0.8067	0.9855	1.0385
91	988.0573	799.9433	4.3565	3.6126	6.0526
92	293.829	1021.771	3.1564	2.9067	1.7773
93	178.411	630.8943	0.905	1.1575	1.0854
94	298.351	964.5621	3.0682	3.1826	2.0974
95	1001.796	801.5891	4.3056	3.605	5.8814
96	158.8948	650.0343	0.8593	1.0945	1.0774
97	278.2378	991.8914	2.9667	3.0496	1.8586
98	283.6434	966.2962	3.093	3.253	2.4188
99	935.8522	898.663	4.6975	3.6379	7.2202
100	115.3983	370.507	3.8796	3.3179	3.8653

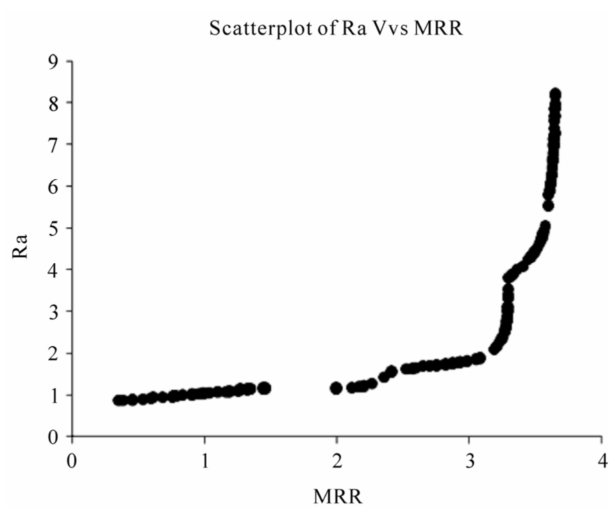

Figure 4. Pareto-optimal set.

product, the process engineer can chose the parameter setting according to that to obtain maximum material removal rate at the specified value of surface roughness.

From the experiments results, material removal and surface roughness are 3.58 mm^3/min and 7.34 µm respectively. In this case the pulse on and pulse off times and also the current settings are 850 µs, 900 µs and 5A respectively. For solution number 1 in **Figure 1**, material removal rate and Surface roughness are 3.6446 mm^3/min and 7.2561 µm, where the pulse on and pulse off times and also current settings are 858.9584, 924.463 µs and 4.8902A, respectively. Choice of pulse on time and off time will help to achieve higher MRR with same tool wear. This indicates, values obtained from the optimization technique are in close agreement with the experimental values for more or less the same parameter settings.

8. Conclusions

81 experiments have been conducted with a wide range of current, pulse on time and pulse off time. The MRR and surface roughness have been measured for each setting of pulse on time and pulse off time and current. An ANN model has been trained within the experimental data. Various ANN architectures have been studied, and 3-5-5-2 is selected. Material removal rate and surface roughness have been optimized as objectives by using a multi-objective optimization method. Non-dominating sorting genetic algorithm-II and finally pareto-optimal sets of material removal rate and surface roughness are obtained. The results are shown in **Table 2**.

REFERENCES

[1] S. K. Pal, D. Mandal and P. Saha, "Modeling of Electrical Discharge Machining Process Using Back Propagation Neural Network and Multi-Objective Optimization Using Non-Dominating Sorting Genetic Algorithm-II," *Journal of Materials Processing Technology*, Vol. 186, No. 1-3, 2007, pp. 154-162. doi:10.1016/j.jmatprotec.2006.12.030

[2] G. K. M. Rao, G. Rangajanardhaa, D. H. Rao and M. S. Rao, "Development of Hybrid Model and Optimization of Surface Roughness in Electric Discharge Machining Using Artificial Neural Networks and Genetic Algorithm," *Journal of Materials Processing Technology*, Vol. 209, No. 3, 2009, pp. 1512-1520. doi:10.1016/j.jmatprotec.2008.04.003

[3] K. Wang, H. L. Gelgele, Y. Wang, Q. Yuan and M. Fang, "A Hybrid Intelligent Method for Modeling the EDM Process," *International Journal of Machine Tools and Manufacture*, Vol. 43, No. 10, 2003, pp. 995-999. doi:10.1016/S0890-6955(03)00102-0

[4] J. C. Su, J. Y. Kao and Y. S. Tarng, "Optimization of the Electrical Discharge Machining Process Using a GA-Based Neural Network," *International Journal of Advanced Manufacturing Technology*, Vol. 24, 2004, pp. 81-90.

[5] R. Mahdavinejad, M. Tolouei-Rad and H. Sharifi Bidgoli, "Heat Transfer Analysis of EDM Process on Silicon Carbide," *International Journal of Numerical Methods for Heat and Fluid Flow*, Vol. 15, No. 5, 2005, pp. 483-502. doi:10.1108/09615530510593657

[6] K. Dev, A. Pratap, S. Agarwal and T. Meyarivan, "A Fast and Elitist Multi Objective Genetic Algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, Vol. 6, No. 2, 2002, pp. 182-197.

[7] G. K. M. Rao, G. Rangajanardhaa, D. H. Rao and M. S. Rao, "Development of Hybrid Model and Optimization of Surface Roughness in Electric Discharge Machining Using Artificial Neural Networks and Genetic Algorithm," *Journal of Materials Processing Technology*, Vol. 209, No. 3, 2009, pp. 1512-1520. doi:10.1016/j.jmatprotec.2008.04.003

