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Multi-objective optimization of electric-discharge machining process using controlled elitist NSGA-II †

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Abstract

Parametric optimization of electric discharge machining (EDM) process is a multi-objective optimization task. In general, no single combination of input parameters can provide the best cutting speed and the best surface finish simultaneously. Genetic algorithm has been proven as one of the most popular multi-objective optimization techniques for the parametric optimization of EDM process. In this work, controlled elitist non-dominated sorting genetic algorithm has been used to optimize the process. Experiments have been carried out on die-sinking EDM by taking Inconel 718 as work piece and copper as tool electrode. Artificial neural network (ANN) with back propagation algorithm has been used to model EDM process. ANN has been trained with the experimental data set. Controlled elitist non-dominated sorting genetic algorithm has been employed in the trained network and a set of pareto-optimal solutions is obtained.

Keywords: Artificial neural networks; Electric discharge machining; Genetic algorithm; Material removal rate; Optimization; Pareto-optimal solutions; Surface roughness.

1. Introduction

Inconel 718 is one of the most difficult-to-cut nickel based alloys. Formation of complex shapes (of this material) along with reasonable speed and surface finish is very difficult by traditional machining. Electric discharge machining (EDM) is one of the most suitable non-conventional material removal processes to shape this alloy. EDM is a thermo-electric process in which material is removed from work piece by erosion effect of series of electric discharges (sparks) between tool and work piece immersed in a dielectric liquid. The EDM process has a very strong stochastic nature due to the complicated discharge mechanisms making it difficult to optimize the process [1]. The process performance can be improved by selecting the optimal combination of process parameters. Optimization of process parameters of EDM is a multi-objective optimization task as, in practice, the performance measures (Material Removal Rate and Surface Roughness) are conflicting in nature. Though much work has been reported in literature to improve the process performance, proper selection of process parameters still remains a challenge. There are several multi-objective optimization techniques for the same like goal programming, simulated annealing (SA), grey relation, and genetic algorithms (GA).

SA is an optimization process whose operation is strongly reminiscent of the physical annealing of crystalline compounds such as metals and metallic alloys [2]. Tarng et al. [3] and Yang et al. [4] employed SA technique for optimizing the parameters of EDM. Grey relation analysis has been employed successfully as a multi-objective optimization technique in EDM by many authors [5-7].

Literature review shows that to employ SA, two objectives are transformed into a single objective by simple weighted method in which weight values are user defined in the range of 0 and 1. A single combination of input parameters has generally been reported in literature by employing SA. In grey relation method also, the authors (in literature) have generally reported a single combination of input parameters as optimal combination corresponding to the grey relation grade of higher rank. Since, the performance measures are conflicting in nature in case of EDM, a single combination does not provide satisfactory solutions for the best performance measures simultaneously. In some of the classical techniques, multi-objective optimization problem is directly converted to a single-optimization problem which deviates from the exact solutions. Some of the techniques terminate at local optima and global optimum solutions are not reached. As a result, the true optimal solutions are not obtained.

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GA is very different from most of the traditional optimization methods. GA finds applicability in the field of EDM. It works with a random population of solution points and a set of pareto-optimal solutions is obtained for the best performance measures.

Su et al. [8] optimized the process parameters of EDM by employing GA. A neural network was trained to establish the relationships between process parameters and performance measures and then GA was adapted to the trained network to determine the optimal process parameters. Mandal et al. [9] used ANN for modeling EDM process and then employed non-dominating sorting genetic algorithm-II (NSGA-II) to find pareto-optimal solutions. Kuriakose and Shunmugan [10] employed NSGA to optimize the EDM process. There are many references where GA has been applied as a multi-objective optimization technique in the field of EDM [11-14].

There are several variants of GA like multi-objective genetic algorithm (MOGA), vector evaluated genetic algorithm (VEGA), non-dominated sorted genetic algorithm and NSGA-II. In this work, controlled elistist NSGA-II has been employed to obtain the optimal combination of process parameters. To employ GA, fitness function value is required which, in EDM, is the objective function value. So, the need of some function or equation arises that relates the process parameters with the performance measures. Since, EDM is very complex process, it is difficult to establish a mathematical equation that serves the purpose. Hence, the mathematical modeling of EDM process is needed. Many empirical, statistical and regression techniques have been used in literature [15-18]. These techniques are not found very successful because of non-linearity and noise factors involved in EDM process. Artificial neural network (ANN) forms an alternative approach to model the system efficiently as it is capable of mapping input variable and performance measures of EDM. Several researchers have shown the applicability and superiority of ANN in machining process in literature [19-23]. Hence an ANN tool has been used to model EDM process. In this work, L 36 ($2^1 3^6$) orthogonal array is taken for experiment design. Shape factor (SF), Pulse-on-time (T_{on}), Discharge current (I_d), Duty cycle (ζ), Gap voltage (V_g), Flushing pressure (P) and Tool electrode lift time (T_L) are taken as input parameters. Material removal rate (MRR) and Surface roughness (SR) are taken as performance measures. Experiments have been conducted on die-sinking EDM by taking Inconel 718 as work piece and copper as tool electrode. ANN model of EDM process is developed by training of ANN with the experimental data. Prediction ability of trained ANN model has been verified experimentally. Finally, controlled elitist NSGA-II has been employed on the trained network to obtain the pareto-optimal set of solutions. Simulation has been performed in MATLab.

2. Experimentation

Experiments have been conducted on Elecktra Plus S-50 ZNC oil die-sinking electric discharge machine in which the Z-axis is servo controlled and X and Y axis are manually controlled. The working range of input parameters and their levels taken are shown in Table 1. L_{36} ($2^1 \times 3^6$) orthogonal array, shown in Table 2, has been used which contains 36 experimental runs at various combinations of seven input parameters. Since stable machining conditions are achieved after 10 minutes, a study of 15 minutes machining or 0.5 mm depth of cut (whichever is earlier) is taken in this work. MRR and SR have been used to valuate machining performance. MRR (mm^3/min) is calculated by measuring the amount of material removed per unit machining time. The center line average (CLA) surface roughness parameter R_a was used to quantify the surface roughness. The experimentally obtained values of the performance measures for the different combinations of input parameters are shown in Table 2.

Table 1. Machining Parameters and their levels.

Input parameters	Unit	Levels and values		
		1	2	3
Shape factor (SF)	-	Square	Circular	-
Pulse-on-time (T_{on})	μs	50	100	150
Discharge current (I_d)	A	3	8	12
Duty cycle (ζ)	%	0.7	0.75	0.83
Gap voltage (V_g)	V	50	70	90
Flushing pressure (P)	Kg/cm^2	0.3	0.5	0.7
Tool electrode lift time (T_L)	sec	1	2	3

3. Artificial neural network

Artificial Neural Networks are simplified models of biological nervous system inspired by human brain. Kohonen [24] defined neural network as "massively parallel interconnected networks of simple (usually adaptive) elements and their hierarchical organizations which are intended to interact with the objects of the real world in the same way as biological nervous system do." ANNs have the capability to capture knowledge domain from examples. ANNs are built by connecting processing units, called nodes or neurons. Each of the input (x_i) is associated with some weight (w_i) which takes a portion of the input to the node for processing. The node combines the inputs (x_i w_i) and produces net input which in turn is transformed into output with the help of transfer function/activation function. ANNs are broadly classified into feed forward and recurrent networks. Feed forward networks are those in which computation flows from the input node(s) to the output node(s) in a sequence. The nodes of one layer are connected to all or a subset of the nodes of the previous layer nodes as well as the subsequent layer nodes. The layers in between the input and output layer are known as hidden layers.

Table 2. Design experiment of $36(2^1\times3^6)$ array with different experimental parametric levels.

Exp. No.	SF	T_{on} (μs)	I_d (A)	ζ (%)	V_g (V)	P (kg/ cm^2)	T_L (sec)	MRR	SR
1.	1	1	1	1	1	1	1	4.52	4.25
2.	1	2	2	2	2	2	2	25.18	7.3
3.	1	3	3	3	3	3	3	36.63	9.46
4.	1	1	1	1	1	2	2	4.76	6.145
58.	1	2	2	2	2	3	3	30.61	7.9
6.	1	3	3	3	3	1	1	49.03	8.55
7.	1	1	1	2	3	1	2	2.71	5.05
8.	1	2	2	3	1	2	3	29.91	9
9.	1	3	3	1	2	3	1	35.27	11.07
10.	1	1	1	3	2	1	3	1.91	5.36
11.	1	2	2	1	3	2	1	11.25	7.03
12.	1	3	3	2	1	3	2	34.49	10.73
13.	1	1	2	3	1	3	2	27.89	8.05
14.	1	2	3	1	2	1	3	55.51	9.8
15.	1	3	1	2	3	2	1	2.73	4.92
16.	1	1	2	3	2	1	1	17.21	7.16
17.	1	2	3	1	3	2	2	30.86	9.63
18.	1	3	1	2	1	3	3	7.45	5.2
19.	2	1	2	1	3	3	3	17.09	6.33
20.	2	2	3	2	1	1	1	47.45	10
21.	2	3	1	3	2	2	2	4.94	4.29
22.	2	1	2	2	3	3	1	12.04	5.76
23.	2	2	3	3	1	1	2	42.08	7.25
24.	2	3	1	1	2	2	3	4.36	4.67
25.	2	1	3	2	1	2	3	39.59	7.09
26.	2	2	1	3	2	3	1	4.00	6.11
27.	2	3	2	1	3	1	2	14.54	8.31
28.	2	1	3	2	2	2	1	16.72	6.88
29.	2	2	1	3	3	3	2	3.38	5.82
30.	2	3	2	1	1	1	3	31.83	7.28
31.	2	1	3	3	3	2	3	34.94	6.9
32.	2	2	1	1	1	3	1	4.96	4.49
33.	2	3	2	2	2	1	2	22.61	7.03
34.	2	1	3	1	2	3	2	38.64	7.19
35.	2	2	1	2	3	1	3	2.60	6.03
36.	2	3	2	3	1	2	1	25.66	7.32

In a recurrent network, signals may propagate from the output of any neuron to the input of any neuron. Primarily there are two types of learning methods- supervised and unsupervised learning. In supervised learning method, every input pattern that is used to train the network is associated with an output pattern (i.e. the target or desired pattern). A teacher is assumed to be present during the learning process to determine the error after comparing the network's computed output and desired output. This error is used to change network parameters which results in improvement in performance. In unsupervised learning method, the system learns by its own by discovering and adapting to structural features in the input pattern in the absence of a teacher. Back propagation (BP) algorithm is one of the most studied and used algorithm for neural networks training. BP neural networks applies the error-back procedure for learning. The back-propagation procedure uses a gradient descent method, which adjusts the weight in its original and simplest form by an amount proportional to the partial derivative of the error function (E) with respect to the given weight. The formula used for the adjustment (at the t^{th} iteration of the training algorithm) is:

$$w_{ij}(t+1) = w_{ij}(t) - \eta\frac{\partial E}{\partial w_{ij}} + \mu\Delta w\,. \tag{1}$$

In which η and μ are user-selected, positive constants (between 0 and 1) called learning rate coefficient and momentum term respectively. Δ w is the weight change in earlier layer. The error-back propagation is typical supervised learning procedure. They are the most popular neural network models in EDM. A representative single hidden layer back propagation network is shown in Fig. 1. Literature review shows that ANN has been used, in the field of EDM, mainly for prediction of performance measures, on-line monitoring of the process and optimization of process parameters [25-28]. In this work, ANN model of the EDM process has been developed. Experimental data is used for training the ANN model. Different architectures were studied and 7-9-2 architecture was found as the best amongst studied architectures. Architecture 7-9-2

Table 3. Comparison of experimental results with the ANN model prediction.

Exp. No.	Machining parameters							MRR (mm^3/min)		SR (micron)		Relative error (%)	
	SF	T_{on} (μs)	I_d (A)	ζ (%)	V_g(V)	P (kg/ cm^2)	T_L (sec)	ANN predicted	Experi-mental	ANN predicted	Experi-mental	Error in MRR	Error in SR
1.	1	50	3	0.7	50	0.3	2	5.76	6.02	4.6	4.51	4.51	1.95
2.	1	50	8	0.7	70	0.3	2	33.51	34.55	5.9	5.8	3.12	1.69
3.	1	50	12	0.7	90	0.5	3	40.77	44.17	7.92	8.45	8.34	6.94
4.	1	100	3	0.75	90	0.5	3	6.06	5.93	5.25	5.1	2.06	2.85
5.	1	100	8	0.7	70	0.5	3	33.8	31.35	7.9	7.05	7.24	10.75
6.	2	100	12	0.83	50	0.5	2	45.82	46.8	8.24	8.91	2.13	8.13
7.	2	150	3	0.7	50	0.7	2	3.67	3.64	4.96	4.71	0.8	5.04
8.	2	150	8	0.75	70	0.3	3	27.9	27.06	6.72	6.55	3.0	2.52
9.	2	150	12	0.75	90	0.3	3	42.96	44.35	9.82	10.3	3.23	4.88
10.	2	150	8	0.83	90	0.7	1	16.47	15.52	6.87	6.73	5.6	2.03
Average error (%)												4.00	4.67

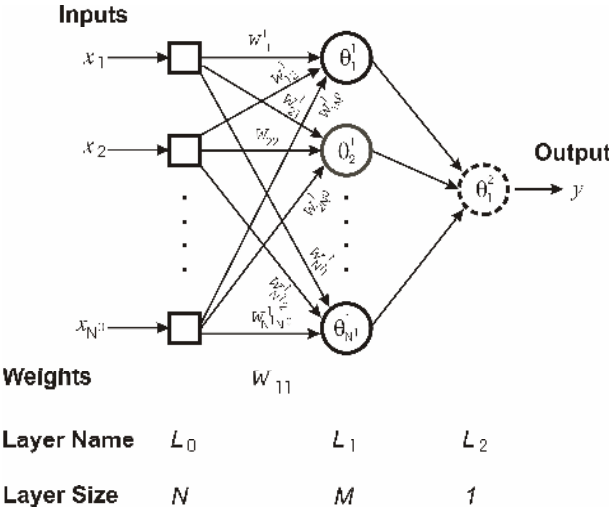

Fig. 1. A representative 1 hidden layer Back-Propagation network.

denotes the number of nodes in input, hidden and output layer. Since the operating ranges of the parameters are different, scaling or normalization helps in avoiding skewing the results by any particular variable significantly during training. Input data is scaled (or normalized) between -1 to 1, while the output data is scaled between 0 to 1 to impose the condition of positivity on the output (irrespective of the error of modeling). The values of learning rate coefficient and momentum term have been taken as 0.4 and 0.1 respectively. Several algorithms have been used and the best results were obtained using Bayesian regularization (BR) algorithm. Log-sigmoid activation function has been used for both the layers (hidden and the output layers). For testing the prediction ability of the model, prediction error in each output node has been calculated as follows:

$$prediction\ \ error(\%) = \frac{(actual\ value - predicted\ value)}{actual\ value} * 100 . \quad (2)$$

This prediction error is calculated as absolute percentage error (APE). Mean absolute percentage error (MAPE) is mean of APE *i.e.* MAPE = APE of all the nodes/number of nodes. MAPE, for all patterns, has been calculated and the network, for which MAPE is minimum (i.e., 2.74%), is selected for prediction. Prediction ability of the trained network has been verified experimentally. The average percentage difference between experimental and ANN's predicted value is 4 and 4.67 for MRR and SR respectively as reported in Table 3.

4. Optimization

The objective, in this work, is to find the optimal combination of input parameters that provides maximum cutting speed (i.e., maximum MRR) and maximum surface finish (i.e., minimum SR). It is observed that when cutting speed increases, surface finish deteriorates. Because of the conflicting nature of performance measures, a single combination of input parameters does not serve the purpose. As a result, a set of optimal solutions (i.e., pareto-optimal solutions) is obtained instead of a single optimal combination.

4.1 Elitist NSGA

This algorithm was proposed by Deb et al. [29]. In this, a random population P (called parent population) of size N is selected and the offspring population O is created using P. As a part of elite-preserving strategy P and O are combined together to form T of size $2N$. Then, non-dominated sorting is applied to classify the entire population (T) into different fronts of non-dominated solutions. None of the solutions in a front is absolutely better than the other solutions of the same. Each solution is assigned a rank that is equal to its non-domination level. In order to identify the non-domination level, each solution is compared with every other solution. If solutions 1 and 2 are compared and it is observed that solution 1 is better than solution 2 in objective function 1 and solution 1 is also better than solution 2 in objective function 2. Then solution 1 dominates solution 2 or solution 1 is non-dominated by solution 2. However, if the solution 1 is better than solution

2 in objective function 1, but solution 1 is worse than solution 2 in objective function 2, solution 1 is dominated by solution 2. The concept of dominance and approach used to obtain the pareto-optimal set is mathematically explained as below [30]:

$x^{(1)}$ is said to dominate the other solution $x^{(2)}$, if both the conditions 1 and 2 are true:

1. The solution $x^{(1)}$ is no worse than $x^{(2)}$ in all objectives, or $f_j\left(x^{(1)}\right) \not\rhd f_j\left(x^{(2)}\right)$, for all $j = 1,2,.....,M$. $i \rhd j$ implies that solution i is worse than solution j on a particular objective.

2. The solution $x^{(1)}$ is strictly better than $x^{(2)}$ in at least one objective, or $f_j\left(x^{(1)}\right) \lhd f_j\left(x^{(2)}\right)$ for at least one $j \in \{1, 2,.....M\}$. $i \lhd j$ implies that solution i is better than solution j on a particular objective.

To provide the diversity in the new population (of size N), crowded tournament selection operator is used to fill N solutions in the new population. Any of the following condition is true to fill the new population of size N:

1. If solution i has a better rank, that is, $r_i < r_j$

2. If they have same rank but solution i has a better crowding distance than solution j, that is $r_i = r_j$ and $d_i > d_j$, where d is the local crowding distance.

Crowding distance is the distance between neighboring solutions. The solution lying in the less crowded area, will have larger crowding distance and so is selected. The crowd sorting of the solution of each front is performed by using a crowding distance metric.

4.2 Controlled elitist NSGA-II

It may happen that in a generation, we have a population (to fill N) where most of the members lie on the non-dominated front of rank one and this front is distant from true pareto-optimal front. The elitism operators will select the members of the non-dominated front of rank one and members of the other fronts will be deleted. As a result, diversity is lost and the solutions obtained are not true pareto-optimal solutions.

To counteract this, Deb and Goel [31] proposed a controlled elitist NSGA-II which restricts the number of individuals in the currently best non-dominated front adaptively. In this, each solution is assigned rank in the same manner as it is applied in elitist NSGA-II (as discussed in the previous section). To provide diversity in the population in the new population of size N, the maximum number of individual allowed in the i^{th} front is restricted and generally given by the following relation:

$$n_i = N\frac{1-r}{1-r^F}r^{i-1} \tag{3}$$

where r is reduction rate, a user-defined value, that is less than 1 and F is the number of non-dominated fronts. The strategy employed here forcible allows the solutions from all non-dominated fronts to co-exist in the population. If a particular front is having more solutions than required (to fill N), Eq. (3) is used to restrict the number of solutions taken from the concerned front. And if the number of solutions (in a particular front) is less than required (to fill N), the difference is added in the maximum allowed solutions in the next front and so on. After filling N solutions in the new population, the same process is repeated over a number of generations and the pareto-optimal solutions are obtained. Since the solutions from all non-dominated fronts co-exist in the population, the diversity is maintained and the solutions obtained are true optimal solutions.

To solve optimization problem using GA, fitness value is required. Fitness values, in fact, are the objective function values. In this work, ANN model has been developed to establish the relation between input and output. The objective function values are obtained by the trained network.

5. Results and discussions

The present work aims to maximize MRR and minimize SR. Since the objectives are conflicting in nature, modification of first objective (MRR) is done to get it converted for minimization. The objective functions are given below:

$$Objective\,1 = \frac{1}{MRR}$$
$$Objective\,2 = SR\,.$$

Initially, a population of 1000 size has been chosen. The values of the objective functions are obtained from trained network. Trained network provides the function which relates the input parameters with the performance measures. Pareto fraction is taken as 0.1. For better convergence, 500 generations are taken in this work. One hundred three non-dominated solutions (pareto-optimal solutions) are obtained at the end of 500 generations. The pareto-optimal solutions (along with corresponding performance measure values) are reported in Table 4. Fig. 2 shows the formation of pareto-optimal front that consists the final set of solutions. The shape of the pareto optimal front is a consequence of the continuous nature of the optimization problem posed. The results reported in Table 4 clearly show that in 103 pareto-optimal solutions, the whole given range of input parameters is reflected and no bias towards higher side or lower side of the parameters is seen. This may be attributed to the controlled NSGA that forcible allows the solutions from all non-dominated fronts to co-exist in the population. Since the performance measures are conflicting in nature, surface quality decreases as MRR increases and the same behavior of performance measures is observed in the solutions obtained. Since none of the solutions in the pareto-optimal set 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 surface finish is more desirable (than SR), any solution from 1 to 25 will be more suitable. But at the same time MRR will be

Table 4. Pareto-optimal solutions.

Solution No.	SF	T_{on} (μs)	I_d (A)	ζ (%)	V_g (V)	P (kg/ cm^2)	T_L (sec)	MRR	SR
1.	1.79	117.42	3	0.79	55.19	0.31	1.88	4.67	4.33
2.	1.80	118.47	3	0.79	55.09	0.32	1.92	4.67	4.33
3.	1.75	117.66	3	0.79	55.12	0.32	1.87	4.83	4.33
4.	1.77	117.70	3	0.79	55.19	0.33	1.94	4.94	4.33
5.	1.74	118.75	3	0.78	55.32	0.35	1.92	5.15	4.33
6.	1.74	118.06	3.14	0.78	54.76	0.34	1.91	5.27	4.33
7.	1.74	119.76	3.50	0.79	55.44	0.34	1.96	5.81	4.34
8.	1.72	121.80	3.31	0.78	57.12	0.36	2.17	6.09	4.35
9.	1.71	120.94	3.41	0.78	54.97	0.35	2.15	6.39	4.35
10.	1.73	117.52	3.60	0.77	54.67	0.34	2	6.61	4.35
11.	1.71	122.90	3.80	0.78	55.50	0.34	2	6.82	4.36
12.	1.73	119.65	3.69	0.77	56.12	0.34	2.18	6.95	4.36
13.	1.68	120.24	3.80	0.77	55.37	0.33	2.21	7.37	4.36
14.	1.74	117	3.82	0.77	56.00	0.34	2.29	7.56	4.37
15.	1.76	120.93	4.18	0.78	55.90	0.36	2.14	8.01	4.38
16.	1.72	118.91	4.08	0.77	55.84	0.35	2.21	8.23	4.38
17.	1.73	124.29	4.23	0.77	56.18	0.35	2.20	8.72	4.38
18.	1.74	114.57	4.79	0.79	55.86	0.34	2.11	9.48	4.41
19.	1.74	114.73	4.83	0.79	55.59	0.34	2.07	9.66	4.41
20.	1.69	116.36	4.75	0.77	55.09	0.32	2.13	10.23	4.41
21.	1.65	120.38	4.82	0.76	54.82	0.35	2.44	13.12	4.46
22.	1.73	116.31	5.40	0.77	56.15	0.34	2.20	13.86	4.48
23.	1.75	115.39	5.75	0.77	55.59	0.35	2.34	17.40	4.55
24.	1.73	117.31	5.94	0.77	56.62	0.37	2.67	19.18	4.60
25.	1.77	112.42	6.26	0.77	56.16	0.35	2.86	21.28	4.64
26.	1.62	138.69	8.36	0.82	85.71	0.35	1.75	35.19	4.94
27.	1.59	138.24	8.49	0.83	86.22	0.36	1.66	36.84	5.01
28.	1.65	139.00	9.13	0.83	86.31	0.38	1.81	40.01	5.15
29.	1.64	139	9.47	0.83	86.88	0.35	1.66	42.01	5.20
30.	1.57	139.11	9.87	0.83	85.93	0.34	1.64	43.77	5.35
31.	1.63	139.17	10.20	0.83	86.89	0.33	1.65	44.69	5.38
32.	1.54	139.53	10.23	0.83	86.72	0.34	1.68	45.06	5.47
33.	1.63	139.40	10.28	0.83	85.42	0.36	1.71	45.11	5.52
34.	1.55	139.49	10.57	0.83	86.66	0.34	1.64	46.20	5.61
35.	1.63	139.42	10.79	0.83	86.63	0.36	1.77	46.38	5.63
36.	1.53	139	10.70	0.82	86.31	0.34	1.72	46.48	5.69
37.	1.57	138.83	10.96	0.82	86.84	0.34	1.68	47.10	5.74
38.	1.50	139.81	10.91	0.83	86.78	0.33	1.64	47.18	5.81
39.	1.60	137.25	11.75	0.83	86.89	0.33	2.02	48.05	5.89
40.	1.50	139.95	11.29	0.83	86.90	0.33	1.60	48.13	5.98
41.	1.60	136.25	11.81	0.83	86.96	0.38	1.83	48.43	6.04
42.	1.56	140	11.65	0.83	86.78	0.33	1.66	48.71	6.09
43.	1.52	138.69	11.72	0.82	86.67	0.33	1.75	48.76	6.15
44.	1.53	139.92	11.74	0.83	86.92	0.34	1.70	48.88	6.17
45.	1.49	140.17	11.67	0.83	86.88	0.33	1.59	48.92	6.23
46.	1.49	140.17	11.67	0.83	86.88	0.33	1.58	48.93	6.24
47.	1.49	140.16	11.76	0.83	86.92	0.32	1.58	49.13	6.30
48.	1.49	140.16	11.76	0.83	86.92	0.32	1.58	49.15	6.31
49.	1.86	108.01	10.36	0.77	59.95	0.41	3.00	49.20	6.38
50.	1.76	109.50	10.01	0.76	59.27	0.39	2.95	49.26	6.43
51.	1.86	108.82	10.41	0.77	59.45	0.40	2.98	49.51	6.46
52.	1.77	110.23	10.01	0.77	58.35	0.40	2.89	49.54	6.55
53.	1.77	110.24	10.19	0.77	58.69	0.39	2.94	49.70	6.56
54.	1.74	110.61	10	0.76	58.95	0.40	2.94	49.84	6.61
55.	1.75	111.23	10.23	0.77	58.63	0.40	2.93	49.86	6.67
56.	1.77	110.10	10.16	0.76	58.10	0.40	2.91	50.06	6.70
57.	1.74	110.57	10.21	0.76	58.45	0.39	2.91	50.22	6.75
58.	1.79	109.87	10.64	0.76	57.96	0.39	2.98	50.75	6.89
59.	1.76	110.87	10.40	0.76	58.13	0.39	2.91	50.75	6.96
60.	1.81	108.06	11.08	0.77	59.16	0.39	2.95	51.10	7.04

Table 4 (continued)

61.	1.81	109.48	11	0.77	59.06	0.40	2.97	51.30	7.09
62.	1.75	111.17	10.69	0.76	58.32	0.39	2.95	51.30	7.16
63.	1.75	109.55	10.78	0.76	58.10	0.39	2.94	51.37	7.20
64.	1.76	110.11	10.91	0.77	58.24	0.39	2.94	51.49	7.24
65.	1.76	109.68	10.96	0.76	58.80	0.39	2.96	51.60	7.27
66.	1.74	112.09	10.88	0.77	58.99	0.40	2.97	51.67	7.34
67.	1.80	110.68	11.18	0.76	57.30	0.39	2.95	51.89	7.46
68.	1.76	109.80	11.20	0.76	58.67	0.40	2.97	52.04	7.51
69.	1.78	110.36	11.18	0.76	58.09	0.39	2.94	52.09	7.59
70.	1.74	111.41	11.24	0.76	58.00	0.39	2.97	52.25	7.68
71.	1.77	110.89	11.26	0.76	57.04	0.39	2.96	52.34	7.76
72.	1.74	111.84	11.24	0.76	57.99	0.39	2.92	52.37	7.80
73.	1.76	111.20	11.48	0.76	58.41	0.39	2.95	52.49	7.82
74.	1.73	111.90	11.26	0.76	58.01	0.39	2.90	52.49	7.90
75.	1.73	112.35	11.31	0.76	58.80	0.39	2.90	52.54	7.94
76.	1.75	110.38	11.71	0.76	58.49	0.39	2.97	52.70	7.98
77.	1.75	110.20	11.85	0.77	58.83	0.39	2.97	52.77	8.02
78.	1.74	110.50	11.50	0.76	57.40	0.39	2.95	52.77	8.08
79.	1.72	111.45	11.51	0.76	58.16	0.38	2.90	52.80	8.14
80.	1.75	111.31	11.74	0.76	58.13	0.39	2.93	52.95	8.22
81.	1.75	110.45	11.66	0.75	57.70	0.39	2.96	52.97	8.24
82.	1.72	111.82	11.49	0.75	57.50	0.39	2.95	52.97	8.31
83.	1.73	110.36	11.85	0.76	57.53	0.40	2.95	53.18	8.42
84.	1.70	110.72	11.82	0.75	58.26	0.39	2.98	53.29	8.53
85.	1.70	110.81	11.80	0.75	57.51	0.39	2.97	53.33	8.58
86.	1.71	111.62	11.89	0.76	56.68	0.39	2.94	53.35	8.63
87.	1.72	111.87	11.85	0.75	57.90	0.39	2.89	53.36	8.67
88.	1.68	110.26	11.91	0.75	57.28	0.39	2.97	53.46	8.73
89.	1.67	110.95	11.86	0.75	57.83	0.40	2.92	53.48	8.79
90.	1.71	111.55	11.89	0.75	56.64	0.38	2.93	53.49	8.82
91.	1.72	111.84	11.87	0.74	56.60	0.39	2.93	53.49	8.88
92.	1.66	111.37	11.90	0.75	57	0.39	2.91	53.60	8.95
93.	1.67	111.48	11.95	0.74	56.72	0.40	2.95	53.66	9.02
94.	1.64	111.35	11.91	0.75	56.26	0.39	2.86	53.68	9.10
95.	1.66	111.32	11.94	0.74	53.94	0.37	2.91	53.74	9.16
96.	1.58	111.98	11.97	0.74	56.15	0.38	2.89	53.87	9.33
97.	1.62	111	11.94	0.74	54.53	0.38	2.82	53.87	9.42
98.	1.61	111.68	11.96	0.74	54.16	0.38	2.83	53.91	9.44
99.	1.58	113.29	11.94	0.74	54.10	0.38	2.82	53.94	9.54
100.	1.56	111.98	11.98	0.73	55.33	0.38	2.79	53.96	9.57
101.	1.55	113.04	11.98	0.73	52.70	0.36	2.76	54.06	9.70
102.	1.55	113.04	11.99	0.72	52.59	0.37	2.75	54	9.76
103.	1.52	112.97	11.99	0.72	52.53	0.36	2.74	54	9.77

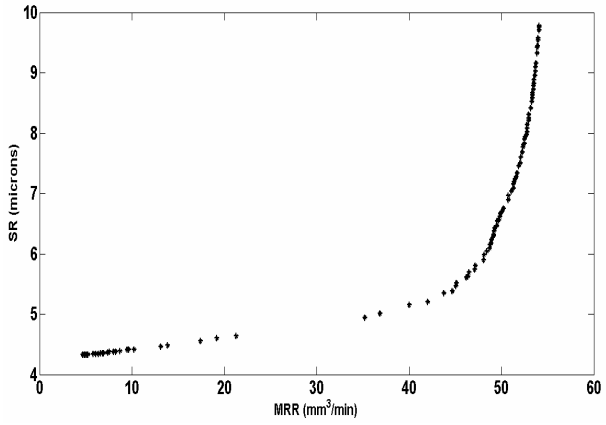

Fig. 2. Pareto-optimal front.

compromised because of conflicting nature of MRR and SR. If MRR is more desirable (than MRR), any solution from 56 to 103 will be more suitable but surface finish will be compromised at the same time. Solutions 26 to 55 may be used when both cutting speed and surface quality are given more or less equal weightage. However, this explanation is just an approximation and the choice of any solution will actually depend on the working requirement.

6. Conclusions

This work employs a new variant of GA i.e., controlled elitist NSGA to optimize the process parameters of EDM. A pareto-optimal set of 103 solutions has been obtained and

reported by employing controlled elitist NSGA. The solutions obtained are true representation of the given range of the input parameters and are not biased. This asserts the fact that controlled elitist NSGA controls elitism and forcibly allows the solutions from each non-dominating front to co-exist in the population. This leads to true optimal solutions. Fitness value (i.e., objective function in case of EDM) has been obtained by developing the neural network model of EDM process. For this, a large number of experiments were conducted on die-sinking EDM with a wide range of input parameters. The performance measures were measured for each combination of input parameters. A feed forward back-propagation neural network was used to model the EDM process. Experimental data was used to train neural network. Various ANN architectures were studied and 7-9-2 architecture was found as the best amongst studied architectures. The corresponding MAPE was as low as 2.74. The prediction ability of the trained network has been verified experimentally. The average percentage difference between experimental and ANN's predicted value is 4 and 4.67 for MRR and SR respectively.

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