Scientific Journal Impact Factor (SJIF): 4.364
International Journal of Modern Trends in Engineering and Research
ISSN (ONLINE) : 2349 - 9745
ISSN (PRINT) : 2393 - 8161

MULTIOBJECTIVE OPTIMIZATION DURING WIRE EDM OF WC-4.79%CO COMPOSITE USING CONTROLLED NSGA II

Sachin Dev Barman[1], Shravan Kumar Yadav[2] and Uday Kumar Paliwal[3]
[1]*Department of Mechanical Engg., B.I.E.T Jahnsi, India*
[2]*Department of Mechanical Engg.,Gudlavalleru Engineering College,A.P,India*
[3]*Department of Mechanical Engg.,Lokmanya Tilak College of Engineering, Navi Mumbai, India*

Abstract-Wire EDM being an effective machining process for composite materials needs proper selection of control factors to get the desired performance characteristics. But due to conflicting nature of performance characteristics it is unfeasible to find a single combination of control factors because desired combination may vary from situation to situation. That is why it is preferred to find a set of combination of control factors. In this work an attempt has been made to find set of combination of control factors for each workpiece thickness. Taguchi based L_{18} orthogonal array has been used for conducting experiments. The performance characteristics considered are cutting rate and surface roughness. Workpiece thickness, peak current, pulse on time, pulse off time and wire feed rate are considered as input parameters. A mathematical model has been developed for each machining performance using least square method to create relationships between process factors and responses. Multi-objective optimization has been performed using controlled NSGA II to find a set of machining conditions for each thickness of workpiece using the obtained mathematical models as objective functions. The predicted results have been verified by conducting confirmation experiments.

Keywords–Wire EDM, Tungsten carbide, Controlled NSGA II, Taguchi

I. INTRODUCTION

Machining of composites is notoriously known to be difficult due to presence of two or more distinct phases, the hard ceramic reinforcement and the ductile metal matrix. However Wire EDM has proved to be an efficient machining process for machining of composite materials due to advantages such as comparatively high material removal rate along with high surface finish and ability to machine very low conductive materials also. That’s why Wire EDM being widely used for machining of composites in many industries.

Wire EDM process consists of numerous control factors and for getting above mentioned advantages, proper selection of these control factors is desired. However proper selection of combination of control factors, according to desired machining conditions is not an easy task due to conflicting nature of performance characteristics. It takes time and skill for an operator to manually select the combination of control factors. For fulfilling this purpose numerous researches have been performed in the area of multi-objective optimization of wire EDM parameters using different kinds of multi-objective optimization strategies such as grey relational analysis, principal component analysis, grey relational analysis integrated with principal component analysis, genetic algorithm etc.

R. Ramakrishnan et al. [1] proposed multi response optimization method using Taguchi’s robust design for wire electrical discharge machining of heat treated tool steel. Probir Saha et al. [2] developed a multi-variable regression model and a feed-forward back-propagation neural network model while wire electro-discharge machining of tungsten carbide-cobalt composite material. It has been found that neural network model can predict cutting speed and surface roughness with 3.29% overall mean prediction error. Hsien et al. [3] performed multi objective optimization of wire electrical discharge machining during manufacture of pure tungsten profiles using neural network integrated simulated annealing approach. Kamal Jangra et al. [4] performed optimization of multi machining characteristics namely material removal rate, surface roughness, angular error and radial overcut using grey relational analysis (GRA) coupled with entropy measurement method, while wire EDM of WC-5.3%Co composite. Kapil Kumar et al. [5] optimized the machining conditions for maximum material removal rate and maximum surface finish based on multi-objective genetic algorithm for wire EDM of high-speed steel (M2, SKH9). Ali Vazini et al. [6] performed multi objective optimization using mathematical model-desirability function approach and neural network integrated particle swarm optimization approach during dry wire cut machining of WC-10%Co. Tarang et al. [7] developed a feed forward neural network to associate the cutting parameters pulse on time, pulse off time, peak current setting, no-load voltage, servo reference voltage, capacitor setting, servo speed setting, and workpiece thickness with the cutting performance machining speed and surface finish for wire EDM of SUS-304 stainless steel. A simulated annealing (SA) algorithm is then applied to the neural network for solving the optimal cutting parameters based on a performance index within the allowable working conditions. W.M. Lee et al. [8] proposed a control system to improve the efficiency of machining a workpiece with varying thickness in the wire electrical discharge machining process. A gain self-tuning fuzzy control algorithm was used so that the transient situation as sudden increase of cutting thickness can be suppressed immediately. D. Kanagarajan et al. [9] performed optimization of electrical discharge machining characteristics of WC/Co composites using non-dominated sorting genetic algorithm (NSGA-II).

Literature survey reveals that, in very less research works controlled NSGA II has been used for optimization purpose. So in this research work study has been focused to find a set of combination of control factors for Wire EDM of tungsten carbide cobalt composite using controlled NSGA II. For this purpose experiments have been performed using L_{18} orthogonal array. Mathematical model for each performance characteristics has been developed using least square regression method. These models have been used as objective functions for optimization purpose. After optimization a set of combination of control factors for each workpiece thickness has been obtained.

II. EXPERIMENTAL DETAILS

The experiments were carried out on a wire-cut EDM machine (ELECTRONICA ELPULS 40A DLX SPRINTCUT) with deionized water as dielectric. The composition of WC-Co composite used as workpiece material having 5 mm and 35 mm thickness is given in Table 1. Brass wire with 0.25 mm diameter was used in the experiments. The performance characteristics in wire EDM process were considered as cutting rate and surface roughness. Based on the influence over the performance characteristics and literature survey four most effective parameters have been selected as: peak current, pulse on time, pulse off time and wire feed rate shown in Table 2 with their selected levels. Workpiece thickness is also considered as input parameter. The length of cut during machining was kept 8 mm. Photographic view of workpiece after experimentation shown in Fig. 1.

Table 1 Chemical composition of WC-Co composite used in experimentation

Material	W	Ti	Co	Fe	P	S	Mo	C
WC-Co	78.66	16.23	4.79	0.18	0.042	0.039	0.031	0.028

Table 2 Input Process parameters and their levels

Input parameters	Unit	Level 1	Level 2	Level 3
Workpiece thickness	mm	5	35	
Peak current	A	170	200	230
Pulse on time	µs	11	18	25
Pulse off time	µs	30	40	50

Wire feed rate	m/min	3	5	7

In this work cutting rate was calculated using the following mathematical formula

$$\text{Cutting Rate} = \frac{\text{Length of cut} \times \text{Workpiece thickness}}{\text{Machining Time}}$$

The surface roughness was measured with Talysurf surface roughness profilometer at 0.8 μm cut-off value after machining of workpiece.

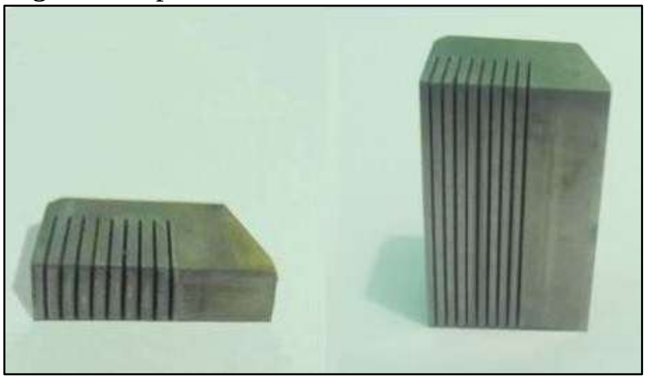

Fig.1 Photographic view of workpiece after machining

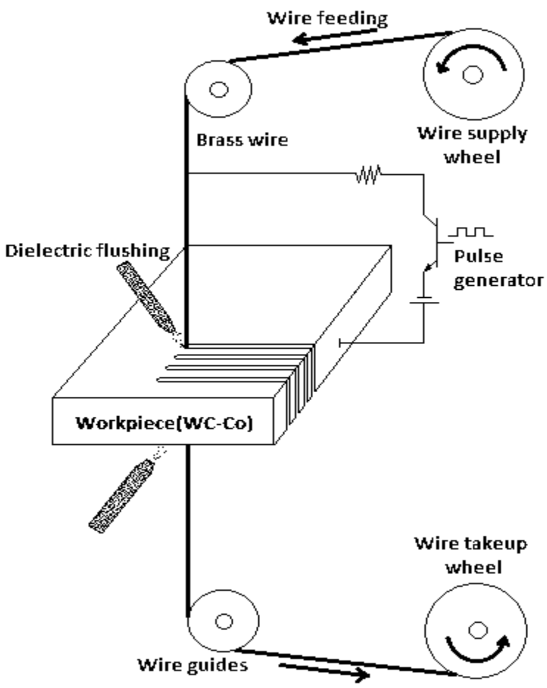

Fig.2 Schematic diagram of wire EDM

III. ROBUST DESIGN OF EXPERIMENTS USING TAGUCHI APPROACH

The fundamental principle of robust design is to improve the quality of a product by minimizing the effect of the cause of variation without eliminating the causes. This is achieved by optimizing process design to make the performance minimally sensitive to the various causes of variation. The two major tools used in robust design are:

(1) Signal to noise ratio, which measure quality
(2) Orthogonal arrays, which are used to study many design parameters simultaneously

The S/N ratio combines both the parameters (the mean level of the quality and variance around this mean) into a single metric. The equation for calculating S/N ratios for “smaller is better” (LB) and “larger is better” (HB) types of characteristics are as follows:

$$\frac{S}{N} = -10\text{Log}_{10}(\text{MSD})$$

Where MSD = Mean squared deviation from the target value of the quality characteristic.

Table 3 Experimental observations using L_{18} orthogonal array

Workpiece thickness (mm)	Peak Current (A)	Pulse ON time (μs)	Pulse OFF time (μs)	Wire feed rate (m/min)	Cutting rate (mm^2/min)	Surface roughness (μm)
5	170	11	30	3	3.187	1.56
5	170	18	40	5	4.21	2.6
5	170	25	50	7	5.457	3.48
5	200	11	40	7	5.673	1.79
5	200	18	50	3	5.174	2.63
5	200	25	30	5	4.206	3.54
5	230	11	50	5	5.333	1.67
5	230	18	30	7	3.921	2.92
5	230	25	40	3	5.517	4.06
35	170	11	30	3	6.542	1.02
35	170	18	40	5	8.076	1.93
35	170	25	50	7	8.3	2.93
35	200	11	40	7	12.65	2.02
35	200	18	50	3	14.532	3.38
35	200	25	30	5	16.457	3.98
35	230	11	50	5	9.868	1.55
35	230	18	30	7	16.627	2.76
35	230	25	40	3	20.628	4.01

For cutting rate (larger the better)

MSD = $\left(\frac{1}{y_1^2} + \frac{1}{y_2^2} + \frac{1}{y_3^2} + \cdots\cdots\cdots\cdots\cdots\right)/n$

For surface roughness (smaller the better)

MSD = $(y_1^2 + y_2^2 + y_3^2 + \cdots\cdots\cdots\cdots\cdots)/n$

Where y_1, y_2, etc. = Results of experiments, observations or quality characteristics

n = number of repetitions

Conducting matrix experiments using special matrices called orthogonal arrays allows the effects of several parameters to be determined efficiently and is an important technique in robust design. In this case one factor (workpiece thickness) at two levels and other four factors (peak current, pulse on time, pulse off time and wire feed rate) are to be studied at three levels. Hence L_{18} orthogonal array is most appropriate for this experimentation. The experimental results based on L_{18} orthogonal array have been summarized in Table 3.

IV. STATISTICAL MODELLING

Cutting Rate Model

CR = − (19.635×H) + (0.72031×Ip) + (0.0399×Ton) + (1.0366×Toff) − (2.3095×WF) + (0.47961×H^2) − (0.0018257×Ip^2) − (0.0021263×Ton^2) − (0.011587×$Toff^2$) + (0.24808×WF^2) + (0.0041274×H×Ip) + (0.012173×H×Ton) −(0.0064311×H×Toff)−(0.014717×H×WF)

Table 4 ANOVA table for Regression model for cutting rate

	SumSq	DF	MeanSq	F	pValue	%age contribution

Volume 04, Issue 1, [January– 2017] ISSN (Online):2349–9745; ISSN (Print):2393-8161

Model	457.73	13	35.21	12.911	0.012123	97.672
Residual	10.909	4	2.7271			2.328
Total	468.64	17	27.567			100

R-squared: 0.977, Adjusted R-Squared 0.901

Surface Roughness Model

SR = − (3.9656×H) + (0.15947×Ip) + (0.19403×Ton) + (0.088389×Toff) – (0.41694×WF) + (0.097692×H^2) − (3.8796×10^{-4}×Ip^2) − (0.0014116×Ton^2) − (0.0011667×$Toff^2$) + (0.042083×WF^2) + (2.6481×10^{-4}×H×Ip) + (2.1429×10^{-4}×H×Ton) + (1.8889×10^{-4}×H×Toff) −(0.0017778×H×WF)

Table 5 ANOVA table for Regression model for surface roughness

	SumSq	DF	MeanSq	F	pValue	%age contribution
Model	14.754	13	1.1349	6.4663	0.042531	95.4581
Residual	0.70206	4	0.17552			4.5419
Total	15.456	17	0.90919			100

R-squared: 0.955, Adjusted R-Squared 0.807

R^2 describes the amount of variation in the observed response values that is explained by the predictors. The value of R^2 for regression model of cutting rate is 0.977 and for regression model of surface roughness is 0.955, which shows that the obtained regression model for cutting rate describes 97.7% and 95.5% variation of cutting rate data and surface roughness data respectively. Table 4 and Table 5 show the ANOVA table for regression analysis the model estimated by regression procedure is significant at an α-level of 0.05.

V. MULTIOBJECTIVE OPTIMIZATION

In Wire EDM for successful machining operation two contrary objectives (maximization of cutting rate and minimization of surface roughness) needs to be fulfilled simultaneously. For achieving both the objectives simultaneously multiobjective optimization has been performed using controlled NSGA II.

Multiobjective optimization problems give rise to a set of pareto optimal solutions, none of which can be said to be better than any other solution in all objectives. Since no one solution is better than any other solution in the pareto optimal set, it is also a goal in multiobjective optimization to find as many such Pareto optimal solutions as possible.

In the case of vmulti-objective optimization, all solutions that belong to the currently best non dominated front are best solutions in the population and are equally important. Thus all these solutions are elite solutions. In many occasions a population may be mostly comprised of currently best non dominated solutions. When this happens the preservation of elitism means acceptance of all such solutions. In such a scenario, not many new solutions can be accepted in the population. As a result the search process may stagnate or prematurely converge to a suboptimal set. Thus there is a need of introducing elitism in a controlled manner, in the context of multi-objective optimization.

Algorithm

Step 1: Initially, a random parent population P_0 is created.

Step 2: The population is sorted based on the non-domination. A special book-keeping procedure is used in order to reduce the computational complexity to $O(MN^2)$.

Step 3: Each solution is assigned fitness equal to its non-domination level.

Step 4: Binary tournament selection, recombination, and mutation operators are used to create a child population Q_0 of size N.

Step 5: First, a combined population $R_t = P_t U Q_t$ is formed. This allows parent solutions to be compared with the child population, thereby ensuring elitism. The population R_t is of size 2N.

Step 6: Then, the population R_t is sorted according to non-domination and different non-dominated fronts F_1, F_2 and so on are found.

Step 7: According to the geometric distribution, the maximum number of individual allowed in the i-th front (i = 1, 2…………., K) in the new population of size N is

Step 8: Choose n_i solutions using the crowded tournament selection. Individuals of each front are used to calculate the crowding distance (the distance between the neighbouring solutions). Thereafter, the solutions of the last accepted front are sorted according to a crowded comparison criterion and a total of N points are picked. Since the diversity among the solutions is important, the crowded comparison criterion uses a relation $\prec_n$ as follows:

Solution i is better than solution j in relation $\prec_n$

If ($i_{rank} < j_{rank}$) or ($i_{rank} = j_{rank}$) and ($i_{distance} > j_{distance}$)

That is, between two solutions with differing non-domination ranks we prefer the point with the lower rank. Otherwise, if both the points belong to the same front then we prefer the point which is located in a region with smaller number of points (or with larger crowded distance). In this way solutions from less dense regions in the search space are given importance in deciding which solutions to choose from R_t. This constructs the population P_{t+1}.

Step 9: This population of size N is now used for selection, crossover and mutation to create a new population Q_{t+1} of size N. We use a binary tournament selection operator but the selection criterion is now based on the crowded comparison operator. The above procedure is continued for a specified number of generations.

Implementation

The statistical models obtained by regression method for cutting rate and surface roughness were used as objective function, using the range of input parameters as bound to the objective function (see table 6).

Table 6 Range of input parameters as bound to the objective function

For H = 5 mm	For H = 35 mm
$170 \le Ip \le 230$	$170 \le Ip \le 230$
$11 \le Ton \le 25$	$11 \le Ton \le 25$
$30 \le Toff \le 50$	$30 \le Toff \le 50$
$3 \le WF \le 7$	$3 \le WF \le 7$

In order to determine the population size, several numbers of trial runs were made. The results of trial runs showed that the objective function value reaches its maximum value for a population size of 50. With further increase in the population size, no appreciable change in the value of objective function was observed. Hence, a population size of 50 has been taken in this work.

Tournament selection has been used with tournament size 2 in this work due to its ability to adjust its selective pressure and population diversity.

Since crossover fraction specifies the fraction of the next generation that crossover produces hence crossover rate should generally be high. In order to determine the crossover probability for this work, different values of crossover fraction have been tried out. The results of the optimization show that the 0.8 crossover rates produce faster initial convergence, and hence a crossover rate of 0.8 has been chosen in this study.

In order to determine the better crossover function for this work, various crossover functions such as single point, two point, scattered, intermediate, arithmetic and heuristic have been tried out. By using arithmetic and heuristic crossover, objective function value reached its maximum compared to other crossover functions. But in case of arithmetic crossover almost straight pareto front was achieved compared to heuristic crossover which represents the lager values of second objective for the same values of first objective, hence heuristic crossover preferred for this work.

$$\text{Offspring1} = \text{parent2} + \text{Ratio} \times (\text{parent1} - \text{parent2})$$

$$\text{Offspring2} = \text{Ratio} \times \text{parent2} + (1-\text{Ratio}) \times \text{parent1}$$

Where ratio = 1.2

In order to determine the better mutation function for this work, two different mutation functions uniform mutation and adaptive feasible mutation (Gaussian mutation cannot be used for constrained problems) has been tried out.

International Journal of Modern Trends in Engineering and Research (IJMTER)
Volume 04, Issue 1, [January– 2017] **ISSN (Online):2349–9745; ISSN (Print):2393-8161**

Distance measure function is a measure of density of solution in the neighbourhood. In this work *distancecrowding* was used as distance measure function.

Pareto front population fraction is used to keep the fittest population down to the specified fraction in order to maintain a diverse population. In this work several fractions have been tried out but at 0.4 maximum value of objective function has been achieved.

Stopping criteria

Generations: 500
Time limit: infinite
Fitness limit: -infinite
Stall generations: 100
Stall time limit: 100
Function tolerance: 10^{-4}
Constraint tolerance: 10^{-6}

VI. RESULT AND DISCUSSION

By using controlled NSGA II, the non-dominated Pareto front for each workpiece thickness has been obtained. None of the solutions in the Pareto optimal set is better than any other solution in the set. By using the controlled NSGA II for both the objective functions, 20 optimal solutions for each workpiece thickness are obtained within the range considered. The process engineer can select optimal combinations of parameters from the Pareto optimal solution set, depending on the requirements.

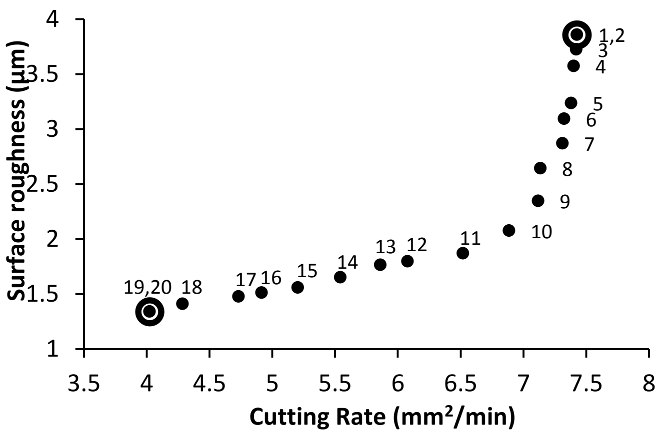

Fig.3 Pareto optimal front for 5 mm thickness

Table 7 Optimal solutions for 5 mm thickness

H	Ip	Ton	Toff	WF	CR	SR
5	174.3242	11.0459	49.0179	4.7875	4.0248	1.3392
5	203.4788	23.6825	43.5655	6.9998	7.4271	3.8570
5	190.7339	11.1343	44.6709	6.7255	6.5209	1.8688
5	203.4788	23.6825	43.5655	6.9998	7.4271	3.8570
5	206.0766	11.8093	47.0078	6.9385	6.8883	2.0743
5	173.3825	11.0643	44.6502	4.6398	4.2857	1.4093
5	203.111	22.6676	43.5431	6.9972	7.4227	3.7242

5	198.1813	13.3026	43.2931	6.9639	7.1188	2.3450
5	201.9938	16.5729	43.5138	6.9943	7.3125	2.8685
5	202.0773	21.5669	43.5821	6.9874	7.4032	3.5723
5	181.2707	11.3309	48.9816	6.6660	5.5430	1.6509
5	200.3292	18.1373	43.1214	6.9788	7.3270	3.0913
5	177.3508	11.1133	46.5254	5.9634	4.9174	1.5105
5	187.7826	11.1274	43.6850	6.3630	6.0792	1.7947
5	182.0293	11.1970	41.0927	6.6193	5.8617	1.7622
5	179.8564	11.1347	49.1844	6.4544	5.2056	1.5577
5	205.3924	15.2839	45.9913	6.9552	7.1373	2.6406
5	174.3242	11.0459	49.0179	4.7875	4.0248	1.3392
5	202.7583	19.0909	43.5601	6.9989	7.3816	3.2361
5	176.8463	11.1021	46.9408	5.7674	4.7334	1.4753

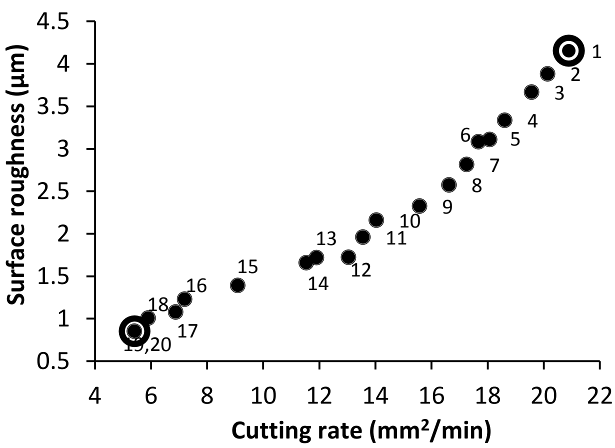

Fig.4 Pareto optimal front for 35 mm thickness

Table 8 Optimal solutions for 35 mm thickness

H	Ip	Ton	Toff	WF	CR	SR
35	170.4632	11.0149	30.030	5.6620	5.4130	0.8525
35	220.6962	11.0686	30.3355	5.5350	13.0423	1.7233
35	229.5243	14.4067	34.7617	3.1658	16.6260	2.5757
35	170.9205	11.6846	30.9437	5.5358	5.9050	1.0054
35	203.6493	11.0406	30.7409	5.4725	11.5435	1.6591
35	218.1681	13.2656	33.1034	5.2874	14.0378	2.1584
35	229.9409	24.9967	35.0066	3.0047	20.8932	4.1556

Volume 04, Issue 1, [January– 2017] ISSN (Online):2349–9745; ISSN (Print):2393-8161

35	176.0762	12.0251	30.4868	5.4434	7.2026	1.2294
35	176.3486	11.0628	30.4449	5.2649	6.8873	1.0797
35	229.7302	17.7013	34.6592	3.0624	18.0733	3.1094
35	229.8934	22.9875	35.0057	3.0217	20.1382	3.8834
35	203.6493	11.0406	30.7409	4.4725	11.9010	1.7198
35	218.9999	12.3106	31.4604	5.5157	13.5630	1.9618
35	170.4632	11.0149	30.0302	5.6620	5.4130	0.8525
35	229.7787	15.9021	34.7956	3.1486	17.2550	2.8148
35	229.9263	21.3969	35.0966	3.0050	19.5701	3.6671
35	229.4467	19.2561	34.8258	3.1067	18.6118	3.3369
35	186.8829	11.0745	30.5186	4.9903	9.1008	1.3896
35	228.6251	13.7205	32.7844	3.7913	15.5777	2.3242
35	229.7302	18.2013	34.6592	3.5624	17.6775	3.0847

By analysing Pareto front of 5 mm and 35 mm workpiece thickness some decision could be made depending upon specific conditions of the desired machining process. Since the performance measures are conflicting in nature surface quality decreases as cutting rate increases and the same behaviour of performance measures is observed in the solutions obtained. At first point 1 must be analysed. At this point highest value of cutting rate is achieved but at the cost of very high surface roughness. Therefore this point corresponds to high productivity having very low surface quality. On the other extreme of the front is located point 20. At this point lowest value of surface roughness (high surface quality) is achieved but at the cost of very low cutting rate (low productivity). All the other points are intermediate cases. Choice of any solution will depend upon the working requirement.

VII. CONFIRMATION TEST

Confirmation experiments were performed for selected combination of different factors obtained from optimized set of parameters for both the performance characteristics and obtained experimental results compared with the expected results as shown in Table 9 and Table 10.

Table 9 Confirmation experiment result for cutting rate

H	Ip	Ton	Toff	WF	Expected	Actual	Error%
5	170	11	39	7	4.8885	4.573	6.453
5	190	11	47	7	6.6261	6.296	4.981
35	180	12	31	6	8.0933	8.703	7.533
35	230	15	34	5	15.4013	16.698	8.413

Table 10 Confirmation experiment result for surface roughness

H	Ip	Ton	Toff	WF	Expected	Actual	Error%
5	170	11	39	7	1.5033	1.6	6.432
5	190	11	47	7	1.8378	1.93	5.464
35	180	12	31	6	1.3586	1.28	5.185
35	230	15	34	5	2.4063	2.61	8.465

VIII. CONCLUSION

In the present study controlled NSGA II has been employed for finding optimal set of machining conditions for each workpiece thickness during Wire EDM of WC-Co composite. From the obtained set of machining conditions the process engineer can select any combination of control factors according to desired machining condition. The choice of one combination over the other will depend upon the process requirement. The highest value of cutting rate for 5 mm thickness after optimization has been increased from 5.673 mm^2/min to 7.427 mm^2/min and for 35 mm thickness increased from 20.628 mm^2/min to 20.893 mm^2/min. The lowest value of surface roughness for 5 mm thickness after optimization has been decreased from 1.56 µm to 1.33 µm and for 35 mm thickness decreased from 1.02 µm to 0.85 µm.

REFERENCES

[1]R. Ramakrishnan, L. Karunamoorthy, 2006, Multi response optimization of wire EDM operations using robust design of experiments, International Journal of Advanced Manufacturing Technology, Vol. 29, pp. 105–112.

[2] Probir Saha, Abhijit Singh, Surjya K. Pal, Partha Saha, 2008, Soft computing models based prediction of cutting speed and surface roughness in wire electro-discharge machining of tungsten carbide cobalt composite, International Journal of Advanced Manufacturing Technology, Vol. 39, pp. 74–84.

[3] Hsien-Ching Chen, Jen-Chang Lin, Yung-Kuang Yang, Chih-Hung Tsai, 2010, Optimization of wire electrical discharge machining for pure tungsten using a neural network integrated simulated annealing approach, Expert Systems with Applications, Vol. 37, pp. 7147–7153.

[4] Kamal Jangra, Sandeep Grover, Aman Aggarwal, 2012, Optimization of multi machining characteristics in WEDM of WC-5.3%Co composite using integrated approach of Taguchi, GRA and entropy method, Frontiers of Mechanical Engineering, Vol. 7, Issue 3, pp. 288–299.

[5] Kapil Kumar & Sanjay Agarwal, 2012, Multi-objective parametric optimization on machining with wire electric discharge machining, Int J Adv Manuf Technol, Vol. 62, pp. 617–633.

[6] Ali Vazini Shayan, Reza Azar Afza, Reza Teimouri, 2013, Parametric study along with selection of optimal solutions in dry wire cut machining of cemented tungsten carbide (WC-Co), Journal of Manufacturing Processes, Vol. 15, pp. 644–658.

[7] Y. S. Tarang, S. C. Ma and L. K. Chung, 1995, Determination of optimal cutting parameters in wire electrical discharge machining, International Journal of Machine Tools & Manufacture Vol. 35, No. 12, pp. 1693-1701.

[8] W. M. Lee & Y. S. Liao, 2007, Adaptive control of the WEDM process using a self-tuning fuzzy logic algorithm with grey prediction International Journal of Advanced Manufacturing Technology, Vol. 34, pp. 527–537.

[9]D. Kanagarajan & R. Karthikeyan & K. Palanikumar & J. Paulo Davim, 2008, Optimization of electrical discharge machining characteristics of WC/Co composites using non-dominated sorting genetic algorithm (NSGA-II), Int J Adv Manuf Technol, Vol. 36, pp. 1124–1132