Computational Intelligence in Optimization of Wire Electrical Discharge Machining of Cold-Work Steel 2601

[1] Abolfazl Golshan, [2] Soheil Gohari, and [3] Amran Ayob

***Abstract*- In this study, two parameters of surface roughness and volumetric material removal rate are optimized based on computational intelligence method. Wire electrical discharge machine is used for machining of cold-work steel 2601. The relation between Input parameters including electrical current, pulse-off time, open-circuit voltage and gap voltage and output parameters is studied via Experimental result analysis and mathematical modeling. Subsequently, with use of variance analysis, importance and effective percentages of each parameter are studied. Outputs extracted from Non-dominated Sorting Genetic Algorithm used for optimization of output parameters resulted in optimal solutions.**

***Index Term*-- Wire electrical discharge machining, Surface roughness, volumetric material removal rate, Multi-objective optimization, none dominated sorting genetic algorithm**

I. INTRODUCTION

WEDM is generally used for machining of work pieces with complex geometry and hard stiffness [1]. This process is based on creation of alternative spark between tool (wire) and piece work, machining process of piece work is implemented. In addition, the use of WEDM has dramatically increased due to high application of materials with high stiffness in molding. Considering WEDM process, it is vital to choose best machining parameters to economize choosing process whereas WEDM is a nonconventional, applicable and required machining process with high initial investment. Choosing the appropriate parameters in order to achieve the corresponding surface roughness and maximum material removal rate will be possible with having the knowledge of the way these parameters influence on mentioned factors which is also prioritized by this study. [1]

In the recent years, diverse theoretical and experimental methods have been used in order to model and optimize wire electrical discharge machining (WEDM) process.

Scott and his associations formulized and solved a multifunctional optimization problem aimed at choosing the best adjustment of wire electrical discharge machining (WEDM) machining parameters [2]. Their corresponding performance was material removal rate and surface-finished quality. Spedding and Wang optimized this process with use of nerves network. They considered surface roughness, value of being wavy in a surface and material removal speed as outputs [3]. Rozenek and his associations used a piecework made of composite material with metal matrix composite and investigated the variation in feed rate and surface roughness led by changing the corresponding parameters [4]. Tosun and his associations used a statistical model for determining optimal parameters in order to minimize the holes led on the wire during the process [5]. Tosun and Cogun conducted a research regarding the effect of machining parameters on the rate of wire corrosion considering lessened weight from wire while being machined [6].

In the researchers conducted, the optimal conditions are led by piecework property and machining conditions and they cannot be used for other materials or different manufacturing conditions.

In this investigation, wire electrical discharge machining (WEDM) optimal machining conditions are introduced in one sort of applicable cold-work steal 2601 using non-dominated sorting genetic algorithm (NSGA-II) aimed at achieving the appropriate conditions of surface roughness (Ra) and volumetric material removal rate (VMRR).

II. EXPERIMENTAL SETUP AND EQUIPMENT

In this study, the experiments are done using ONA R250 Series 5-axis CNC Wire EDM on a piecework ,made of cold-work steel 2601 with thickness of 30 [mm]. Chemical synthesis of this steel is X165CrMoV12. For machining, brass wire (Cu Zn37) without cover with diameter of 0.25 [mm] and yield strength of 900 [MPA] is used.

In this experimental analysis, sections with the length of 20 [mm] (to depth of piecework thickness) are made. Since the exact amount of machining period was recorded using chronometer, therefore, this value of time is used for assessing average feed rate and subsequently, for volumetric material removal rate according to Eq.1 and Eq. 2, respectively.

$$F = \frac{60 \times l}{t} \quad (1)$$

$$VMRR = F \times D_w \times H \quad (2)$$

Where F is the average feed rate [mm/min], l is the value of length which is cut in t second and VMRR is volumetric

[1] A.Golshan, Faculty of Mechanical Engineering, Isfahan University Technology, Isfahan, Iran (gabolfazl@gmail.com)

[2] S.Gohari, Faculty of Mechanical Engineering, Universiti Teknologi Malaysia, 81310, UTM Skudai, Malaysia (soheil.gohari7@gmail.com)

[3] A.Ayob, Faculty of Mechanical Engineering, Universiti Teknologi Malaysia, 81310, UTM Skudai, Malaysia (amran@fkm.utm.my)

material removal rate $[mm^3/\min]$, D_w is wire diameter [mm] and H is piecework thickness [mm].

After obtaining the experimental samples, surface roughness was measured using a mobile roughness measurement (Mahr Perthometer M2) on each piece work 3 times for achieving more accuracy and, subsequently, the average of it was selected.

III. EXPERIMENTAL DESIGN

The experiments were planed based on Taguchi's orthogonal array for the design of experiments DOE. It can help to reduce the number of experiments. In addition, four cutting parameters were chosen including electrical current, pulse-off time, open-circuit voltage and gap voltage. The three level tests for each factor was used whereas the considered factors are multi-level variables whose outcome effects are nonlinear related rather than linearly. The machining parameters which were used and their levels are presented in Table I and the experimental results are presented in Table II.

IV. PROCESS MODELLING AND ANALYSIS OF VARIANCE

In this study, regression method was used to determine the relationship between input and output variables of cold-work steel 2601 using WEDM. For modeling the process, different types of exponential and second-order mathematical functions over 14 sets of outputs acquired from experimental results were fitted. Subsequently, these models were modified using statistical method of stepwise

TABLE I
MACHINING PARAMETERS AND THEIR LEVEL

Control parameters	Unit	symbol	Levels			
			1	2	3	4
current	[A]	I	11	10	9	12
pulse-off time	[µS]	T_{off}	14	10	8	22
Volt	[volt]	V	140	130	110	120
Servo	[volt]	S	28	32	30	26

TABLE II
EXPERIMENTAL RESULTS

S. No.	I [A]	T_{off} [µS]	V [volt]	S [volt]	R_a [µS]	VMRR $[mm^3/\min]$
1	11	14	140	28	3.169	12.555
2	11	10	130	32	3.410	13.785
3	11	8	110	30	3.229	12.645
4	11	22	120	26	2.707	7.995
5	10	14	130	30	3.018	11.108
6	10	10	140	26	3.035	12.255
7	10	8	120	28	3.046	10.913
8	10	22	110	32	2.754	6.698
9	9	14	110	26	2.421	7.725
10	9	10	120	30	2.845	8.205
11	9	8	140	32	3.270	9.593
12	9	22	130	28	2.575	6.000
13	12	14	120	32	3.462	11.033
14	12	10	110	28	3.293	12.435
15	12	8	130	26	3.528	14.288
16	12	22	140	30	3.408	8.250

for volumetric material removal rate and surface roughness were measured.

Correlation coefficients calculated for each of the equations are used to choose the model. Meanwhile, model of second-order polynomial equations for volumetric material removal rate and exponential model for surface smoothness are taken into account. For both of them, the correlation coefficients became 99.99% representing appropriate fitting between these models and experimental data. The results are shown in Table III.

The normal probability plots for surface roughness and volumetric material removal rate are illustrated in fig.1 and fig.2, respectively. It is noticeable that residuals fall on a straight line. It basically shows that the errors are dispersed and the regression model completely matches the observed values.

Table IV and Table V show that test results are valid. Predicted machining factors performance was compared with the actual machining performance and, subsequently, a good agreement was made. Since the amount of errors was proved to be acceptable, so these models can be selected as the best ones and use them in optimization level.

TABLE III
FITTING EQUATIONS WITH THEIR CORRELATION PERCENTAGE

Respond value	Model type	Fitting equation	Correlation (%)
Volumetric material removal rate	Second-order polynomial equation	VMRR=15.8+22.9I-9.19S-0.742 I^2 -0.0319 T_{off}^2 +0.19 S^2 -0.1I T_{off} -0.00599IV-0.143IS+0.0132 T_{off} V+0.00188 T_{off} S-0.00220VS	99.99
Surface roughness	Exponential	Ra=exp(2.22-0.120 T_{off} +0.523I-0.259S-0.00519 I^2 +0.00602 S^2 -0.000677IV-0.00949IS+0.000606 T_{off} V+0.00125 T_{off} S+0.000078VS)	99.99

TABLE IV
RESULTS OF CONFORMATION TEST FOR Ra

Run	I [A]	T_{off} [µS]	V [volt]	S [volt]	Results of model	Results of experiments	Error (%)
1	10	8	120	28	2.98	3.05	-2.3
2	12	14	120	32	3.33	3.46	-3.76

TABLE V
RESULTS OF CONFORMATION TEST FOR VMRR

Run	I [A]	T_{off} [µS]	V [volt]	S [volt]	Results of model	Results of experiments	Error (%)
1	10	8	120	28	10.67	10.91	-2.2
2	12	14	120	32	12.21	11.03	9.66

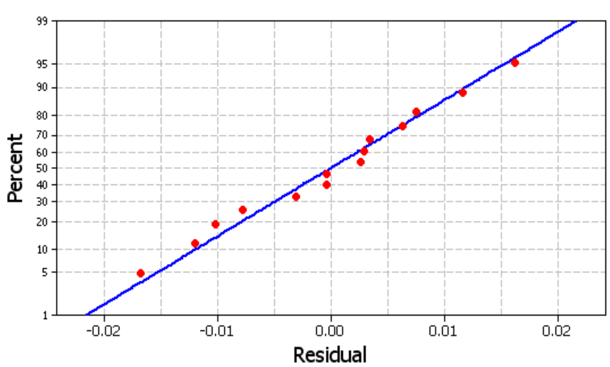

Fig. 1. Normal plot of residuals for average surface roughness

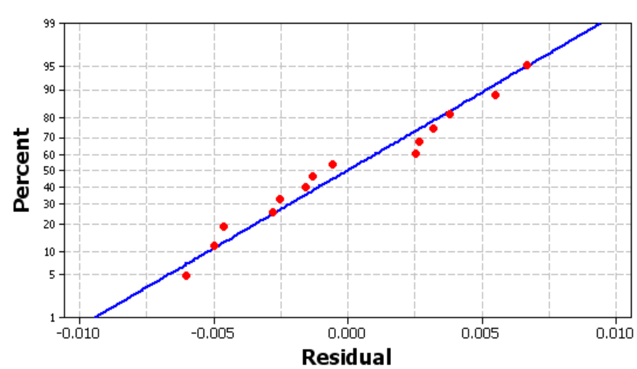

Fig. 2. Normal plot of residuals for volumetric material removal rate

After choosing the appropriate models for investigation of each input parameter effect on outputs using variance analysis method, distribution percentage for each of parameters was calculated considering Table VI and Table VII. According to these calculations, the most effective parameters concerning surface roughness (Ra) and volumetric material removal rate (VMRR) are demonstrated to be electrical current and pulse-off time, respectively. Moreover, gap voltage doesn't have any influence on volumetric material removal rate (VMRR) statistically.

V. MULTI-OBJECTIVE OPTIMIZATION

In this study, two objectives are put into consideration, volumetric material removal rate (VMRR) and surface roughness (Ra). It is noticed that if VMRR rises, Ra also increases. But our objective is aimed at maximizing VMRR and minimizing surface roughness. A single optimal solution does not help to achieve our goals as our purpose, since these objectives are opposing in nature. Choice of VMRR and surface roughness is also dependent on user and environment of the problem. Optimizing both of the output parameters requires multi-objective optimization [7].

VI. NSGA-II ALGORITHM

One of the powerful and comprehensive algorithms is what was introduced by Srinivas and Deb [8] named as the non-dominated sorting genetic algorithm. It deals with a possible solution regarding a population and, therefore, it can have some applications in problems of multi-objective optimizations. It leads to have a number of simultaneous solutions. Despite, this algorithm is fast, but it has been either a controversial method or opposed due to have some difficulties and complexities when it comes to computational approach. The elitism is also disregarded in this method. The selection operator differs from simple genetic algorithm (SGA). Crowded comparison is the operator in which selections can be achieved considering ranking and crowding distance. The solution of initially parent population is checked with other solutions and eventually, put into consideration to make aware of solutions validation. They must satisfy rules given below [9]:

$$Obj.1[i] \succ Obj.1[j] \text{ and } Obj.2[[i] \geq Obj.2[j] \;, \tag{3}$$

$$\text{Or } Obj.1[i] \geq Obj.1[j] \text{ and } Obj.2[i] \succ Obj.2[j], i \neq j \tag{4}$$

Where, chromosome numbers can be shown as i and j, respectively. Subsequently, it can be noticeable that the selected solution is validated by rules introduced in Eq.3 and Eq.4 and makes it be marked as dominated. If the rule doesn't satisfy the corresponding equations above, it will be marked as non-dominated. The corresponding process must continues until all solution selected are ranked. Fitness which is as equal as its non-dominated level assigns to each solution.

There is no result to demonstrate none of the solutions is better compared with other solutions. They are considered as part of a special rank or the non-dominated level. The crowding distance is considered to be as an average distance between two points on both sides of selected solution point along each objectives function. Subsequently, each objective function's boundary solution with the largest and smallest values is assigned as an infinity value in this step.

TABLE VI
RESULTS OF VARIANCE ANALYSIS ON VOLUMETRIC MATERIAL REMOVAL RATE

Factors	d.f.	sum of squares	Variance	F	Distribution percentage
I	3	37.52164687	12.50721562	149.92	37.13
T_{off}	3	55.13897813	18.37965938	220.31	54.56
V	3	7.51227188	2.50409062	31.01	7.43
S	3	0.62510625	0.20836875	2.5	0.08
Error	3	0.2502844	0.0834281	-	0.8
Total	15	101.0482875	-	-	100

TABLE VII
RESULTS OF VARIANCE ANALYSIS ON SURFACE ROUGHNESS

Factors	d.f.	sum of squares	Variance	F	Distribution percentage
I	3	0.89816618	0.29938873	23538.8	53.79
T_{off}	3	0.36541701	0.12180507	9576.7	21.88
V	3	0.20304333	0.06768111	5321.28	12.16
S	3	0.20300948	0.06766983	5320.39	12.15
Error	3	0.00003816	0.00001272	-	0.02
Total	15	1.66967416	-	-	100

The algorithm flowchart is illustrated in Fig.3. For solving optimization problem using GA, fitness value is required. it connects the objective with decision variable. Based on the present study, objectives are considered as average surface roughness (Ra) minimized and volumetric material removal rate (VMRR) maximized. They are classified as function of decision variables named, electrical current, pulse-off time, open-circuit voltage and gap voltage.

VII. DISCUSSION

A non-dominated sorting genetic algorithm, NSGA-II can be was exploited for optimization issues including multi performance of non-linear models. The individuals are ranked by the use of NSGA-II concerning dominance. In order to achieve the high performance, the controlled factors in NSGA-II are adjusted. These factors are: crossover probability= 0.8, mutation probability 0.2 and population size 100. It was shown that for better convergence and optimal solution distribution, above controlled factor must be produced. The 100 generations were generated to acquire the true optimal solution. The none-dominated set obtained over the entire optimization is shown in Fig.4. The 40 out of 100 sets were illustrated in Table VIII. If the engineer desires to have a better surface finish, or more volumetric material removal rate (VMRR), a suitable combination of variables can be selected from Table VIII. Considering the experimental results shown in the Table II, the parameters of trial number 8 resulted to surface roughness of 2.754 [μm] and VMRR of 6.698 $[mm^3/\min]$. After optimization of machining parameters using GA, it can be noticed Ra reduced to value of 2.7168 [μm] while VMRR increased to 11.0936$[mm^3/\min]$ (Refer to Table VIII, trial no.8). Thus, considering the data given, it can be observed as the electrical current setting is kept nearly same, by changing pulse-off time, open-circuit voltage and gap voltage, higher VMRR and lower Ra can be achieved which is more desirable.

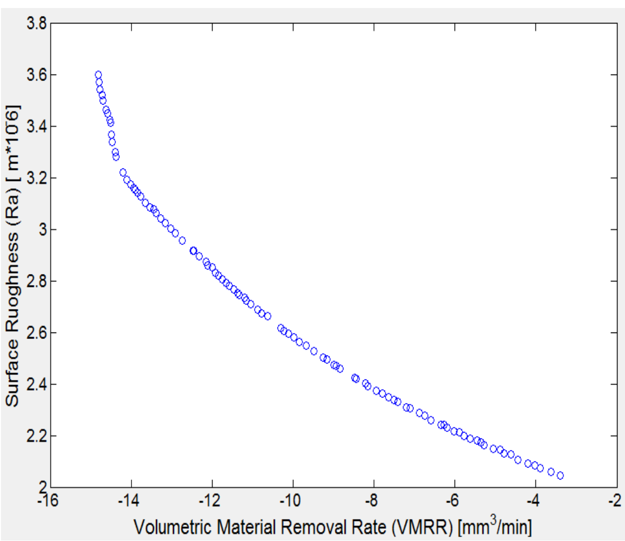

Fig. 4. Pareto optimal set with use of NSGA-II

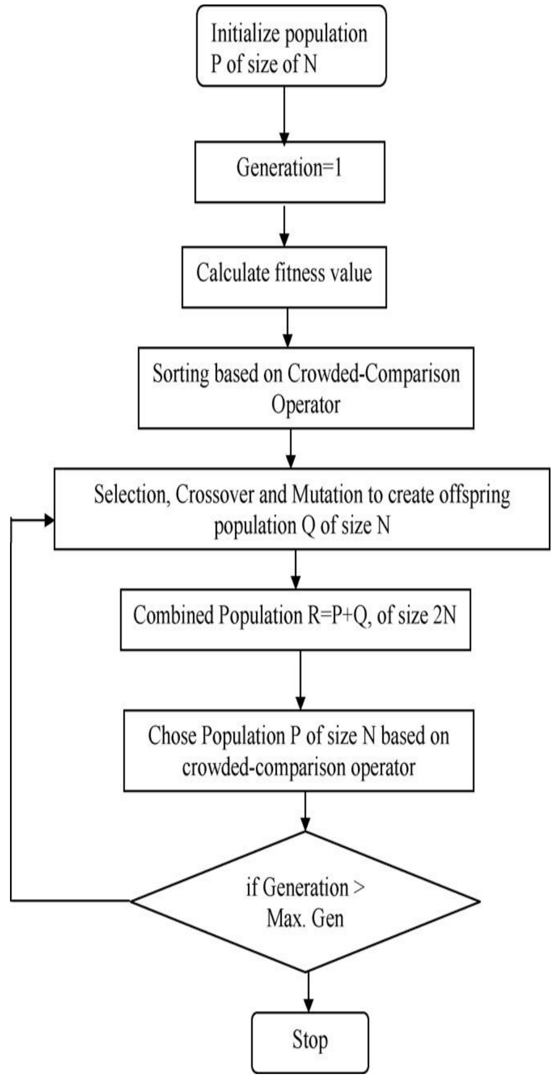

Fig. 3. Flow chart for the NSGA-II algorithm [9]

XII.CONCLUSION

As follows from forgoing analysis, the study based on the influence of WEDM on surface roughness and volumetric material removal rate was carried out. The nonlinear polynomial models were developed for volumetric material removal rate and average surface roughness were used for optimization. In this study, a multi-objective evolutionary algorithm regarding efficient methodology, NSGA-II, was exploited for optimization of machining parameters in cold-work steel 2601.

The emphasis must be put on providing a preferred solution for the process engineer in the short period of the time. The choice of one solution over other ones is dependent on the requirements of process engineer. If the requirement is based on a better surface roughness, or a maximum volumetric material removal rate, an appropriate combination of variables can be selected accordingly. Moreover, this method contributes to increase production rates noticeably via reducing machining time [10].

TABLE VIII
OPTIMUM MACHINING PARAMETERS

S.No	I [A]	T_{off} [μS]	V [volt]	S [volt]	VMRR [mm^3/min]	R_a [μS]
1	11.9408	8	110	26	14.8051	3.60172
2	9.00864	19.0527	110	26	5.51053	2.17754
3	11.2154	10.1345	115.279	26.0002	14.0368	3.25687
4	9.4186	18.2553	110	26	7.22106	2.31251
5	11.3383	9.68431	111.509	26	14.206	3.313
6	9.69215	16.8455	111.641	26.0001	8.9144	2.47216
7	10.9145	11.5133	112.256	26	13.3383	3.08477
8	10.1355	14.3525	112.042	26.0001	11.0936	2.71683
9	10.533	13.2829	112.633	26.149	12.1026	2.87564
10	9.31417	18.4155	110	26	6.83269	2.27977
11	9.21881	19.7488	110.072	26.0391	5.68039	2.19631
12	10.3919	13.647	110.047	26	11.7309	2.80346
13	9.09484	19.6862	110.15	26.0003	5.39878	2.17158
14	9.21473	18.9688	110.108	26.0002	6.21653	2.23184
15	9.59278	18.1595	110.246	26.0092	7.75439	2.36281
16	10.8651	12.6542	110	26.009	12.7956	2.98754
17	11.3575	9.10328	110.398	26	14.3497	3.35745
18	10.0092	14.0966	112.782	26.1045	10.8747	2.70129
19	10.5417	12.9806	114.371	26	12.4629	2.91711
20	9.04483	20.5948	110.012	26.0003	4.5982	2.11716
21	9	20.2219	110	26	4.7201	2.12314
22	9.27153	19.6138	110.415	26	6.00383	2.2206
23	11.5427	9.11275	112.195	26.0002	14.4511	3.40698
24	10.6649	12.5934	110.932	26.0001	12.6131	2.94522
25	9.04886	20.2557	110.061	26.0146	4.84626	2.13402
26	11.0202	11.8512	110.475	26.0071	13.2788	3.08246
27	9	20.8024	110	26.1916	4.16298	2.09936
28	10.16	15.5331	110.36	26.0001	10.4755	2.64053
29	9	21.5803	110	26	3.72492	2.06388
30	9.85522	15.849	110.254	26.0002	9.66865	2.54511
31	9.03137	21.7991	110.01	26.0056	3.64393	2.06172
32	11.0075	11.3271	114.737	26.0001	13.561	3.13217
33	10.7551	11.9279	110.046	26	12.9338	3.00429
34	9.56651	17.697	111.471	26.0001	8.11878	2.39761
35	11.1364	10.5588	110.102	26	13.8002	3.19697
36	9.73676	16.5452	112.288	26.0002	9.24353	2.50688
37	11.6163	8.48069	111.766	26	14.6101	3.47068
38	9.93861	15.4074	111.685	26	10.1953	2.60697
39	9.72237	17.4035	110.012	26	8.49891	2.4285
40	10.7629	12.0185	115.936	26	13.1316	3.03675

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