# An Optimization on the DIN1.2080 Alloy in the Electrical Discharge Machining Process Using ANN and GA

# Masoud Azimi<sup>1</sup>, Amin Kolahdooz<sup>2</sup>\*, Seyyed Ali Eftekhari<sup>2</sup>

<sup>1</sup>Department of Mechanical Engineering, Khomeinishahr Branch, Islamic Azad University, Isfahan, Iran <sup>2</sup>Young Researchers and Elite Club, Khomeinishahr Branch, Islamic Azad University, Isfahan, Iran \*Email of Corresponding Author: aminkolahdooz@iaukhsh.ac.ir *Received:April 5,2017; Accepted:June 6, 2017* 

#### Abstract

Electrical Discharge Machining (EDM) process is one of the most widely used methods for machining. This method is used to form parts that conduct electricity. This method of machining has used for hard materials and therefore selects the correct values of parameters which are so effective on the quality machining of parts. Reaching to optimum condition of the DIN1.2080 alloy (D3) machining is very important due to the rapid and widespread use of different industry such as Molding, lathe tools reamer, broaching, cutting guillotine and etc. Therefore the purpose of this study is to consider the effect of the inlet parameters such as current, voltage, pulse on time and pulse off time on the machining chip rate and optimize the inlet parameters for D3 alloy. So to reach better result after doing some experiments to predict and optimize the rate of removing chip, neural network method and genetic algorithm are used. Then optimizing input parameters to maximize the rate of removing chip are performed. In this condition by decreasing time, the product cost is decreased. In this condition, the optimum parameters are obtained under the current of 20 (A), 160 (V), pulse on time of 100 (ms) and pulse off time of 12 (ms). At this condition, the rate of machining chip is obtained 0.063 ( $cm^3/min$ ). Also, surveying the level of error and its accuracy are evaluated. According to the obtained error value that is about 5.18%, the used method is evaluated suitable for genetic algorithm.

#### Keywords

EDM, Taguchi Method, Optimum determining, Optimization, Genetic algorithm, ANN

## 1. Introduction

Electrical discharge machining process which is subset of thermoelectric machining is the most widespread method of non-traditional machining of metals and conductive materials. In this method, consecutive electrical sparks between the electrodes and workpiece are done in dielectric liquid. Since in the EDM, high energy thermal-electrical is used instead of shear-mechanical forces, so in this method cut-resistant materials such as hardened steel, tungsten carbide and alloys with high strength and complex shape can be machined. Also in this method, because of absence of mechanical force, there is the possibility for machining delicate and fragile parts [1]. Electrical discharge machining process (EDM) due to the lack of several effective parameters is considered as multivariate process. So studies done in electrical discharge machining are mainly concentrated on the changing and control of optimum setting of machining parameters according to workpiece material [2]. The major focus of researchers has been also on the use of statistical methods and especially on design of experiments (DOE) subject. Using of DOE in order to optimum EDM

parameters of alloy MAR-274M has been subjects of research of Olmen et al. [3]. In this paper, it has been shown that the current and pulse on-time are the most effective parameters. Also, increasing voltage causes to increasing gap and better washing and thus better material removal. Aista et al. [4] by using Taguchi DOE and analyze of variance (ANOVA) have investigated the impact of current, voltage and pulse on-time in grooving process of alloy 1023. The study has shown that increasing current and time of pulse causes to reduction of tool wear rate, as well as lower current and voltage lead to reduction of material removal rate. Gopakalannan et al. [5] have examined the impact of each input parameter on material removal rate, tool wear and surface roughness. This investigation has indicated that current and on-time pulses have the greatest impact on output. It means that by increasing current, material removal rate at first rises and then decreases. Also by boosting current and pulse on-time, surface finish is improved. Investigation of material removal rate and surface finish in machining of ceramic by taking into account of input parameters, such as current, voltage and pulse on/off time is done in paper of k [6]. Liu [6] showed that high energy setting causes to instability of machining. Also for rough machining, current and pulse on time should be high and for achieving surface finish, machining speed should be low. Tseng [7] optimized EDM for tool steel SKD11. His analysis tests illustrate that current and pulse on time parameters are the most important parameters and respectively have the most influence on material removal rate and surface finish. Rajmohan et al. [8] by considering voltage, current, pulse on time and pulse off time as main parameters optimized the material removal rate for stainless steel 304. Their paper depicted that current and pulls off time have the most effect on material removal rate (MRR). Also optimum setting level is calculated to have the most MRR by using method of ratio of signal to noise. They showed that despite the small number of experiment in the Taguchi method, this method presents acceptable results. Zarepour et al. [9] examined the corrosion of cooper tool by using Taguchi method in EDM process of tool steel Din 12714. They found that current has the most effect on corrosion rate of tool. Also, they specified optimum surface of parameters by utilizing signal -to- noise method. Tzeng et al. [10] by using Fuzzy logic and Taguchi optimized EDM process for high speed machining of tool SKD11.In this study, the most effective parameters on accuracy and precision of process are announced respectively pulse on time and current. As well as it has been suggested that the size and amount of particles added to dielectric have no effect on quality. Sabuni [11] in its own research project investigated the influence of EDM parameters with graffiti tool on mechanical properties of memorable alloys NITI. In this study, the effect of input parameters such as current, pulse on time, voltage and pulse off time on output parameters such as tool wear, MRR and surface finish is investigated. It is shown that the most effective parameter on output is current which by increasing current, MRR and tool wear go up and surface finish goes down. As well as, voltage has the least effect, that by increasing voltage, MRR and tool wear decrease and it is interesting to say that voltage has no effect on surface finish. Also, in this paper, the numerical value of pulse on time and off time is specified in order to optimize the output. Andalib [12] performed the EDM on super alloy Inconel 718 in this study, after collecting experimental data and using Taguchi and optimum determinant in DOE, by utilizing two methods of signal to analyze (S/N) and mathematical modeling, the optimum surface of parameters are specified. In this paper, setting parameters include voltage, gap current, and pulse on time, and work parameters. The results of optimization and experimental results are compared

with each other, which have good agreement. In reviewing MRR, it becomes clear that for achieving maximum MRR, All the parameters have to be set on maximum level. It is found that current parameters have the most effect and then pulse on time and work parameters respectively have the most influence on output. As well as, during investigation of surface roughness, it becomes clear that voltage and work parameters have no effect. But current and pulse on time respectively have the most effect. Josh et al. [13] by using finite element method (FEM), artificial neural network (ANN) and genetic algorithm optimized the EDM for machining molds steel AISIP20. Prediction error was less than 7%. Their test results have good agreement with experimental results of other studies.

For optimization and increasing MRR, the combination of pulse on time 420-400 (ms), work period 80-75%, current 40-38 (A) and gap voltage 50-45 (V) and for decreasing surface roughness, the combination of pulse on time 25-30 (ms), work period 55-50% current 5-7 (A) and gap voltage 35-30 (V) are considered. Tsai et al. [14] matched ANN with MRR in EDM process. They first compared various algorithm of ANN for prediction of material removal rate of work piece with different materials by taking into account change of electrode polarity among 6 disparate neural networks and one fuzzy-neural network separately. They reported that adaptive network based adaptive neuron fuzzy inference system (ANFIS) is the best method for prediction material removal rate. Also, it is shown that prediction error in extended condition is about 16.33% and although the EDM process is known for its complexity and unpredictability but ANFIS can model it accurately. Rao et al. [15] developed a combined model and optimized material removed rate in EDM process of Ti6Al4V, HE15, 15CVD6, M-250 by using ANN and genetic algorithms. The tests were carried out by changing the maximum voltage and current in order to measure material removal rate. It is shown that the mean square error when network extended with genetic algorithm is significantly reduced. It is declared that in constant voltage by increasing current, material removal rate goes up. Also, maximum MRR is happened in voltage 40 (V) and current 16 (A).In the case of titanium alloy, the best MRR and the least tool wear is happened in current 16 (A), and voltage 40 (V). The sensitivity of analysis showed that the material has the most effect on value. Zabah et al. [16] optimized EDM process by presenting method based on genetic algorithm for finding optimized inputs. They illustrated that although All the input parameters such as current, pulse on time pulse off time and gap are in continues space, genetic algorithm can find best inputs for machine by searching in the continues space. In the other words, optimization of EDM process for machining hard materials based carbon or non-oxide ceramics can be possible by using genetic algorithm and select of suitable function. Reviewing papers showed that little research has been done on EDM of special material such as cold work tool steel. since, the effect of setting parameter and determination of optimized levels are depend on material and machining condition, it is necessary to carry out experimental tests for each alloy and material.

Despite the increasing use of alloy DIN 1.280 especially in Iran, there is no study in the field of EDM optimization of this kind of alloy by using ANN and genetic algorithm and by utilizing simultaneously of DOE and optimized determinant. In generally the objectives of this research can be summarized in following items:

1- Estimation of various parameters named above with acceptable accuracy for better control by using ANN and genetic algorithm.

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2- Present a model for efficient prediction and optimization in order to determine optimal levels of setting parameters to achieve optimum output characteristic of ANN and genetic algorithm process.

# 2. Method of Experiment

# 2.1 Material

D3 a cold work high alloy steel with standard number DIN 1.2080 and symbol 210Cr12 and about 2% carbon, 12% chrome, is very widely used in industry since the hardness of this alloy is very high. High abrasion resistance, high compressive strength and ability to work hard are some features of this steel. Tables (1) and (2) show chemical composition and some mechanical properties of this alloy respectively [17].

Table1. Alloy Mechanical composition according to percent weight							
		Cr	S	Р	Mn	Si	С
Min	%	11.00			0.20	0.10	1.90
Max	%	13.00	0.03	0.03	0.60	0.60	2.20

Table2. Mechanical properties of D3 alloy					
characteristic	value				
Density	7.67 g/cm3				
Hardness	60 Rc				
Ultimate yielding stress	415 Mpa				
Melting point	1191-1204°C				

The electrode material is copper with purity of 99.9% and its diameter is 40 mm. For easy installation of electrode in tool holder, the length and diameter of it are considered 10 and 11 (cm) respectively. The samples are cut by band saw machine with same thickness from a cylinder profile with diameter 70 (mm). It is necessary to say that all the samples are finished by lathe and grinding machines and for more accurate controlling and tracing are coded. Figure (1) showed one of the samples and electrode used in this study.

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Figure 1. Sample and electrode utilized in EDM

# 2.2 Equipments

Spark model 50A-501 is used for performing tests designed, which is showed in Figure 2. The most important characteristics of this spark machine are possibility of changing most setting parameters, high accuracy and efficient washing system. The washing system of machine is immersion and spraying. It means that during machining, the work piece is completely immersed in the dielectric and the spraying fluid aid to wash better, for measuring material removal rate, the mass of samples is measured after and before machining. For this purpose, digital scale model FEJ200 with accuracy of 0.01 (gr) is used.



Figure 2. Spark machine model 50A-501

#### 2.3 Design of experiments

In this study four important parameters including voltage, current, pulse on time and pulse off time are considered for inputs and material removal rate are considered as output. As mentioned before, the material is alloy DIN 1.2080. By performing initial tests and studying obtainable setting in machine and also considering electrode diameter and upper and lower limit of parameters, the table 3 is considered for level of parameters.

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	-		-			
Input parameters	unit			Levels		
input parameters	um	1	2	3	4	5
(V)	V	100	160	220		
(I)	А	5	10	15	20	
(T <sub>on</sub> )	ms	12	25	50	100	200
$(T_{off})$	ms	12	25	50	100	200

Table3. The parameters of experiment

After specifying parameters and their levels, the manner of performing tests should be determined. According to number of parameters and levels, 300 tests are required  $(3 \times 4 \times 5^2)$ , but because of time consuming and cost, in this study, two methods of Taguchi and optimum determinant are used. For designing matrix of Taguchi tests MINITAB software is utilized. This software proposed 3 matrixes L36, L18, L54 and Taguchi by using one parameter with 2 levels and two parameters with 3 levels. The matrix 36 is the matrix 18 which repeats each test two times. Matrix 54 cannot be selected according condition mentioned. So, taking account of condition and equipment matrix L18 is selected. Therefore by dividing levels, Table (4) and (5) show the ordering of test based on Taguchi L18. In these tables each row indicates one test. In last column, the output (material removal rate) is shown. Table (6) illustrates the matrix of performing tests according to optimum determinant derived from design expert software in this design just one ordering L26 is proposed by statistical software. The results of measuring outputs in the form of design test matrix provide suitable space for analyze the electrode discharge machining by using ANN and genetic algorithms.

			1		U
		Input par	Output parameter		
No.	T <sub>On</sub>	T <sub>Off</sub>	Ι	V	MRR
	(ms)	(ms)	(A)	(V)	(cm <sup>3</sup> /min)
1	12	12	5	100	0.00261
2	50	50	5	100	0.00261
3	100	100	5	100	0.00478
4	12	12	10	100	0.00478
5	50	50	10	100	0.00695
6	100	100	10	100	0.01173
7	50	12	15	100	0.01260
8	100	50	15	100	0.02129
9	12	100	15	100	0.04433
10	100	12	5	160	0.00217
11	12	50	5	160	0.00521
12	50	100	5	160	0.00782
13	50	12	10	160	0.00391
14	100	50	10	160	0.00913
15	12	100	10	160	0.01651
16	100	12	15	160	0.00956
17	12	50	15	160	0.04172
18	50	100	15	160	0.04042

Table4. The inlet and outlet parameters in the first Taguchi method

	.Input parameters				Output parameter
No	T <sub>On</sub>	T <sub>Off</sub>	Ι	V	MRR
	(ms)	(ms)	(A)	(V)	(cm <sup>3</sup> /min)
1	25	25	10	100	0.00739
2	100	100	10	100	0.01217
3	200	200	10	100	0.00869
4	25	25	15	100	0.02521
5	100	100	15	100	0.03737
6	200	200	15	100	0.02825
7	100	25	20	100	0.02043
8	200	100	20	100	0.02781
9	25	200	20	100	0.05085
10	200	25	10	220	0.00391
11	25	100	10	220	0.01347
12	100	200	10	220	0.01173
13	100	25	15	220	0.02216
14	200	100	15	220	0.02173
15	25	200	15	220	0.04042
16	200	25	20	220	0.01217
17	25	100	20	220	0.05519
18	100	200	20	220	0.04302

Table5. The inlet and outlet parameters in the second Taguchi method

		Input pa	Output parameter		
No.	T <sub>On</sub>	T <sub>Off</sub>	Ι	V	MRR
	(m)	(ms)	(A)	(V)	(cm <sup>3</sup> /min)
1	25	200	15	220	0.04042
2	200	100	10	100	0.00999
3	25	25	20	220	0.03433
4	100	100	15	100	0.03737
5	100	200	15	220	0.03216
6	200	25	20	100	0.00826
7	100	200	10	220	0.01173
8	25	100	15	220	0.04519
9	100	200	20	100	0.03954
10	25	100	10	100	0.00999
11	100	25	20	220	0.02651
12	25	100	20	100	0.05302
13	25	25	15	100	0.02521
14	25	25	10	220	0.00956
15	200	100	15	220	0.02173
16	25	200	20	220	0.05894
17	200	200	10	220	0.00826
18	100	25	15	100	0.01434
19	100	25	10	100	0.00521
20	100	100	10	220	0.01130
21	100	100	20	100	0.03737
22	200	200	20	100	0.03042
23	200	25	15	220	0.01043
24	25	200	10	100	0.01086
25	200	100	20	220	0.02781
26	200	200	15	100	0.02825

An Optimization on the DIN1.2080 Alloy in the Electrical Discharge Machining Process Using ANN and ..., pp.33-47 Table6. The inlet and outlet parameters in the optimum determine method

#### 3. Results

#### 3.1 Neural Network

By using data obtained from the experiments, neural network is trained. In general, the data are divided into three groups. The first group is the training data which are used for training and adjustment of network weights and bias and by default 70% of initial information is dedicated to this group. The second group, assessment data, each time that network passes the training cycle, assessment data enter the network and calculate the error between output and actual value. By default 15% of initial information is dedicated to this group. The third group of data is the test data which are used for testing network and 15% of remaining initial information is assigned to this group [17]. It should be noted that choosing data for each group will be randomly. The trained neural network includes four inputs (voltage, current, pulse on time and pulse off time) and one output (material removal rate).

# 3.2 Neural Networks Characteristic

In this paper, feed forward method is used. The neural network produced has 4 neurons which are related to input parameters (voltage-current-pulse on time and pulse off time) and one hidden layer with 52 neurons and one output layer with one neurons related to output parameter (material removal rate). The function of first hidden layer is Tansig and function of output layer is pure line; Figure (3) shows a schematic neural network used in this study. Since the objective is to find the network that by presenting new data has the best performance, so for assessment of performance, the mean square error method is used.



Figure3. Neural network used in this paper

It should be noted that assessment and testing data are used for drawing error curve. Figure (4) illustrates the error curve and efficiency of network. The value of error in eighth repeat is  $6.97 \times 10^{-6}$ .



Figure4. Error curve of network

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Figure (5) shows the error histogram that indicates the error of three levels of train, assessment and test. As it can be seen, the average error of most of the data is about 0.00014, which is near zero and acceptable and indicative of suitable choice and train.



Figure 5. Histogram graph indicating error of three level

Regression graph of this network after training for three levels of train, validation and test and also for adding all three levels is shown in Figure (6).



Figure6. Regression graph of this network after training (a) training data (b) evaluation data (c) test data (d) total data

The horizontal and vertical axes belong to target and output respectively. The more close the line passed through the points, the more matching between network output and target, and it is one of the reasons that indicate the suitable design of neural network. The graph shown in Figure (7) indicates the history of training in which the gradient, the number of step and the number of fails for approaching to target are illustrated.



Figure 7. History of ANN after training (a) training data (b) evaluation data (c) test data (d) total data

In Figure (7), it is shown that correction trend is disappeared after eighth repetition and the performance of network does not become better so it is enough until eight levels. In total according to Figures (4), (5) and (6), it is obvious that selected network is suitable for estimation and prediction of this process, and it can be used for goal function in genetic algorithm.

#### 3.3 Characteristics of Selected Genetic Algorithm

Genetic algorithm has variety variables that changing any of those has influence on precision and accuracy of solution. The appropriate of parameters which are used in genetic algorithm are shown in table (7). Since genetic algorithm is a random search algorithm and presents different answer in various repetitions, for this reason a number of repetitions are considered for optimization in order to ensure that algorithm will converge to an optimal solution.

Table7. Setting parameters in genetic algorithm					
SETTING PARAMETERS	VALUE				
Size population	275				
(beta) Select pressure	10				
(pc) Cross over probability	0.8				
(pm) Mutation probability	0.3				
(mu) Mutation rate	0.02				
(Max It) Maximum iteration	130				

In case of repetition and not changing in the results optimal value is achieved. In this situation because of high calculation cost, continuation of repeat is not logical.

#### 4.3 Determine Optimal Value of Parameters for Material Removal Rate and Analyze Them

After performing program with above adjustments, optimal value for input parameters are achieved for getting maximum material removal rate. Current 20 (A), voltage 160 (V), pulse on time 700 (ms), pulse of time 12 (ms) and material removal rate is 0.063 ( $Cm^3/min$ ). As it can be seen current

and pulse on time have to be adjusted on maximum level and pulse off time has to be set on minimum level and voltage influence is negligible. Choosing high level of current leads to maximum rate of discharge energy on work piece surface and therefore melt and evaporation of larger volume of work piece resulted increase of MRR. Regarding pulse on time, this parameter determines the time of create and actual presence of spark between workpiece and electrode. By increasing this parameter in each cycle, a larger quantity can be detached and therefore larger material removed. In pulse off time, current is cut and detached particles are gotten away by dielectric fluid.

By decreasing these parameters, the average of spark number per time unit increases and material removal speed goes up. Voltage parameters have no effect on material removal rate because it just causes to perform ionization in suitable speed and facilitate the control of servo motors. In next step, the accuracy of this method is calculated by doing validation test. For this step, according to optimal value achieved by ANN and genetic algorithm, validation test is performed accurately. As it can be seen, the error value of prediction is about 5.18%, Table (8). This error is because of environmental and uncontrollable factors in machining. Due to uncertainty in EDM and its industrial nature this error value of prediction is acceptable.

Table8. Validation tests for MRR						
Test result	Program prediction	Error percent				
0.05590	0.06300	5.18				
•	Test result 0.05590	Test resultProgram prediction0.055900.06300				

It should be noted, in this study, the limitation of machine necessitate to set the input parameters in limited levels for this reason. The neural network program is written discretely that its output can be set on machine. Otherwise, doing validation test and adjusting optimal value is impossible on machine.

#### 4. Conclusion

In order to maximum material removal rate, two parameters of current and pulse on time have to be set on maximum level and pulse off time has to be adjusted on minimum level. By doing this, maximum discharged energy and material removing are resulted. Voltage parameter has no effect, while current parameter with highest impact is the most important setting parameter. After that, pulse on time and pulse off time are the most effective parameters respectively. Work voltage also has no fundamental impact on material removal rate, and just causes to better ionization with desired speed. Current in spark is changed linearly and has the most effect on output parameter. It should be noted that mismatch between pulse on time and pulse off time leads to excessive increase and decrease of pulse off time and thus decomposition of dielectric and create of arc and formation of graphite, also setting high voltage after optimal limit lead to increase gap clearance that in turn decreases depth of surface melting and then reduce material removal rate. Finally by studying the results of optimization and validation test and according to error achieved which is 5.18%, it can be said that ANN and genetic algorithm are suitable method and have higher accuracy than order optimization methods.

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#### 5. References

- [1] Kalpakjian, S. 1995. Manufacturing Engineering and Technology. Addison-Wesley.
- [2] Sadr, P., Koahdooz, A. and Eftekhari, S.A. 2015. The Effect of Electrical Discharge Machining Parameters on Alloy DIN 1.2080 Using the Taguchi Method and Optimal Determinant. Journal of Solid Mechanics in Engineering. 8(2): 71-89. (In Persian)
- [3] Uhlmann, E. and Domingosb, D.C. 2013. Development and Optimization of the Die-Sinking EDM Technology for Machining the Nickel-Based Alloy MAR-M247 for Turbine Components. Procedia CIRP. 6: 180-185.
- [4] Ayestaa, I., Izquierdob, B., Sánchez, J.A., Ramos, J.M., Plaza, S., Pombo, I., Ortega, N., Bravo, H., Fradejas, R. and Zamakona, I. 2013. Influence of EDM Parameters on Slot Machining in C1023 Aeronautical Alloy. Procedia CIRP. 6: 129-134.
- [5] Gopakalannan, S. and Sinthelevan, T. 2012. Modeling and Optimization of EDM Process parameter on Machining of AL7075-B4 MMC using RSM. Procedia Engineering. 38: 685-690.
- [6] Clijsters, S. and Liu, K. 2010. EDM Technology and Strategy Development for the Manufacturing of Complex Parts in SiSiC. Journal of Materials Processing Technology. 210: 631-641.
- [7] Tzeng, Y.F. 2008. Development of a Flexible High-Speed EDM Technology with Geometrical Transform Optimization. Journal of Materials Processing Technology. 203: 355-364.
- [8] Rajmohan, T. and Prubho, R. 2012. Optimization of Machining Parameter in EDM of 304 Stainless Steel. Procedia Engineering. 38: 1030-1036.
- [9] Zarepour, H. and FadaeiTehrani, A. 2007. Statistical Analysis on Electrode Wear in EDM of Tool Steel DIN 1.2714 Used in Forging Dies. Journal of Materials Processing Technology. 187-188: 708-714.
- [10] Tzeng, Y.F. and Chen, F. 2007. Multi-Objective Optimization of High-Speed Electrical Discharge Machining Process Using a Taguchi Fuzzy-based Approach. Materials and Design. 28: 1159-1168.
- [11] Sabouni, H.R. 2012. Research Project. IDM with Tools Graphite Machining Parameters on Mechanical Properties of Alloys Keeper NITI. Islamic Azad University, Khomeinishahr Branch. (In Persian).
- [12] Andalib, M. 2013. Thesis, Electrical Discharge Machining Inconel 718 Super Alloy and Study the Effect of Setting Parameters on Surface Quality and Material Removal Rate Parts. A master's thesis, Department of Mechanical Engineering, Ferdowsi University of Mashhad. (In Persian).
- [13] Joshi, S.N. and Pandeb, S.S. 2011. Intelligent Process Mmodeling and Optimization of Die-Sinking Electric Discharge Machining. Applied Soft Computing. 1: 2743-2755.
- [14] Tsai, K.M. and Wang, P.J. 2001. Predictions on Surface Finish in Electrical Discharge Machining Based upon Neural Network Models. International Journal of Machine Tool Manufacturing. 41: 1385-1403.
- [15] Rao, G.K.M., Ganardhana, G.R., Rao, D.H. and Rao, M.S. 2009. Development of Hybrid Model and Optimization of Surface Roughness in Electric Discharge Machining Using Artificial Neural Networks and Genetic Algorithm. Journal of Materials Process Technology. 209: 1512-1520.

- [16] Zabah, I. 2011. Optimization of EDM Machining Process Using Genetic Algorithm. The first Modern Writing Area in Computer Engineering and Information lat. 56: 1-28.
- [17] http://www.esttoolsteel.com, 2/2015.
- [18] Kia, M. 2011. Neural Networks in MATLAB, Qian Academic Press. Second edition. (In Persian)
- [19] Kia, M. 2012. Genetic Algorithms in MATLAB, Qian Academic Press. Third edition. (In Persian)