Penerbit Akademia Baru

Journal of Advanced Research in Materials Science
ISSN (online): 2289-7992 I Vol. 21, No.1. Pages 14-26, 2016

Experimental Study of Genetic Algorithm Optimization on WC/Co Material Machining

Y. Yusoff[*,a], *A. Mohd Zain*[b] *and H. Haron*[c]

Department of Computer Science, Faculty of Computing, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor Bahru, Johor, Malaysia

[a,*]*yusliza@utm.my*, [b]*azlanmz@utm.my*, [c]*habib@utm.utm.my*

Abstract – *In materials machining, using multi objective genetic algorithm to obtain optimal solutions is a trend in recent researches. Non dominated sorting genetic algorithm (NSGA-II) and also multi objective genetic algorithm (MOGA) are capable to optimize more than one objective functions concurrently. This study presents combination of regression (second order polynomial) and soft computing techniques to maximize material removal rate (MRR) and minimize surface roughness (Ra) simultaneously for cobalt bonded tungsten carbide material using die sinking electrical discharge machining (WC/Co EDM). Single objective genetic algorithm (SoGA), MOGA and NSGA-II are used to search for the optimal solutions of WC/Co EDM parameters, pulse on time (T), pulse current (I), flushing pressure (P) and electrode rotation (R). The optimization performances are investigated using Matlab 7.12 (R2011a). The maximum value of material removal rate is obtained from NSGA-II optimization, 178.324 mg/min meanwhile the lowest surface roughness from SoGA optimization, 0.155 µm. MOGA optimization shows medium level of output in the conditions whereby did not dominate for either maximum material removal rate or minimum surface roughness, however the solutions are within the acceptable range of experimental results.* ***Copyright © 2016 Penerbit Akademia Baru - All rights reserved.***

Keywords: Genetic Algorithm, multi objectives, regression, EDM, Optimization, Cobalt Bonded, Tungsten Carbided

1.0 INTRODUCTION

Machining of materials can be divided into modern and traditional machining. Broadly used in industrial application, an important die material, cobalt bonded tungsten carbide has very high resistance and strength which resulted to difficulties in the cutting process. One of the earliest modern machining, EDM has taken wide interest among the researchers [1-4] these days in machining such, difficult to cut materials. EDM is an electrical thermo process that is used to remove material throughout the act of electrical discharge in fast manner and high current. The purpose of this work is to examine the capability of SoGA, MOGA and NSGA-II in order to obtain optimal parameters in machining the cobalt bonded tungsten carbide.

In many optimization problems, modeling is used to correlate the relationship between input and output. There are conventional modeling techniques such as Taguchi [5], regression [6] and etc. Artificial neural network (ANN) is one of the most well known advanced modeling

Journal of Advanced Research in Materials Science
ISSN (online): 2289-7992 I Vol. 21, No.1. Pages 14-26, 2016

technique being used to solve various real world applications [7]. However, to observe the competency of the optimization algorithms, only one type of established modeling technique which is known as second order polynomial regression is applied. The model is chosen based on the analysis of variance of the experimental results.

Soft computing techniques have recently been used to assist in optimizing machining parameters such as simulated annealing (SA), genetic algorithm (GA), particle swarm optimization (PSO), artificial bee colony (ABC) algorithm and etc. [8-12]. It is observed that genetic algorithm and multi objective genetic algorithm are increasingly used in machining parameter optimization. A genetic algorithm is a robust, easy to use and highly efficient algorithm [13, 14]. The multi objective genetic algorithm is then enhanced in order to satisfy multiple objective problems such as vector evaluated GA (VEGA) [15], MOGA [16], niched Pareto GA (NPGA) [17] etc. As in machining, Bouzakis et al. [18] used MOGA to obtain the optimal parameters which applicable in various cases of milling operation. Mahdavinejad [19] optimized the turning parameters of steel using MOGA and multi objective harmony search algorithm. Sultana and Dhar [20] used MOGA to optimize machining parameters in turning. NSGA-II is mainly a trusted MoGA in machining optimization [21, 22].Thus; trials are conducted to study the capabilities of three algorithms, SoGA, MOGA and NSGA-II in EDM parameters optimization.

Material removal rate, tool wear rate and surface roughness are some of the most widely considered material machining performances in sequence to obtain the optimal solution of machining parameters [23-26]. In order to achieve the desired level of machining performances, the parameters have to be set correctly for each machining operation. Therefore, we reconsider the data of Kanagarajan et al. [27] to investigate the the most popular techniques (SoGA, MOGA and NSGA-II) to support in reducing the material machining process cost and time particularly to the non experienced machinist.

2.0 METHODOLOGY

Genetic algorithm is a soft computing optimization technique that mimics the process of natural evolution. Genetic algorithm is applied widely in optimizing machining process parameters to satisfy three conflicting objectives of manufacturing world, (i) maximize production rate, (ii) maximize product quality, and (iii) minimize production cost [28]. Genetic algorithm is reliable in searching the optimal solutions of machining parameters [29-31]. Surface roughness and removal rate are the machining performances or the objective functions for this study. The optimal solutions of EDM process parameters using three genetic algorithm optimization techniques, SoGA, MOGA and NSGA-II are observed. The process of this study is given in Figure 1. Four considered process parameters are pulse on time (T), pulse current (I), flushing pressure (P) and electrode rotation (R).

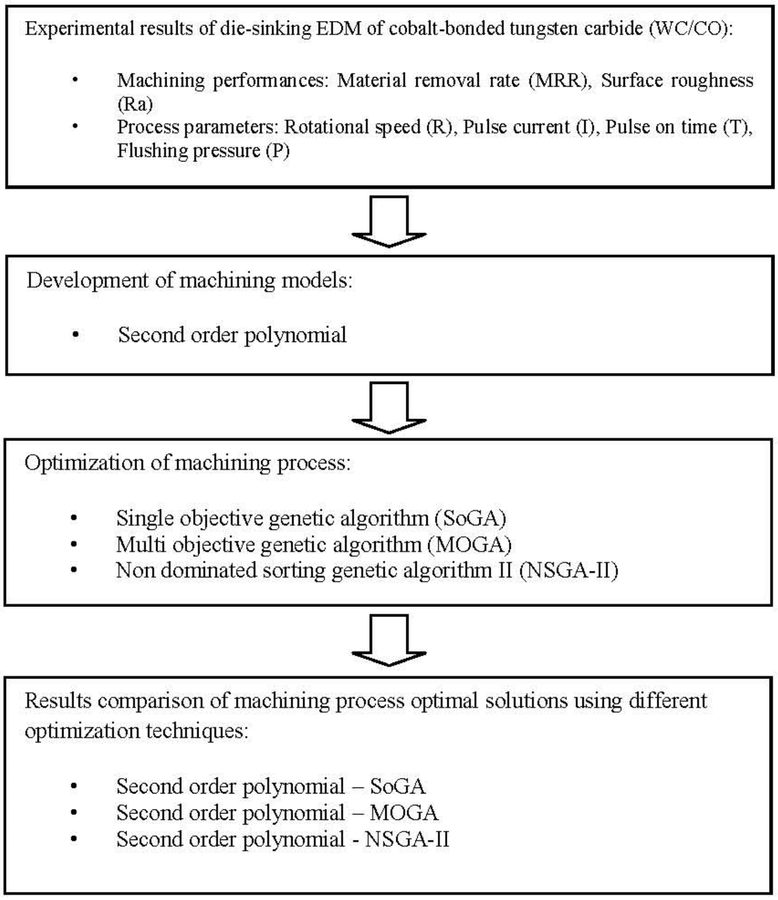


Figure 1: Research flow

3.0 EXPERIMENTAL STUDY

This study is based on the machining experimental results by Kanagarajan et al. [27]. The authors conducted the experiments using an M100 model Electronica die sinking EDM with a transistor controlled power supply. Density for tungsten carbide (WC) is 15.7 g/cc and cobalt (CO) is 13.55 g/cc, where the granule sizes are 6µm and 3µm respectively.

The machining performances are material removal rate and surface roughness. Surface roughness is calculated on a Surfcoder SE1200 and an average of 5 readings is judged as the absolute surface roughness value. The outcomes are based on L27 orthogonal array.

4.0 MATHEMATICAL MODEL

The mathematical model based on second order polynomial regression for material removal rate and surface roughness are shown in equations (1) and (2).

$$\mathrm{MRR} = -30.3660 + 0.1589R + 9.5259I - 0.1241T + 20.8585P - 0.0001R^2 - 0.2318I^2 + 0.0001T^2 - 9.2131P^2 - 0.0002RI - 0.0000RT + 0.0220RP + 1.9991IP - 0.0199TP \quad (1)$$

$$\mathrm{Ra} = 4.2307 - 0.0116R + 0.5816I + 0.0099T - 4.7481P + 0.0000R^2 + 0.0085I^2 - 0.0000T^2 + 2.1239P^2 - 0.0002RI - 0.0000RT - 0.0020RP - 0.2462IP - 0.0018TP \quad (2)$$

5.0 OPTIMIZATION

Known for its elitism in searching global optimum, genetic algorithm is chosen as the base of the experimental study. Realistic and robust concept of this evolutionary algorithm, make it reliable to be applied in real world applications.

5.1 Single Objective Genetic Algorithm (SOGA)

Genetic algorithm selects individuals randomly from current population to be parents and uses them to produce the children for the next generation. Finally, the population develops toward an optimal solution from the succeeding generations. Figure 2 depicted the conceptual basic algorithm.

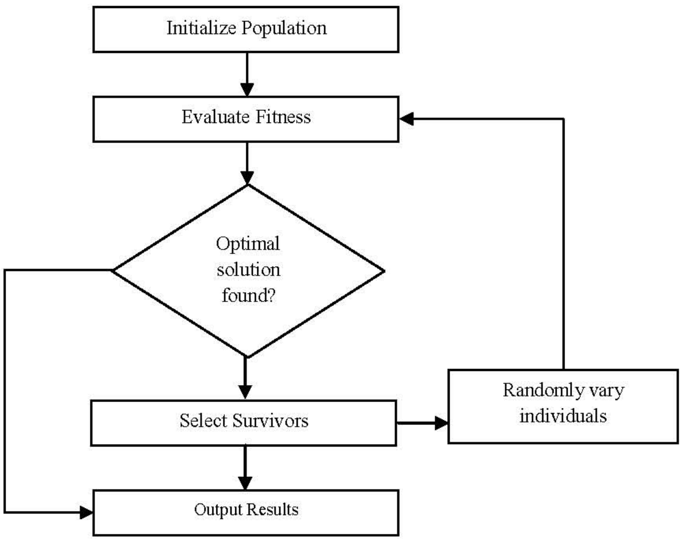


Figure 2: Flow of Genetic Algorithm

5.2 Multi Objective Genetic Algorithm (MOGA)

Originated from Fonseca and Fleming [16]; multi objective genetic algorithm is developed based on flow in Figure 3. As shown in Figure 3, the initial population is created randomly, followed by fitness function evaluation, selection, crossover and mutation. To maintain the best parents for children reproduction, the elitism concept is utilized. When the criteria are not

Journal of Advanced Research in Materials Science
ISSN (online): 2289-7992 I Vol. 21, No.1. Pages 14-26, 2016

fulfilled, the algorithm returns to initial population. And finally, the Pareto solutions are obtained.

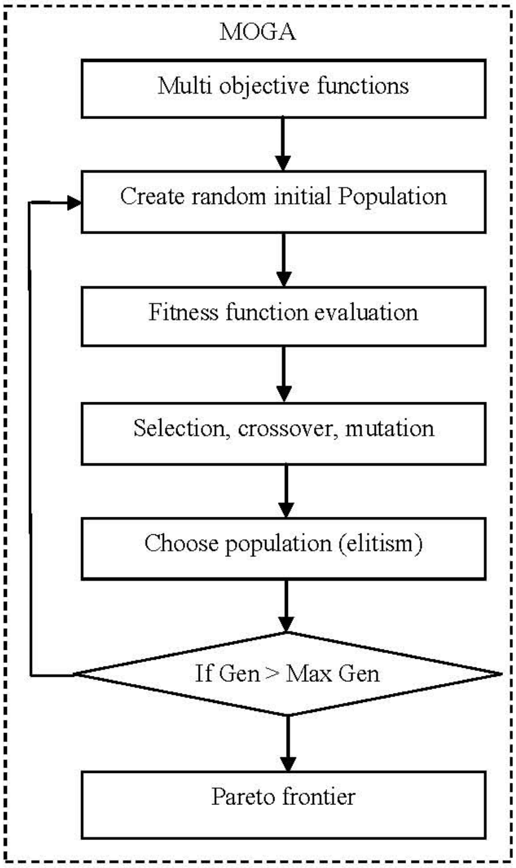


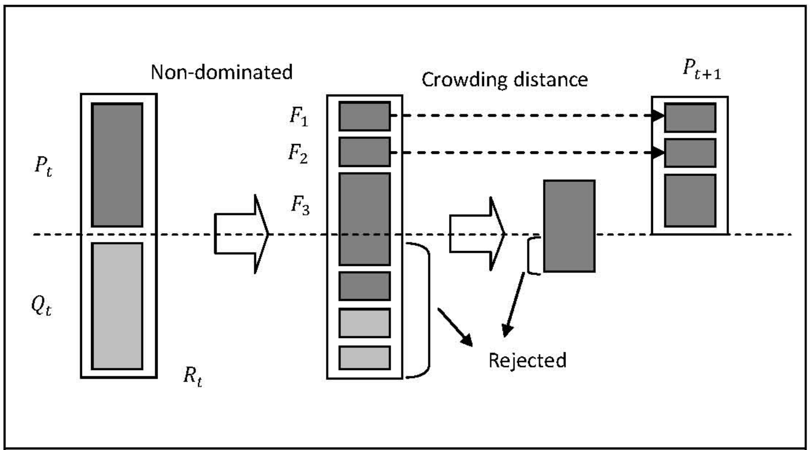
Figure 3: Flow of Genetic Algorithm

5.3 Non Dominated Sorting Genetic Algorithm II (NSGA-II)

NSGA-II (Figure 4) is developed by Deb et al. [21] and widely used in machining parameters optimization. The optimization process can be detailed as below:

NSGA-II description can be detailed as below steps:
Step 1: Population initialization base on the problem range and constraint.
Step 2: Non dominated sorting based on non domination criteria of the population that has been initialized.
Step 3: The crowding distance value is assign front wise, when the sorting is complete. The individuals in population are selected based on rank and crowding distance.
Step 4: The selection of individuals is carried out using a binary tournament selection with crowded-comparison operator.
Step 5: Crossover and polynomial mutation.
Step 6: Offspring population and current generation population are combined and the individuals of the next generation are set by selection by recombination and selection. The new

generation is filled by each front subsequently until the population size exceeds the current population size.



$R_t = P_t \cup Q_t$	combine parent and offspring population
F = fast-non-dominated-sort (R_t)	$F = (F_1, F_2, \ldots)$, all non dominated fronts of R_t
$P_{t+1} = \emptyset$ and $i = 1$	
Until $\lvert P_{t+1}\rvert + \lvert F_i\rvert \leq N$	until the parent population is filled
Crowding-distance-assignment (F_i)	calculate crowding-distance in F_i
$P_{t+1} = P_{t+1} \cup F_i$	include ith non dominated front in the parent pop
$i = i + 1$	check the next front for inclusion
Sort($F_i, \prec_n$)	sort in descending order using $\prec_n$
$P_{t+1} = P_{t+1} \cup F_i[1:(N - \lvert P_{t+1}\rvert)]$	choose the first $(N - \lvert P_{t+1}\rvert)$elements of F_i
Q_{t+1} = make-new-pop(P_{t+1})	use selection, crossover and mutation to create a new population Q_{t+1}
$t = t + 1$	increment the generation counter

Figure 4: NSGA-II concept

6.0 RESULTS AND DISCUSSION

The objective functions are listed in equations (2) and (3); the lower bound and upper bound are set to the values as shown in Table 1. Each objective function, material removal rate and surface roughness, have to be run separately with same random state to get optimal solutions. Due to random initial population and to search for better optimal solutions, the solver is run twenty seven times for both material removal rate and surface roughness. The optimal solution for material removal rate is obtained at 25th run. While the optimal solutions for surface roughness is obtained at 21st run. The maximum value for material removal rate is 171.759 mg/min with combination of process parameters R = 998.365 rpm, I = 14.960 A, T = 203.680 µs, P = 0.995 kg/cm^2 and the minimum surface roughness is 0.155 µm with combination of process parameters, R = 996.299 rpm, I = 5.036 A, T = 200.414 µs, P = 0.995 kg/cm^2.

Penerbit Akademia Baru
Journal of Advanced Research in Materials Science
ISSN (online): 2289-7992 I Vol. 21, No.1. Pages 14-26, 2016

Table 1: Process parameters

Parameters	Lower Bound	Upper Bound
Rotational speed, rpm	250	1000
Pulse current, A	5	15
Pulse on time, μs	200	1000
Flushing pressure, kg/cm^2	0.5	1.5

MOGA is an expansion of SoGA optimization technique in order to resolve multi objective problems for the real world application. It is experiential that the results of maximum material removal rate and minimum surface roughness are simultaneously acquired with single run. Maximum material removal rate is 152.660 mg/min and minimum surface roughness is 5.825 μm. The optimal parameters are R = 978.929 rpm, I = 14.944 A, T = 212.372 μs and P = 0.973 kg/cm^2. The Pareto front for optimal solutions is shown in Figure 5.

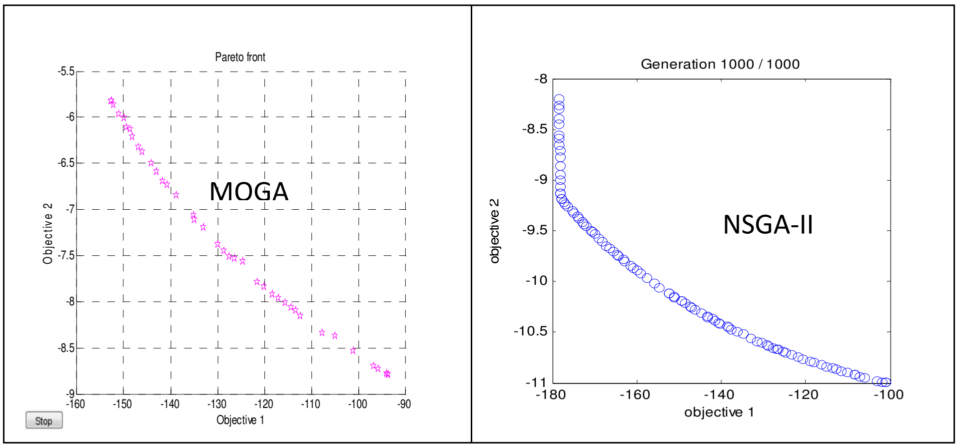


Figure 5: Pareto front of MRR (objective 1) and Ra (objective 2) using MOGA and NSGA-II optimization

NSGA-II is a diversification of multi objective genetic algorith which is a well known algorithm for its elitism. Maximum material removal rate, 178.324 mg/min and minimum surface roughness, 8.199 μm values are obtained simultaneously using NSGA-II with *R, I, T, P* values are 944.516 rpm, 15 A, 200 μs, 1.5 kg/cm^2 respectively. The same results of optimal solutions are generated twice. Figure 5 depicts the Pareto front of material removal rate and surface roughness where NSGA-II is claimed to be good in searching for best spread of solutions compared to MOGA.

Optimization helps in reducing the machining time and increase production rate. The assortment of results is based on the requirement of the process engineer, either to have lower surface roughness or higher material removal rate. The WC/Co EDM process parameters are optimized using SoGA, MOGA and NSGA-II. The second order polynomial model used to maximize material removal rate and minimize the surface roughness values. 100 sets of

Journal of Advanced Research in Materials Science
ISSN (online): 2289-7992 I Vol. 21, No.1. Pages 14-26, 2016

solutions are obtained for each optimization technique but the best solutions among them are chosen and figured out manually in Table 2. The total solutions obtained for MOGA and NSGA-II optimization are 100 solutions each, but to compare with SoGA and experimental results, we only used the first 27 solutions. It is observed that in order to get optimal solutions of material removal rate and surface roughness, the *R* values considered are near to level 3 which is in the range of 869.172 - 1000 rpm and most of the *T* values are near to lower bound which is in between 200 – 212.372 µs. The run time of MOGA is much faster than NSGA-II due to the complexity of the coding of NSGA-II.

Table 2: Best set of solutions with maximum MRR and minimum Ra.

	R, rpm	I, A	T, µs	P, kg/cm^2	MRR, mg/min	Ra, µm
Experimental	1000	10	200	1.5	164.62	2.52
	1000	5	1000	1.5	54.46	2.37
SoGA	998.365	14.960	203.680	0.995	171.759	-
	996.299	5.036	200.414	0.995		0.155
MoGA	978.929	14.944	212.372	0.973	152.660	5.825
NSGA-II	944.516	15.000	200.000	1.500	178.324	8.199
	944.516	15.000	200.000	1.500	178.324	8.199

The relations of SoGA, MOGA and NSGA-II in EDM optimization of material removal rate and surface roughness are represented in Figure 6. It is proven that SoGA, MOGA and NSGA-II are efficient optimization techniques since the predicted values of material removal rate and surface roughness for all techniques are near to the experimental values. However, optimization of multi objectives problem using SoGA is a waste of time where the optimal solutions for two or more conflicting objectives cannot be obtained with a single run. The value of material removal rate and surface roughness using SoGA technique are almost similar for all 27 times run, subjected to a very limited solution of optimal parameters. SoGA outperforms MOGA and NSGA-II with the lowest value of surface roughness, nevertheless the value obtained is lower than the experimental results. NSGA-II outperforms other techniques in searching maximum material removal rate but less efficient in searching minimum surface roughness. In spite of that, the predicted material removal rate and surface roughness values are trustable since the results are still in the range of material removal rate and surface roughness experimental results. The maximum value of material removal rate is attained from NSGA-II optimization, 178.324 mg/min meanwhile the lowest surface roughness from SoGA optimization, 0.155 µm. MOGA optimization of EDM shows medium level of output whereby it did not dominate either maximum material removal rate or minimum surface roughness.

Journal of Advanced Research in Materials Science
ISSN (online): 2289-7992 I Vol. 21, No.1. Pages 14-26, 2016

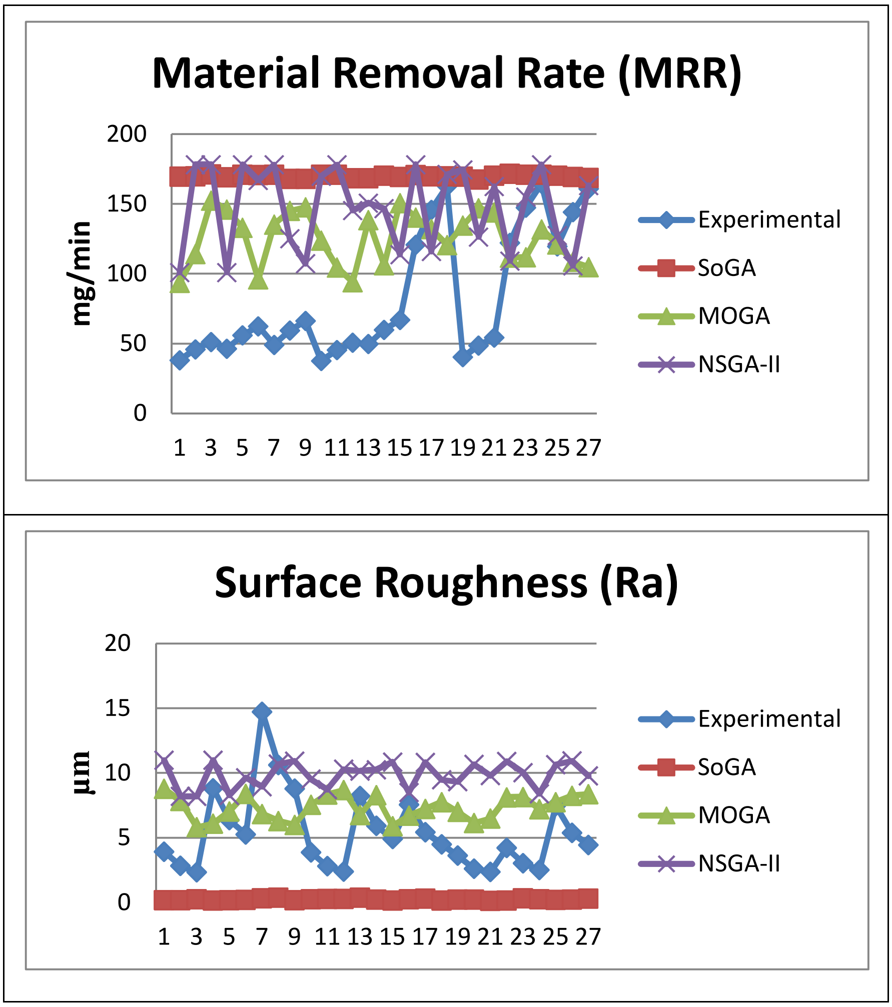


Figure 6: MRR and Ra values for 27 solutions

In this case, percentage errors of material removal rate and surface roughness between experimental and SoGA, MOGA and NSGA-II are summarized in Table 3. The bold fonts are the lowest value of percentage error for each SoGA, MOGA and NSGA-II compared to the experimental results. The lowest percentage value of material removal rate is obtained from MOGA optimization which is equal to 121.193 mg/min. Meanwhile the best surface roughness value, 10.694 µm is obtained from NSGA-II optimization. MOGA produced the lowest percent error for both material removal rate and surface roughness on the 25th solution which shows that these values are reliable in solving both objective functions at same time in single run.

Overall, we summarized the comparison of SoGA, MOGA and NSGA-II in terms of objective, solution and time in Table 4. SoGA is able to search for either the highest and lowest optimum value in a single run. MOGA and NSGA-II are capable to optimize process parameters while considering two or more machining performances in a single run.

Journal of Advanced Research in Materials Science
ISSN (online): 2289-7992 I Vol. 21, No.1. Pages 14-26, 2016

Table 3: Lowest percent error

	Solution No.	Percent Error SoGA, %	Percent Error MOGA, %	Percent Error NSGA-II, %
MRR	24	**3.953**	19.830	8.316
	25	42.393	**1.213**	6.601
	27	4.841	34.844	**1.445**
Ra	8	96.327	40.64	**0.51**
	12	**87.555**	263.84	330.84
	25	96.981	**4.07**	42.63

Table 4: Comparison of EDM optimization

	SoGA	**MOGA**	**NSGA-II**
Objective	Single objective	Multiple objectives	Multiple objectives
Solution	Single set of solutions	Many sets of solutions without neglecting any of the onjective	Many sets of solutions with better spread and convergence of solutions
Time	Run time is very short for single objective but very time consuming for multi objectives	Time efficient	Slower optimization time compared to MOGA

4.0 CONCLUSION

This paper presented and discussed the usage of SoGA, MOGA and NSGA-II in solving multiple objective problems of EDM operation in machining cobalt bonded tungsten carbide (WC/Co). This study proven that genetic algorithm as a soft computing technique is reliable in assisting the materials machining process especially to the non machinist experienced. Unlike single objective genetic algorithm, multi objective genetic algorithm can give variety of choices at one time run to the engineers in choosing the process parameters.

REFERENCES

[1] Kumar, Anil, Sachin Maheshwari, Chitra Sharma, and Naveen Beri. "Research Developments in Additives Mixed Electrical Discharge Machining (Aedm): A State of Art Review." Materials and Manufacturing Processes 25, no. 10 (2010): 1166-80.

Journal of Advanced Research in Materials Science
ISSN (online): 2289-7992 I Vol. 21, No.1. Pages 14-26, 2016

[2] Srivastava, Vineet, and Pulak M. Pandey. "Performance Evaluation of Electrical Discharge Machining (Edm) Process Using Cryogenically Cooled Electrode." Materials and Manufacturing Processes 27, no. 6 (2011): 683-88.

[3] Subramanian, Rajendran, K. Marimuthu, and M. Sakthivel. "Study of Crack Formation and Re-Solidified Layer in Edm Process on T90mn2w50cr45 Tool Steel." Materials and Manufacturing Processes (2012).

[4] Yu, Po-Huai, Hsiang-Kuo Lee, Yang-Xin Lin, Shi-Jie Qin, Biing-Hwa Yan, and Fuang-Yuan Huang. "Machining Characteristics of Polycrystalline Silicon by Wire Electrical Discharge Machining." Materials and Manufacturing Processes 26, no. 12 (2011): 1443-50.

[5] Kumar S., and Panneerselvam K. "Optimization of Friction and Wear of Nylon 6 and Glass Fiber Reinforced (Gfr) Nylon 6 Composites against 30wt. % Gfr Nylon 6 Disc." Journal of Advanced Research in Materials Science 19, no. 1 (2016): 14 – 32

[6] Asraf A., Sorooshian S. and Cheng J. K. . "Formulation of Logit Regression." Journal of Advanced Research Design 21, no. 1 (2016): 6 - 9.

[7] Parveen R., Nabi M. , Memon F. A. , Zaman S. and Ali M. . "A Review and Survey of Artificial Neural Network in Medical Science." Journal of Advanced Research in Computing and Applications 3, no. 1 (2016): 8 - 17

[8] Dou, Jianping, Xingsong Wang, and Lei Wang. "Machining Fixture Layout Optimisation under Dynamic Conditions Based on Evolutionary Techniques." International Journal of Production Research 50, no. 15 (2011): 4294-315.

[9] Lee, Yi Zheng, and S. G. Ponnambalam. "Optimisation of Multipass Turning Operations Using Pso and Ga-Ais Algorithms." International Journal of Production Research (2012): 1-20.

[10] Rao, Ravipudi Venkata, P. J. Pawar, and J. P. Davim. "Parameter Optimization of Ultrasonic Machining Process Using Nontraditional Optimization Algorithms." Materials and Manufacturing Processes 25, no. 10 (2010): 1120-30.

[11] Yusup, N., A. M. Zain, and S. Z. M. Hashim. "Evolutionary Techniques in Optimizing Machining Parameters: Review and Recent Applications (2007-2011)." Expert Systems with Applications 39, no. 10 (2012): 9909-27.

[12] Zain, A. M., H. Haron, and S. Sharif. "Application of Ga to Observe the Optimal Effect of the Radial Rake Angle for Minimising Surface Roughness in End Milling." International Journal of Machining and Machinability of Materials 8, no. 3-4 (2010): 283-305.

[13] Colin R. Reeves, Jonathan E. Rowe. Genetic Algorithms: Principles and Perspectives : A Guide to Ga Theory2004.

[14] Davis, Lawrence. Handbook of Genetic Algorithms: Van Nostrand Reinhold, 1991.

[15] Schaffer, J. David. "Multiple Objective Optimization with Vector Evaluated Genetic Algorithms." In Proceedings of the 1st International Conference on Genetic Algorithms, 93-100: L. Erlbaum Associates Inc., 1985.

[16] Fonseca, C. M., and P. J. Fleming. "Multiobjective Genetic Algorithms." Paper presented at the Genetic Algorithms for Control Systems Engineering, IEE Colloquium on, 28 May 1993 1993.

[17] Knowles, J., and D. Corne. "The Pareto Archived Evolution Strategy: A New Baseline Algorithm for Pareto Multiobjective Optimisation." Paper presented at the Evolutionary Computation, 1999. CEC 99. Proceedings of the 1999 Congress on, 1999 1999.

[18] Bouzakis, K. D., Paraskevopoulou, R., Giannopoulos, G. "Multi-Objective Optimization of Cutting Conditions in Milling Using Genetic Algorithms." Paper presented at the Proceedings of the 3rd International Conference on Manufacturing Engineering (ICMEN), Chalkidiki, Greece, 2008.

[19] Mahdavinejad, R. "Optimizing of Turning Parameters Using Multi-Objective Genetic Algorithm." 359-63, 2010.

[20] Sultana, I., and N. R. Dhar. "Ga Based Multi Objective Optimization of the Predicted Models of Cutting Temperature, Chip Reduction Co-Efficient and Surface Roughness in Turning Aisi 4320 Steel by Uncoated Carbide Insert under Hpc Condition." 2010.

[21] Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan. "A Fast and Elitist Multiobjective Genetic Algorithm: Nsga-II." Evolutionary Computation, IEEE Transactions on 6, no. 2 (2002): 182-97.

[22] Yusoff, Y., M. S. Ngadiman, and A. M. Zain. "Overview of Nsga-II for Optimizing Machining Process Parameters." 2011.

[23] Khandekar, S., M. Ravi Sankar, V. Agnihotri, and J. Ramkumar. "Nano-Cutting Fluid for Enhancement of Metal Cutting Performance." Materials and Manufacturing Processes 27, no. 9 (2011): 963-67.

[24] Rajmohan, T., and K. Palanikumar. "Optimization of Machining Parameters for Surface Roughness and Burr Height in Drilling Hybrid Composites." Materials and Manufacturing Processes 27, no. 3 (2011): 320-28.

[25] Saini, Sanjeev, Inderpreet Singh Ahuja, and Vishal S. Sharma. "Residual Stresses, Surface Roughness, and Tool Wear in Hard Turning: A Comprehensive Review." Materials and Manufacturing Processes 27, no. 6 (2011): 583-98.

[26] Satheesh Kumar B., Padmanabhan G. and Vamsi Krishna P. . "Performance Assessment of Vegetable Oil Based Cutting Fluids with Extreme Pressure Additive in Machining." Journal of Advanced Research in Materials Science 19, no. 1 (2016): 1 - 13.

Journal of Advanced Research in Materials Science
ISSN (online): 2289-7992 I Vol. 21, No.1. Pages 14-26, 2016

[27] Kanagarajan, D., R. Karthikeyan, K. Palanikumar, and J. P. Davim. "Optimization of Electrical Discharge Machining Characteristics of Wc/Co Composites Using Non-Dominated Sorting Genetic Algorithm (Nsga-Ii)." International Journal of Advanced Manufacturing Technology 36, no. 11-12 (2008): 1124-32.

[28] Cus, F., and U. Zuperl. "Approach to Optimization of Cutting Conditions by Using Artificial Neural Networks." Journal of Materials Processing Technology 173, no. 3 (2006): 281-90

[29] Kilickap, Erol, and Mesut Huseyinoglu. "Selection of Optimum Drilling Parameters on Burr Height Using Response Surface Methodology and Genetic Algorithm in Drilling of Aisi 304 Stainless Steel." Materials and Manufacturing Processes 25, no. 10 (2010): 1068-76.

[30] Shrivastava, Pankaj Kumar, and Avanish Kumar Dubey. "Intelligent Modeling and Multi-Objective Optimization of Electric Discharge Diamond Grinding." Materials and Manufacturing Processes (2012).

[31] Somashekhar, K. P., N. Ramachandran, and Jose Mathew. "Optimization of Material Removal Rate in Micro-Edm Using Artificial Neural Network and Genetic Algorithms." Materials and Manufacturing Processes 25, no. 6 (2010): 467-75.