Experimental Investigation and Optimization of Machining Parameters of CNC Milling

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***Abstract*-CNC milling is widely used in manufacturing industry for material removal process to manufacture the components with complex shapes and profiles. During end milling operation the end mill cutter is used as a tool. In this work plain milling operation is performed on CNC milling using High Speed Steel as milling cutter having 14 mm diameter, M2 grade. Mild steel containing 20% Carbon is used as work piece. Full factorial experimentation has been carried out to study the effects of machining parameter on surface roughness and material removal rate in minimum machining time using Particle Swarm Optimization. The mathematical model has been developed for surface roughness and material removal rate in terms of input variables. During parameter optimizations firstly find out the effects of input parameter on surface roughness, then on material removal rate and finally on both output parameters simultaneously. It is observed that the results of Particle Swarm Optimization are found very close to the output of experimentation. The objective of this study is to find the optimal machining parameter for minimum surface roughness and maximum material removal rate in minimum machining time.**

***Keywords*: CNC Milling Machine, Surface Roughness (SR), Material Removal Rate (MRR), Particle Swarm Optimization (PSO).**

I. INTRODUCTION

In current scenario the technology of CNC milling machine has been improved significantly to meet the requirements of industry personnel as well as Research and Development. Among several CNC machining processes CNC end milling is unique adaption of the conventional milling process where end mill cutter is used as tool. Now-a-days due to increasing demand of modern engineering products, the quality of surface texture with dimensional accuracy has become more vital. The quality of surface plays tremendous role in the performance of milling as a best quality milled surface significantly improves corrosion resistance and fatigue strength. The surface mostly generated during milling is affected by tool geometry, vibration, temperature, tool path, cross-feed, spindle run out, feed and other parameters. The current trends to find optimum combination of machining parameter by thumb rule or trial and error method or sometime the data used in previous experience of process planer or machining hand book. All those methods are very tedious and time consuming. So it is the need of time to develop a technique that could be able to find optimum machining parameters for minimum surface roughness and maximum material removal rate.

In today's scenario more attention is given to the performance measures such as dimensional accuracy and surface roughness of the products by industry personnel as well as Research and Development. Although the dimensions of finished components are within the tolerance limit still there are more chances of rejecting the components for minimum surface finish. The surface finish of any manufacturing process has become more difficult because of increased demands. Moreover surface roughness finds mechanical properties such as lubrication, wear, electrical conductivity, corrosion and fatigue behavior.

Surface roughness is an important characteristic of the quality of a product and greatly influence the production cost. Preparation of good surface finish is depend on many parameters such as spindle speed, feed, depth of cut, cutting force, tool nomenclature, rigidity of machine and work piece, material properties of tool and work piece and so on. Out of this controllable parameter such as spindle speed, feed, depth of cut are easily controllable during the process of machining without wasting time and additional cost.

So it is necessary to develop a robust technique to predict the machining parameters for obtaining the desired surface finish in a minimum machining time. This presented work should not involve cost and time function. In recent years many optimization techniques were implemented for optimization of machining parameters such as Taguchi method, Genetic Algorithm, Ant Colony method and so on.

II. LITERATURE SURVEY

During literature survey it has been observed that the many researchers have studied the effects of machining parameters on various output parameters using different optimization techniques. Sreenivasa Rao M. and Venkaiah N (2015) studied the effects of Nimonic-263 alloy on various parameters such as pulse on time, pulse off time, peak current and servo voltage using RSM and particle swarm optimization. This work suggested the results obtained using PSO is better than RSM [1]. S. Bharathi Raja and N. Baskar (2012) applied particle swarm optimization to find optimal machining parameter for obtaining minimum SR in minimum machining time. This work recommended that the use of higher cutting speed, lower feed and depth of cut results in better surface finish [2]. Hrelja Marko and Klancnik Simon (2014) investigated the effects of machining parameters on tool life, cutting force and SR during turning operation using PSO [3].

T. Tamizharasan and J. Kingston Barnabas (2014) studied the effects of cutting tool geometry based on flank wear using DOE, PSO and SAA. Their works recommend the best result given from SAA when compared with DOE and PSO [4]. N. V. Mahesh Babu Talupula and Nersu Radhika (2015) studied the effects of machining parameters on SR using PSO. This work used Mild Steel and Aluminum as work piece. [5]. Rajendra B. and Deepak D. (2015) investigated the effects process parameters for increasing MRR for turning Al6061 using S/N ratio. Their works recommend that the feed rate is most influential process parameters on MRR while turning of Aluminum 6061 followed by depth of cut and cutting speed [6]. M. Nalbant et al. (2007) presented Taguchi method for optimization of cutting parameters for surface roughness in turning of AISI 1030 steel bars using TiN coated tools. Their works recommend that the use of greater insert radius (1.2 mm), low feed rate (0.15 mm/rev) and low depth of cut (0.5 mm) for better SR in turning [7]. Girish Kant and Kuldip Singh Sangwan (2015) presented Artificial Neural Network and Support Vector Regression models for predicting the power consumed during the machining. This work recommended that the ANN model has shown slightly the better performance as compared to SVR model [8]. Uros Zuperl and Franc Cus (2016) proved that combined system of ANFIS and TLBO is an effective approach for solving multi-objective cutting conditions optimization problem in ball-end milling [9]. R. Venkata Rao and V.D. Kalyankar (2012) studied the optimization of multi-pass turning process parameters using TLBO. This study proved that TLBO is very effective optimization technique [10].

Ali Rıza Yildiz (2009a) developed a new hybrid optimization approach based on PSO algorithm and receptor editing property of immune system. This approach was used to solve a single-objective test problem, tension spring problem, pressure vessel design optimization problem and two case studies for multi-pass turning operation.

The results of statistical analysis and best-known values of both benchmark and case studies showed that the PSRE was a good alternative in solving of real-world optimization problems [11].

Ali Rıza Yildiz et al. (2007) presented a new hybrid improved genetic algorithm to solve the multi-objective design optimization problems. It was proved by computational experiments that the proposed hybrid algorithm provided better results against non-hybrid MOGAs and other compared algorithms [12]. Ali Rıza Yildiz (2013a) presented a novel hybrid combination method based on artificial bee colony algorithm and Taguchi method. This approach was applied to a structural design optimization of a vehicle component and a multi-tooling optimization problem. This work improved the solution quality and reduced the computational efforts [13].

Ali Rıza Yildiz (2013b) presented a comparative study of six population-based optimization algorithms for optimal design of structures using differential evolution algorithm. The results of DE algorithm had given better solutions compared to genetic algorithm, particle swarm, immune algorithm, artificial bee colony algorithm [14]. Ali Rıza Yildiz (2013c) studied a hybrid artificial bee colony algorithm for the optimization of cutting parameters in the multi-pass turning operation. The results proved that HABC is highly competitive compared to other optimization method [15]. Ali Rıza Yildiz (2013d) focused the machining economies problem concerning the multi-pass turning operation by a hybrid differential evolution algorithm. It was found that the proposed algorithm performed quite well on optimization of machining parameters of turning operation finding better results compared to the other approaches [16]. Ali Rıza Yildiz (2013e) stated the new optimization algorithm, called the cuckoo search algorithm (CS). This algorithm was used for solving milling optimization problems. The results of CS algorithm proved that it is a very effective and robust approach for the optimization of machining optimization problems [17].

Ali Rıza Yildiz (2013f) presented a hybrid optimization algorithm for the optimization of machining parameters considering minimum production cost under a set of machining constraints in turning operation. The TLBO was performed quite well on the optimization of machining parameters of turning operation problem finding better solutions compared to other approaches [18]. Ali Rıza Yildiz (2012) presented a comparative study of ten population-based optimization algorithm for the multi-pass turning operation. It was found that DERE is an effective optimization technique compared to other approaches [19]. Morteza Kiani et al. (2015) discussed the efficiency of five well-known optimization algorithms which are differential evolution algorithm, artificial bee colony algorithm, particle swarm algorithm, and simulated annealing algorithm for crash-worthiness and NVH optimization of a full-scale high-fidelity of vehicle model [20]. Hakan Gökdağ and Ali R. Yildiz (2012) described the damage detection in structural elements by means of Particle Swarm Optimization algorithm (PSO). It was proved that modal flexibility is the best among the considered damage indexes. Also, the results show that PSO is an effective optimization approach in structural damage detection [21]. Ali R. Yildiz (2007) presented a new hybrid optimization approach based on immune algorithm and hill climbing local search algorithm. Significant improvements were observed using proposed algorithm compared with other optimization techniques [22].

Ali Rıza Yildiz (2013g) used differential evolution algorithm and receptor editing property immune system. The results of proposed optimization technique was compared with hybrid particle swarm, immune algorithm, hybrid immune algorithm, ant colony algorithm, genetic algorithm and it was found that the proposed optimization technique is more effective [23]. Ali Rıza Yildiz (2012) presented an innovative optimization approach to solve structural design optimization problems in the automotive industry.

The results indicated that the ability of the proposed approach to find better optimal solutions for structural design optimization problems [24]. Ali R. Yildiz (2009b) discussed a new hybrid optimization approach by combining immune algorithm and simulated annealing algorithm. The results showed that the optimization performance of AISA is better than that of the other optimization methods [25]. Ali Rıza Yildiz et al. (2004) discussed topology design and shape optimization approach was used to create an initial design concept which has optimal structural layout. Both compliance and vibration conditions are considered together to achieve an optimal topology. It was found single objective approach can lead to non-efficient design outlines [26]. Nursel Ozturk et al. (2006) described the integrated design optimization approach to improve the strength and performance of the design optimization process, to develop an integrated and optimized product design framework and to support the product design and optimization in CE [27]. Ali R. Yildiz (2008) used hybrid method combining immune algorithm with a hill climbing local search algorithm for solving complex real-world optimization problems [28c].

III. MATERIALS AND METHODOLOGY

In this presented work the mild steel containing 20% Carbon is used as work piece having the dimensions of 55×50×16mm. Experimental work has been carried out at Indo German Tool Room, Aurangabad, M.S India. All experimental work has been performed on CNC milling machine equipped with a maximum spindle speed of 12000 rpm, feed rate of 10 m/min and a 25-kW drive motor.

(a) (b)

Figure 1. (a) CNC Milling Machine (b) Surface Roughness Tester

TABLE I. Chemical composition of High Speed Steel Tool (wt %)

Element	C	Mn	Cr	Ni	Mo	W	S	P	Si	Co	V
%	1.14	0.37	4.33	0.17	9.25	1.35	0.009	0.015	0.46	8.09	1.60

The time is measured using stopwatch. The SR measurement is carried out using stylus type Profilometer at Micronics Calibration Centre, Chikhalthana MIDC, Aurangabad. Micronics Lab is a National accredited board for testing of laboratory and calibration. The range of surface tester is 0-100 μm and least count is 0.1μm. High Speed Steel tool having 4 flute parallel shank end mill cutter has been use to conduct the pilot experiment on a Hass-US five-axis, high-speed CNC milling machine. Figure 1 shows CNC milling machine. Figure 2 shows the surface roughness tester. The chemical composition of work piece and tool material has been tested at S N Metallurgy lab, MIDC, Waluj, Aurangabad, M.S. India. Table 1 and Table 2 show the chemical composition of High Speed Steel tool and AISI 1020 Mild Steel plate respectively. Table 3 shows the mechanical properties of AISI 1020 Mild Steel. Figure 3 and 4 shows High Speed Steel tool and AISI 1020 Mild Steel.

TABLE II. Chemical composition of 1020 AISI Mild Steel (wt %)

Element	C	Mn	Cr	Ni	Mo	S	P	Si
%	1.14	0.37	4.33	0.17	9.25	0.009	0.015	0.46

TABLE III. Mechanical Properties of 1020 AISI Mild Steel

Density (Kg/m^3)	Hardness (BHN)	Tensile strength (MPA)
7.850	115	750

A. Experimental Work

All experimental work has been performed at Indo German Tool Room, Aurangabad, M.S India on a Hass-US five-axis, high-speed CNC milling machine. In experimentation the machining parameters such as spindle speed, feed and depth of cut have been considered as input parameters whereas SR and MRR have been taken as output parameters. Table-4 show machining time, SR and MRR measured for different combination of spindle speed, feed and depth of cut.

B. Mathematical Model

Mathematical model is prepared for SR and MRR. The range of the values of machining parameters like vmin, vmax, fmin, fmax, dmin, dmax have been found out from knowledge of the machining limitations. The objective of this work is to predict optimized machining parameter and also to get the desired surface roughness values of AISI 1020 Mild steel from minimum machining time.

Also this work is to predict optimized machining parameter to achieve maximum material removal rate. Based on the effect of machining parameters on the responses, the surface roughness and material removal rate equations have been formulated in equation (1) and (2).

$$SR=V^{-0.054} f^{0.174} d^{0.15} \tag{1}$$

$$MRRR=V^{-0.220} f^{0.919} d^{0.958} \tag{2}$$

TABLE IV. Experimental results of machining time and surface roughness for the given machining parameters

Sr. No.	Cutting Speed (RPM)	Feed (m/min)	Depth of cut (mm)	Machining time (Sec)		Surface roughness (microns)	MRR (Wf-Wi) /ρ*tm(mm3/sec)
				Theoretical	Experimental		
1.	600	200	0.2	23	20.52	1.4	8.363
2.	600	200	0.4	23	20.26	1.5	12.572
3.	600	200	0.6	23	19.93	1.4	18.443
4.	600	250	0.2	18	16.19	1.2	4.033
5.	600	250	0.4	18	16.23	1.4	14.649
6.	600	250	0.6	18	16.01	1.5	21.514
7.	600	300	0.2	15	13.44	1.5	12.229
8.	600	300	0.4	15	13.30	1.6	17.409
9.	600	300	0.6	15	13.13	1.7	29.044
10.	700	200	0.2	23	19.09	1.3	7.089
11.	700	200	0.4	23	19.75	1.5	13.071
12.	700	200	0.6	23	19.6	1.7	17.003
13.	700	250	0.2	18	15.38	1.3	8.634
14.	700	250	0.4	18	15.40	1.6	15.074
15.	700	250	0.6	18	15.65	1.7	23.566
16.	700	300	0.2	15	13.21	1.5	9.596
17.	700	300	0.4	15	13.14	1.7	20.297
18.	700	300	0.6	15	13.15	1.7	28.1104
19.	800	200	0.2	23	19.05	1.3	5.427
20.	800	200	0.4	23	19.14	1.6	13.015
21.	800	200	0.6	23	19.32	1.6	18.609
22.	800	250	0.2	18	15.56	1.4	8.421
23.	800	250	0.4	18	15.68	1.6	15.074
24.	800	250	0.6	18	15.73	1.6	23.566
25.	800	300	0.2	15	13.03	1.5	10.53
26.	800	300	0.4	15	13.65	1.7	17.664
27.	800	300	0.6	15	13.03	1.8	29.214
28.	900	200	0.2	23	19.35	1.4	5.649
29.	900	200	0.4	23	19.59	1.6	11.631
30.	900	200	0.6	23	19.48	1.7	17.945
31.	900	250	0.2	18	15.56	1.3	8.138
32.	900	250	0.4	18	15.63	1.6	14.861
33.	900	250	0.6	18	15.71	1.7	23.425
34.	900	300	0.2	15	13.33	1.5	11.464
35.	900	300	0.4	15	13.76	1.7	21.316
36.	900	300	0.6	15	13.23	1.8	25.222

By varying the spindle speed in four levels and feed in three levels, depth of cut in levels, full factorial design of experimentation is performed. During experimentation the machining time has been calculated theoretically and counted practically for determination of material removal rate.

$$v_{min} \leq v \leq v_{max} \quad (3)$$

$$f_{min} \leq f \leq f_{max} \quad (4)$$

$$d_{min} \leq d \leq d_{max} \quad (5)$$

$$SR = SR_{desired} \quad (6)$$

$$MRR = MRR_{desired} \quad (7)$$

C. Proposed Methodology

Using machining handbook the suitable combination is prepared for experimentation. During literature survey it was observed that many researchers have used the different optimization techniques so far to find the optimum machining parameters.

It was also observed that the PSO technique always yielded best result as compared with other optimization technique.

a. Particle Swarm Optimization.-Overview

It is a population based stochastic optimization technique developed by Electrical Engineer Dr. Eberhart and Dr. James Kenedy in 1995. This optimization technique is based on principal of social psychological behavior of swarm. Particle Swarm Optimization is vary to implement and some of the parameters need to adjust. The algorithm can be explained on the scenario that there is food kept in the pot. There are number of birds which are searching for food in pot but they don't know where the food is? This bird is termed as particle and each has some velocity. The best solution achieved among all particles is called as 'particle best' and is referred as 'pbest', the best solution obtained among population called as 'global best' and is referred as 'gbest'. Once the two best solutions are found, then each particle updated its velocity and positions.

b. Procedure of PSO

Step 1: Population of 20 and 100 iterations are initialized.

Step 2: All the constant values such as vmin, vmax, fmin, fmax, dmin, dmax, desired surface roughness, co-efficient and constants used in surface roughness equation are initialized.

Step 3: Machining parameters within the limits are found using random numbers.

Step 4: Machining parameters are subjected to SR equation to ensure desired SR.

Step 5: Optimized machining parameters are checked for minimum machining time.

Step 6: Terminate if maximum number of populations are checked.

Step 7: Terminate; if maximum number of iterations are reached.

Step 8: End.

c. Parameters of PSO

The parameters of PSO technique used in the proposed mathematical model are given below.

Number of iteration performed: 100

Population : 20

Learning factor c1 : 2

Learning factor c2 : 2

Calculation of optimum machining parameters-

Spindle speed is calculated randomly within the limits using equation.

$$v = vmin + (vmax - vmin) \text{ rand }(\ ) \tag{8}$$

Similarly feed is also calculated randomly within the limits using equation.(9).

$$f = fmin + (fmax - fmin) \text{ rand }(\ ) \tag{9}$$

Similarly depth of cut is also calculated randomly within the limits using Equation (10).

$$d = dmin + (dmax - dmin)\text{rand}(\ ) \tag{10}$$

After satisfying Eq.(8), (9) and (10), the machining parameter values are substituted in Eq. (11) to check the given SR value obtained from the pilot experiment. Otherwise, the above steps should be repeated with new random numbers.

$$K (v\text{-}afbdc)=SRdesired \tag{11}$$

After satisfying Eq.(11), the optimized machining parameters are substituted in machining time Eq.(1). Otherwise, the above steps should be repeated with new random numbers.

Calculation of pbest value-

The required SR acquired in minimum machining time for each initial solution or for the present iteration is considered as the pbest value.

This is the best value of the particular solution only.

Calculation of gbest value-

The required surface roughness acquired in minimum machining time for the initial solution or for the whole iteration executed so far is considered as the gbest value.

Same procedure is adopted to determine optimum machining parameter on MRR.

IV. RESULT AND DISCUSSION

The effect of machining parameters on the SR and MRR has been studied. Total numbers of 36 trials have been conducted on AISI 1020 Mild steel and their corresponding values of SR and MRR were measured. Then optimization based on PSO was executed using MATLAB 7.5.0 software in which 100 iterations with 20 populations were used to run the program. The program has been performed to find out optimized machining parameters for the desired SR and MRR obtained from experiments. After conducting the experiments it is observed that the SR decreases with an increase in spindle speed and SR decreases with decrease in feed.

After optimization using PSO for surface roughness is only one output parameter, it is found that the desired SR value is 1.36774 µm at 900 RPM spindle speed, feed 200 m/min and 0.2mm depth of cut. Experimentally it is found to be 1.4 µm (trial no.30). Using PSO the effect of machining parameters was observed on MRR. It has been found that the MRR is 28.3629 mm^3/sec at 600 RPM spindle speed, feed 300 m/min and 0.6 mm depth of cut. During experimentation the value of MRR at 600 RPM spindle speed, feed 300 m/min and 0.6 mm depth of cut has been found to be 29.044 mm^3/sec (trial no.9).

There are two different cases explained above. First case is the effect of machining parameters on surface roughness only and second case is the effect of machining parameters on MRR only. The third and last case is considered to optimize the effect of machining parameters on SR and MRR combine. So in this case the different weighting has been given to SR and MRR, it has been observed that the different result is obtained. But considering equal proportion to both output parameters it has been found that 1.7689 µm SR and 28.3929 mm3/sec MRR at 600 RPM spindle speed, feed 300 m/min and 0.6 mm depth of cut. During experimentation the value of SR and MRR it has been found to be 1.7 µm and 29.044 mm^3/sec (trial no.9).

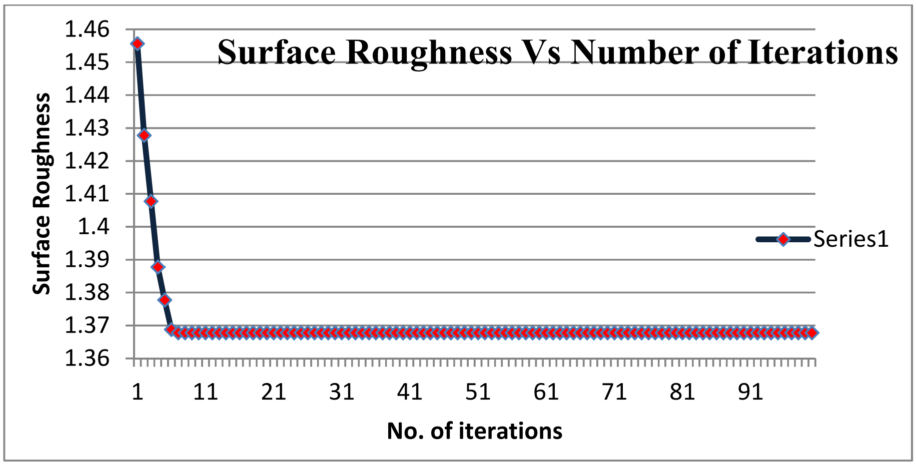

Figure 2. Graph Surface Roughnesses vs. Number of Iterations

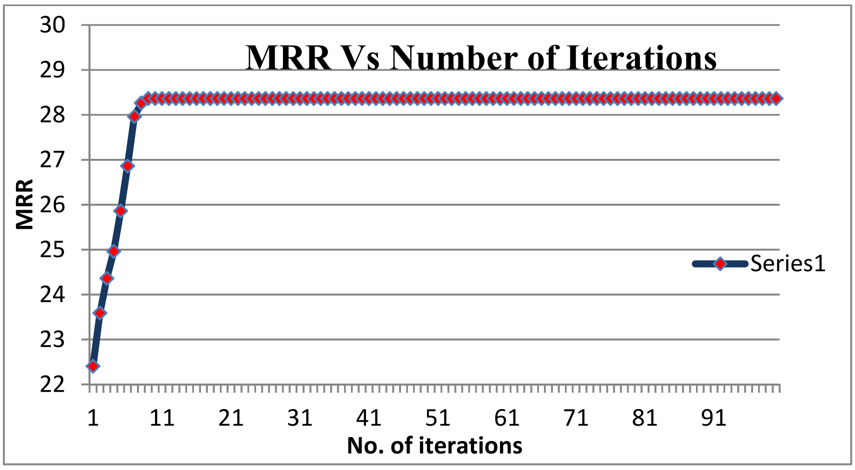

Figure 3. Graph Material Removal Rate vs. Number of Iterations

TABLE V. Combined results of PSO

Sr. No.	1	2	3	SR	MRR	Combined	w1	w2
1	900	200	0.2	1.36774	0	1.36774	1.0	0
2	600	300	0.6	1.7689	28.3929	-25.3497	0.1	0.9
3	600	300	0.6	1.7689	28.3929	-22.3365	0.2	0.8
4	600	300	0.6	1.7689	28.3929	-19.3233	0.3	0.7
5	600	300	0.6	1.7689	28.3929	-16.3101	0.4	0.6
6	600	300	0.6	1.7689	28.3929	-13.2969	0.5	0.5
7	600	300	0.6	1.7689	28.3929	-10.2838	0.6	0.4
8	600	300	0.6	1.7689	28.3929	-7.27058	0.7	0.3
9	600	300	0.6	1.7689	28.3929	-4.25739	0.8	0.2
10	600	300	0.6	1.7689	28.3929	-1.24421	0.9	0.1
11	600	300	0.6	0	28.3629	-28.3629	0.0	1.0

V. CONCLUSION

In this work the effects of machining parameters on AISI 1020 Mild Steel using High Speed Steel as a milling cutter has been studied. During this work the machining parameters of milling were optimized on the basis of maximum material removal rate and minimum surface roughness using Particle Swarm Optimization technique.

After optimization it is observed that the minimum surface roughness is found to be 1.36774 µm at 900 RPM spindle speed, feed 200m/min and 0.2mm depth of cut. Also the maximum material removal rate is found to be 28.3629 mm3/sec at 600 RPM spindle speed, feed 300 m/min and 0.6 mm depth of cut. During experimentation the value of surface roughness at 900 RPM spindle speed, feed 200m/min and 0.2mm depth of cut has been found to be 1.4 µm, whereas the material removal rate at 600 RPM spindle speed, feed 300 m/min and 0.6 mm depth of cut has been found to be 29.044 mm3/sec. It indicates that the Particle Swarm Optimization technique shows the best results. In combine optimization the different rank has been given to both output parameters and the different values of objective function have been

REFERENCES

[1] Sreenivasa Rao M, Venkaiah N (2015), “Parametric Optimization in Machining of Nimonic-263 Alloy using RSM and Particle Swarm Optimization, 2nd International Conference on Nanomaterials and Technologies (CNT 2014)”, *Procedia Materials Science*, pp.70 – 79.

[2] S. Bharathi Raja, N. Baskar (2012), “Application of Particle Swarm Optimization technique for achieving desired milled surface roughness in minimum machining time”, *Expert Systems with Applications*, pp.5982-5989.

[3] Hrelja Marko, Klancnik Simon (2014), “Turning Parameters Optimization Using Particle Swarm Optimization , 24th DAAAM International Symposium on Intelligent Manufacturing and Automation, 2013”, *Procedia Engineering* 69 (2014), pp.670 – 677.

[4] T. Tamizharasan, J Kingston (2014), “Optimization of Cutting Tool Geometry Based On Flank Wear-DOE, PSA, SAA Approach”, *Indian Journal of Engineering and Material Science,* Volume 21, pp.543-556.

[5] N. V. Mahesh Babu Talupula, Nersu Radhika (2015), “Experimental Investigation Of Optimal Machining Parameters Of Mild Steel In CNC Milling Using Particle Swarm Optimization”. *IPASJ International Journal of Computer Science (IIJCS),* Volume 3, Issue 1, January 2015, pp.13-28.

[6] Rajendra B, Deepak D (2015), “Optimization of Process Parameters for Increasing Material Removal Rate for Turning Al6061 Using S/N Ratio”, International Conference on Emerging Trends in Engineering, Science and Technology (ICETEST - 2015), Procedia Technology 24 (2016) pp.399 – 405.

[7] M. Nalbant, H. Gokkya, G. Sur (2007), “Application of Taguchi method in the optimization of cutting parameters for surface roughness in turning”, *Material and Desisn*, 28 (2007), pp.1379-1385.

[8] Girish Kant, Kuldip Singh Sangwan (2015), “Predictive Modeling for Power Consumption in Machining Using Artificial Intelligence Techniques”, *12th Global Conference on Sustainable Manufacturing, Procedia CIRP* 26 (2015), pp.403 – 407.

[9] Uros Zuperl, Franc Cus (2016), “End Milling Optimization Using Teaching-Learning Based Optimization Algorithm Combined With Cutting Force Model”, *Proceedings in Manufacturing Systems,* Volume 11, Issue 2, 2016, pp.57–62.
[10] R. Venkata Rao, V.D.Kalyankar (2013), “Multi-pass turning process parameter optimization using teaching–learning-based optimization algorithm”, *Scientia Iranica E (2013),* 20(3), pp.967-974.
[11] Ali Rıza Yildiz (2009a). “A novel particle swarm optimization approach for product design and manufacturing”, *International Journal of Advanced Manufacturing Technology,* 40, 5-6, pp. 617-628.
[12] Ali Rıza Yildiz, Nursel Öztürk & Necmettin Kaya & Ferruh Öztürk (2007),”Hybrid multi-objective shape design optimization using Taguchi's method and genetic algorithm”, *Structural and Multidisciplinary Optimization,* 34 (4), pp.317-332.
[13] Ali Rıza Yildiz (2013a), “A new hybrid bee colony optimization approach for robust optimal design and manufacturing”, *Applied Soft Computing,* 13, pp. 2906-2912.
[14] Ali Rıza Yildiz (2013b), “Comparison of evolutionary based optimization algorithms for structural design optimization”, *Engineering Applications of Artificial Intelligence,* Vol: 26, Issue 1, pp. 327-333.
[15] Ali Rıza Yildiz (2013c), “Optimization of cutting parameters in multi-pass turning using artificial bee colony-based approach”, *Information Sciences,* Vol: 220, pp. 399-407.
[16] Ali Rıza Yildiz (2013d), “Hybrid Taguchi-differential evolution algorithm for optimization of multi-pass turning operations”, *Applied Soft Computing*, Vol: 13, Issue: 3, pp. 1433-1439.
[17] Ali Rıza Yildiz (2013e), “Cuckoo search algorithm for the selection of optimal machining parameters in milling operations”, *International Journal of Advanced Manufacturing Technology*, Volume 64, Issue:1-4, pp.55-61.
[18] Ali Rıza Yildiz (2013f), “Optimization of multi-pass turning operations using hybrid teaching learning-based approach”, *The International Journal of Advanced Manufacturing Technology,* 66, 9-12, pp.1319-1326.
[19] Ali Rıza Yildiz (2012), “A comparative study of population-based optimization algorithms for turning operations”, *Information Sciences*, Volume 210, pp. 81-88.
[20] Morteza Kiani, Ali R. Yildiz (2015), “A Comparative Study of Non-traditional Methods for Vehicle Crashworthiness and NVH Optimization”, *Archives of Computational Methods in Engineering,* Volume 23, Issue 4, pp 723-734.
[21] Hakan Gökdağ and Ali R. Yildiz (2012), “Structural damage detection using modal parameters and particle swarm optimization”, *Materials Testing,* 54 (6), pp.416-420.
[22] Ali R. Yildiz (2007), “A novel hybrid immune algorithm for global optimization in design and manufacturing”, *Robotics and Computer-Integrated Manufacturing,* 25, 2, pp.261-270.
[23] Ali Rıza Yildiz (2013g), “A new hybrid differential evolution algorithm for the selection of optimal machining parameters in milling operations”, *Applied Soft Computing,* Volume- 13, Issue-3,pp. 1561-1566.
[24] Ali Rıza Yildiz (2012), “A new hybrid particle swarm optimization approach for structural design optimization in automotive industry”, *Journal of Automobile Engineering,* Vol: 226 Issue: D10, pp. 1340-1351.
[25] Ali R. Yildiz (2009b), “Hybrid immune-simulated annealing algorithm for optimal design and manufacturing”, *International Journal of Materials and Product Technology,* Volume-34, Issue-3, pp.217-226.
[26] Ali Rıza Yildiz, Necmettin Kaya and Ferruh Ozturk (2004), “Optimal design of vehicle components using topology design and optimization”, *International journal of vehicle design* 34 (4), pp.387-398.
[27] Nursel Ozturk, Ali R. Yıldız, Necmettin Kaya and Ferruh Ozturk (2006), “Neuro-genetic design optimization framework to support the integrated robust design optimization process in CE”, *Concurrent Engineering Research and Applications* 14 (1), pp.5-16.
[28] Ali R. Yildiz (2009c), “An effective hybrid immune-hill climbing optimization approach for solving design and manufacturing optimization problems in industry”, *Journal of Materials Processing Technology,* 50, 4, pp.224-228.