Optimization of Cutting Conditions in End Milling Process with the Approach of Particle Swarm Optimization

Vikas Pare, Geeta Agnihotri & C.M. Krishna

Mechanical Engineering Department, Maulana Azad National Institute of Technology, Bhopal, India
E-mail: vikaspare@yahoo.com, cmk_manit@rediffmail.com

Abstract - Milling is one of the progressive enhancements of miniaturized technologies which has wide range of application in industries and other related areas. Milling like any metal cutting operation is used with an objective of optimizing surface roughness at micro level and economic performance at macro level. In addition to surface finish, modern manufacturers do not want any compromise on the achievement of high quality, dimensional accuracy, high production rate, minimum wear on the cutting tools, cost saving and increase of the performance of the product with minimum environmental hazards. In order to optimize the surface finish, the empirical relationships between input and output variables should be established in order to predict the output. Optimization of these predictive models helps us to select appropriate input variables for achieving the best output performance. In this paper, four input variables are selected and surface roughness is taken as output variable. Particle swarm optimization technique is used for finding the optimum set of values of input variables and the results are compared with those obtained by GA optimization in the literature.

Keywords - *End milling, Process parameter optimization, Particle swarm optimization.*

I. INTRODUCTION

Surface roughness is one of the most important parameters to determine the quality of a product. Surface roughness consists of the fine irregularities of the surface texture, including feed marks generated by the machining process. The quality of a surface is significantly important factor in evaluating the productivity of machine tool and machined parts.

The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent. Several factors will influence the final surface roughness in a CNC end milling operation such as controllable factors (spindle speed, feed rate and depth of cut) and uncontrollable factors (tool geometry and material properties of both tool and work piece).

Parameter that affect surface roughness

- **Machining Parameters**

  1) Process Kinematics 2) Cutting Fluid 3) Depth of Cut 4) Feed Rate 5) Step over 6) Tool Angle 7) Cutting Speed.

- **Cutting Phenomenon**

  1) Friction in the cutting zone 2) Cutting Force Variation 3) Accelerations 4) Chip Formation

- **Work piece Properties**

  1) Hardness 2) Length 3) diameter

- **Cutting Tool Properties**

  1) Tool Material 2) Tool Shape 3) Nose Radius 4) Run out Errors

The output parameters other than surface roughness are:

1. Material removal rate
2. Tool life
3. Productivity
4. Quality
5. Machining time
6. Machining cost

Process optimization means the resources which are utilizing the process should be used effectively and efficiently at minimum cost & maximum output. In optimization, we focus on different parameters which govern the process. In present scenario, it is a matter of great concern in industry to achieve a good quality product at minimum cost.

The parameters affecting surface roughness are given in Figure-1. Many researchers worked by using the above methodology for optimization using various stochastic techniques in the past for conventional milling processes. However, very few researchers worked on high speed milling by using CNC milling machines. It is found that the prediction models for conventional machines and CNC differ as CNC milling is performed at relatively high speed. In this paper, a case study from the literature has been taken in which genetic algorithm was used as optimization. We used particle swarm optimization technique (PSO) is used for optimization and compared with the results obtained by genetic algorithm. This paper is divided into five sub-sections. In addition to introduction, this paper has relevant literature review in subsection 2. The experimental procedure and optimization is explained in sub-section 3. The results and analysis is explained in sub-section 4. The conclusions are drawn in sub-section 5.

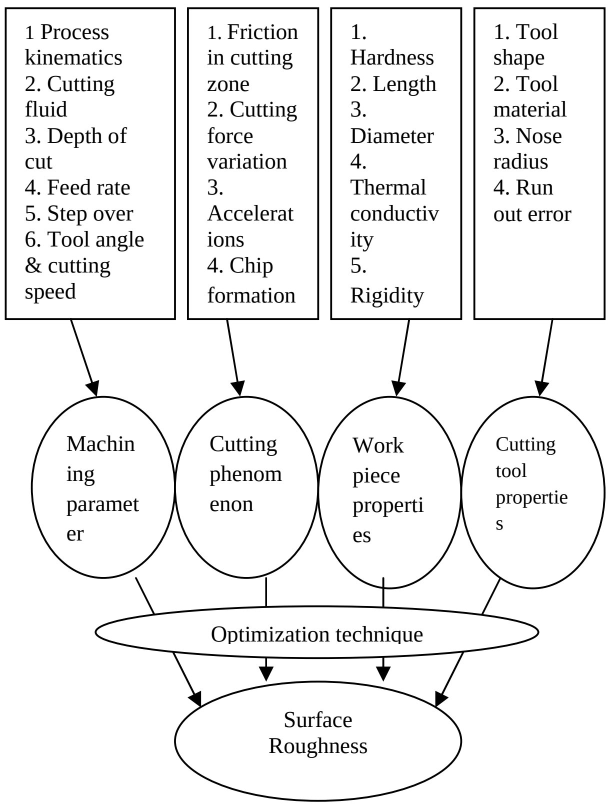

Fig.1: Parameters affecting surface roughness

II. LITERATURE REVIEW

Researchers gave major emphasis in traditional and non traditional optimization techniques in process optimization. They covered both single pass and multipass problems. On number of occasions, it was concluded that non-traditional or soft computing techniques give better results when compared with traditional optimization techniques. Soft computing differs from conventional (hard) computing in the sense that it is tolerant of imprecision, uncertainty, partial truth and approximation. Examples for soft computing techniques include mainly Neural Network (NN) and Fuzzy Logic (FL) and various search techniques such as particle swarm, ant colony optimization techniques.

Many eminent researchers from India such as, Saravanan R Baskar N., Asokan P., and Prabhaharan, G.[1] showed significant improvement in conventional milling process optimization by using various non conventional optimization techniques. They compared their results with the results obtained from hand books. However, in high speed milling process, Cus and Zuperl [2] used Particle Swarm optimization (PSO) and concluded that it is one of the best techniques. The goal of optimization in all the cases is to determine the minimum surface roughness by considering various constraints and input variables. Some researchers tried various combinations of cutting process parameters and nontraditional optimization techniques namely PSO, artificial be colony (ABC) and Simulated annealing (SA) are utilized efficiently to optimize various parameters.

Oktem and Erzurumlu [3] observed closeness in the results between experimental and predicted values in end milling process. They used neural network and genetic algorithm. Azlon zain, Haron and sharif [4] observed the effect of different parameter like cutting speed, feed and rake angle in surface roughness. They compared the result of regression modeling and genetic algorithm. I.N. Tansela, et al., [5] have taken three parameters namely cutting speed, feed rate and radial depth of cut for milling process and applied ANN. They obtained good agreement between predicted and actual values. Response surface methodology is another technique applied by researchers for developing predictive modeling for surface roughness.

Onwubolu & G.C [6] however used the Tribes optimization for determination of cutting parameters in multi pass milling process to obtain better results for a particular context. From the review of various papers, the optimization on milling process has started only in recent past. Most of the researchers in were using soft computing based optimization methods and found good results. The literature related to milling optimization is mainly concerned with minimization of surface roughness.

Alauddin, M., El Baradie, M. A., and Hashmi, M. S. J., [7] used cutting speed, feed and depth of cut which are three important parameters to predict the surface roughness.

Prakasvudhisarn & Siwaporn Kunnapapdeelert & Pisal Yenradee [8] introduced the new approach consist of two parts first one is machine learning technique called support vector machine to predict the surface roughness and second one is Particle swarm optimization technique for parameter optimization.

Chen and Savage used fuzzy net based model to predict surface roughness.

Particle swarm optimazation is used by Tandon, V., El-Mounayri. H. and Kishawy, H., [9] to optimize feed and speed CNC milling process. Wang, Z.G., Rahman, M., Wong, Y.S., Sun, J., (2004), [10] proposed Genetic Simulated annealing (GSA) to determine optimal machining parameters. Chandrasekaran, M., Muralidhar, M., Krishna, C.M., and Dixit, U.S., [11] have given the overall history the application of soft computing technique in machining performance prediction and optimization. Rao, R. V., Savsani, V. J., and Vakharia, D. P., [12] introduced a new optimization method known as Teaching – Learning Based Optimization (TLBO).This algorithm has not only solved many bench mark design problems and given effective and efficient result compared the result with other non-traditional optimization techniques such as PSO, ACO, SA, GA, etc. The results are compared for different performance criteria such as success rate, mean solution, average number of function evaluations required, convergence rate, etc.

Zarei, O., Fesangharyb, M., Farshia, B., JaliliSaffarb, R., Razfarb, M.R., [13] proposed a harmony search (HS) algorithm to estimate the optimum cutting parameters for multi-pass face-milling process to minimize total production cost. Mainly four cutting parameters namely cutting speed, feed depth of cut/pass and number of passes are considered in their work. Harmony search algorithm has given significant improvement in result as compare to GA. Asif Iqbal ,Ning He ,Liang Li,Naeem Ullah Dar [14] applied a fuzzy expert system in high speed milling process. The objective is to predict tool life and surface finish by optimize different parameter.

III. EXPERIMENTAL PROCEDURE AND OPTIMIZATION

The experimental procedure involves four stages viz., (i) Planning for the experiment, (ii) Collection of data by conducting experiments as per the plan, (iii) Establishment of prediction model for the selected output measure, and (iv) Optimization of the predictive model for better results. In the first stage, end milling operation is selected for study. Four input variables are selected as these variables are proved to have significant influence on the output measures such as surface roughness. Surface roughness is the output measure for our case. In the second stage, the data has been referred from the work done by Mohruni in the year 2008. He used annealed alpha beta titanium alloy Ti-6Al-4V (Ti-64) as work piece and three types of end mills were used in the experiment which was uncoated carbide and two TiAlN base coated carbide tools. As Mohruni used only three input variables, we conducted additional set of experiments by including fourth variable. The ranges of four parameters considered are given in Table-1.

With the help of regression modeling, equation developed by Zain, Haron and Shariff (2010) and these equations are

$$R_{uncoated} = 0.451 - 0.00267x1 + 5.671x2 + 0.0046x3$$

$$R_{TIAIN} = 0.292 - 0.000855x1 + 5.383x2 - 0.00553x3$$

$$R_{SNTR} = 0.237 - 0.00175x1 + 8.693x2 - 0.00159x3$$

He has taken three parameter namely speed, feed and rake angle and apply Genetic algorithm technique to optimize the surface roughness. The minimum value of surface roughness by applying GA is 0.138 for equation number 3.

Table 1: Ranges of different parameters

	Range
Surface roughness	
Cutting speed ,V	124.53<v<167.03
Feed rate, f	0.025<f<0.083
Radial rake angle, y	6.2<y<.14.8
Depth of cut	0.5<d<4

We used regression equation to establish a relationship between four selected input variables, such as, speed, feed, depth of cut and rake angle, and the output variable, surface roughness. The following relationships have been established:

$$R_{uncoated} = 0.451 - 0.00267x1 + 5.671x2 + 0.0046x3 + .469x4$$

$$R_{TIAIN} = 0.292 - .000855x1 + 5.383x2 - 0.00553x3 + .469x4$$

$$R_{SNTR} = 0.237 - 0.00175x1 + 8.693x2 - 0.00159x3 + .469x4$$

Where x1 refers to cutting speed of the tool, x2 refers to feed of the work piece, x3 refers to the rake angle of the tool, and x4 refers to depth of cut.

In the fourth stage, particle swarm optimization is used to optimize the predicted models given above. Particle swarm optimization is one of the soft computing which is extensively used in research work.

PSO was developed in 1995 by James Kennedy (social-psychologist) and Russell Eberhart (electrical engineer). It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle is treated as a point in a N-dimensional space which adjusts its “flying” according to its own flying experience as well as the flying experience of other particles. It is a relatively new technique for optimization of continuous non linear functions. It is easy to implement in a few line of computer code. It requires only primitive mathematical operators so is computationally inexpensive in terms of both memory requirement and speed. PSO is an evolutionary computation technique and has merits of both Genetic Algorithm and evolution strategies

GA is only helpful to solve combinatorial optimization problem on the other hand PSO effectively applied in both continuous optimization problem & combinatorial optimization problem.

In this experiment, we used 1000 number of iteration and used 50 number of particle. We have also tried to increase the number of iterations beyond 1000 but the end result is same. So we selected 1000 iterations. We have used 512 RAM and P4 computer. The program code is written in MATALB 10 version. The computational time is less than one minute. We can retrieve the result in a very short period of time so it is really very easy to apply and time saving technique.

IV. RESULTS AND DISCUSSION

In this paper, we applied PSO for three input parameter case in order to compare the results with Zain, Haron and Shariff (2010) to start with. The results obtained by PSO by taking rake angle in radians and degrees are given in Table-2 and Table-3.

Table 2: Optimum Values Obtained by PSO Method

(Three variable case and rake angle taken in radian)

Surface roughness	$R_{uncoated}$ = 0.088	R_{TIAIN} =0.177	R_{SNTR} = .0351
Cutting speed ,V	124.53	124.53	124.53
Feed rate, f	0.0025	0.0025	0.0025
Radial rake angle , y	0.1083	0.1083	0.1083

Table 3: Optimum Values Obtained by PSO Method

(Three variable case and rake angle taken in degree)

Surface roughness	$R_{uncoated}$ = .053	R_{TIAIN} =0.137	R_{SNTR} =0.0186
Cutting speed ,V	124.53	124.53	124.53
Feed rate, f	0 .0025	.0025	0 .0025
Radial rake angle , y	6.2	6.2	6.2

The result obtained is same in both cases and it indicates that application of PSO does not depend on the unit used for rake angle. The results obtained by PSO are superior to the results obtained by GA used by Zain et al., and it indicates that PSO is more suitable for problems of this category. However, depth of cut is also an important factor for surface roughness and it will be interesting to see its effect by adding this input variable. We included depth of cut as fourth input parameter and conducted and experiments and developed a regression relationship between surface roughness and four input parameters. The resultant equations are given in the previous sub-section. The surface roughness values for the three tools used for four variable case is given in **Table-4 and Table-5**. The surface roughness obtained is least in this case as compared to all other cases considered in this paper and the value is 0.32 microns.

Application of GA takes longer time than PSO and it is also proved that PSO gives better results.

Table 4: Optimum Values Obtained by PSO Method

(Four variable case and rake angle is taken in radian)

Surface roughness	$R_{uncoated}$ = .441	R_{TIAIN} =.552	R_{SNTR} = .372
Cutting speed ,V	166.02	159.82	144.25
Feed rate, f	0.029	0.0240	0.00264
Radial rake angle , y	0.2089	0.1987	0.221
Depth of cut	0.5715	0.5819	0.78

Table 5: Optimum Values Obtained by PSO Method

(Four variable case and rake angle is taken in degrees)

Surface roughness	$R_{uncoated}$ = .476	R_{TIAIN} =.453	R_{SNTR} = .3255
Cutting speed ,V	129.6	67.03	124.53
Feed rate, f	0.0140	0.011	0.0025
Radial rake angle , y	6.45	11.46	6.2
Depth of cut	0.5638	0.659	0.50

Here one interesting point we can note in same range of speed, feed, rake angle and depth of cut we are getting the different values of these four parameter for minimum surface roughness when compared to GA. When substituted the values in the objective function, we got better values for surface roughness.

V. CONCLUSION

There is lot of scope for application of particle swarm optimization (PSO) for these kind of problems by taking more number of input variables. It will be interesting to see the results for greater number of variables and trying various combinations of variables. In addition to PSO, application of Teaching learning based optimization (TLBO) is also used by various researchers in this field. Future extension of this work may be in the direction of applying TLBO and comparing the results for various cases. As the recent trends in research is in the area of micro manufacturing process like micro grinding, micro milling, micro drilling and laser application, application of PSO will help the industrialists to find the optimum values of input variables and work for longer periods without changing the manufacturing set up. The work can also be extended by taking output variables such as, material removal rate (MRR) , production cost etc., in addition to surface roughness.

REFERENCES

[1] Baskar, N., Asokan, P., Saravanan, R. and Prabhaharan, G., (2004), "Optimization of machining parameters for milling operations using Non-conventional methods", *Int J Adv Manuf. Technol.*, Vol. 25, pp. 1078–1088.

[2] F.Cus and Zuperl , Particle swarm intelligence based optimization of high speed End milling.

[3] Oktem and Erzurumlu 2006 "Prediction of minimum surface roughness in end milling mold parts using neural network and genetic algorithm" Vol 27,pp 735-744

[4] Haron and Shariff (2010) "Application of GA to optimize cutting condition for minimizing surface roughness in end milling machining process",Vol 37,pp 4650-4659

[5] I.N. Tansela,W.Y. Baoa, N.S. Reena, C.V. Kropas-Hughesb ,Genetic tool monitor (GTM) for micro-end-milling operations Oct 2004.International Journal of machine tools & manufacture ,volume 45,issue 3

[6] Onwubolu, G.C., (2006), "Performance-based optimization of multi-pass faces milling operations using Tribes" *Int. J. Mach. Tools and Manuf.*, Vol. 46, pp. 717-727.

[7] Alauddin, M., El Baradie, M. A., and Hashmi, M. S. J., (1995) "Computer-aided analysis of a surface-roughness model for end milling", *J. Mater. Process. Technol*, Vol. 55, pp. 123–127.

[8] Prakasvudhisarn & Siwaporn Kunnapapdeelert & Pisal Yenradee Optimal cutting condition determination for desired surface roughness in end milling May 2008

[9] Tandon, V., El-Mounayri. H. and Kishawy, H., (2002), "NC end milling optimization using evolutionary computation", *International Journal of Machine Tools & Manufacture*, Vol. 42, pp. 595–605.

[10] Wang, Z.G., Rahman, M., Wong, Y.S., Sun, J., (2004), "Optimization of multi-pass milling using genetic algorithm and genetic simulated annealing" *Int. J. Adv. Manuf. Techno.*, Vol. 24, pp. 727–732.

[11] Chandrasekaran, M., Muralidhar, M., Krishna, C.M., and Dixit, U.S., (2010), "Application of soft computing techniques in machining performance prediction and optimization: a literature review", *International Journal of Advanced Manufacturing Technology*, Vol. 46, Numbers 5–8, pp. 445–464.

[12] Rao, R. V., Savsani, V. J., and Vakharia, D. P., (2011), "Teacher – learning – based optimization: A novel method for constrained mechanical design optimization problems", *Computer – Aided Design*, Vol. 43, pp. 303–315.

[13] Zarei, O., Fesangharyb, M., Farshia, B., JaliliSaffarb, R., Razfarb, M.R., (2008), "Optimization of multi-pass face-milling via harmony search algorithm" *J. Mater. Process. Tech.*, Vol. 5, pp. 1–7.

[14] Asif Iqbal ,Ning He ,Liang Li,Naeem Ullah Dar A fuzzy expert system for optimizing parameters and predicting performance measures in hard-milling process Journal Expert Systems with Application May, 2007.

◈◈◈