OPTIMIZATION OF CNC FACE MILLING PROCESS PARAMETERS USING RESPONSE SURFACE METHODOLOGY AND PARTICLE SWARM OPTIMIZATION ALGORITHM

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ABSTRACT

In this research, multi-objective type of the Particle Swarm optimization algorithm, has been applied, for solving real world's complex problem. In this experimental research, parametric multi-objective optimization of computer numerical control (CNC) face milling on En-8 steel has been done using multi-objective Particle Swarm optimization method. The goal of this investigation is to optimize the process parameters like feed rate, depth of cut, spindle speed for responses like Material Removal Rate (MRR) and Surface Roughness (SR). A Full Factorial Design for three process parameters of three levels each, were selected to plan the experiments. Analysis of Variance (ANOVA) found significant process parameters affecting responses and also check validity of derived modal. In this work, multi-objective type of Particle Swarm Optimization (PSO) was also compared with single objective Particle Swarm optimization and obtained effective difference between both of the optimization results.

KEYWORDS: CNC Face Milling, En-8 Steel, Response Surface Methodology, Analysis of Variance & Particle Swarm Optimization

Received: Apr 15, 2020; **Accepted:** May 06, 2020; **Published:** May 21, 2020; **Paper Id.:** IJMPERDJUN202059

1. INTRODUCTION

Automation in manufacturing processes improve the productivity of modern manufacturing industries. With the help of Computer aided Manufacturing we can easily produce intricate products. Computer Aided Manufacturing processes produce high quality products in less time (Jayakrishnan Unnikrishna Pillai, 2018). Basically, milling process is a manufacturing process, by which we can produce flat, curved or complex surfaces, by feeding the workpiece against a rotating multiple edge cutter (Hemantsinh Pratapsinh Rao, April 2017). In this experimental work, a mixture of emulsion of synthetic oils in water is used as cutting fluid. Cutting fluid is used in CNC milling due to its following properties:

- cutting fluid is used to reduce friction at tool work interface, hence also reduces heat generated between them during machining.
- To wash away the burr during machining, when cutting fluid is used (Milon Selvam Dennison, 2019).
- CNC Milling is very Costly manufacturing process and used to machine precision parts of aeronautical components, hence it is necessary to optimize its process parameters (S. Bharathi Raja, 2012; Paramjit Thakur). In CNC milled final product, different machining performances optimize, like maximize MRR, minimize SR, minimize Overcut, minimize form and orientation tolerance error (N. Manikandan, 2020). In this present study, we have maximized MRR and minimized SR simultaneously. Azlan Mohd Zain et al

studied SR during end milling on Ti-6Al-4V, and SR optimized by Genetic Algorithm (Azlan Mohd Zain, 2010). A lot of work has been done on CNC end milling to optimize different process parameters like spindle speed, feed rate, depth of cut, cooling environment etc to obtain desired quality (Xuewei Zhang, 2019; M. Jebaraj, 2019; S. Sakthivelu, 2017; João Ribeiro, 2017). But CNC end milling on En-8 steel and its multi-objective optimization is very rare. Therefore, in this study CNC end milling perform on En-8 steel, while Experiments design by full factorial design, and process parameters are optimized by Particle Swarm Optimization.

EN-8 steel is broadly utilized material for universally useful axles, shafts, gears, bolts, and studs (Sunil J Raykar, 2014). In metal cutting, the surface roughness of an item is critical in deciding the quality. Minimum surface roughness not only improves quality but also reduces machining cost. Due to minimum surface roughness, assembly time get reduced and secondary operation avoided, hence operation time decreases, this results in overall machining cost reduction. Due to minimum surface roughness in products, their fatigue strength, creep life, and corrosion resistance improves (N. Satheesh Kumar, 2012).

Response Surface Methodology (RSM) is a technique, which is used for mathematical modelling and by statistical analysis finds relationship of process parameters with responses (Balasubramanian K, 2019). In RSM the relationship of input parameters with output responses are given by second order polynomial equation. It can be expressed as in equation 1.

$$Y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i < j} \sum_{j=2}^k \beta_{ij} x_i x_j + \sum_{j=1}^k \beta_{jj} x_j^2 \quad (1)$$

Here, β_0 is constant coefficient, β_i is linear constant, β_{jj} is quadratic effect constant, β_{ij} is interaction effect constant for response y (Gururaj Bolar, 2018; Xiaohong Lu, 2019).

Due to accurate modelling and experimental validation, RSM is being widely used as a design methodology. RSM is used to predict interaction and square terms of parameters for particular response. By 2D and 3D plots we can clearly visualize the effect of process parameters on responses (B. Bawono, 2019). With the help of ANOVA, we can also find the relative importance of machining parameters (Deshmukh, 2017). Hence goal of quality improvement, reduction of variability, improved process and product performance can be obtained through RSM (A. Arun Premnath, 2012).

Now-a-days, manufacturing industries are focussing, on producing high quality, low cost product in less time. Process parameters for optimum machining are selected either by operator's experience knowledge or by design data book. But, availability of valid design data is very rare. This is the main thing that encourage us for optimizing process parameters by full factorial design. Therefore, we also optimize the results by multi-objective nature inspired metaheuristic algorithm (Purohit, 2017).

Munish Kumar Gupta et al. have applied meta heuristic algorithms like PSO and Teaching-learning-based optimization (TLBO) to optimize responses. They found that these algorithms optimize better than traditional desirability approach (Munish Kumar Gupta, 2019). Diptikanta Das et al proposed multi objective PSO algorithm on the aluminium (Al) based metal matrix composite and found that the PSO outperformed the traditional Taguchi approach (Diptikanta Das, 2020). PSO can also accurately predict the responses and so there is good agreement between predicted and actual experimented responses on optimized process parameters (S. Bharathi Raja, 2012; Bobby Oedy Pramoedyo Soepangkat). PSO doesn't need a derivable objective function, so it is suitable for optimizing complex real-world problems (Dong-Dong Chen, 2019).

2. MATERIAL & EXPERIMENTAL PROCEDURE

In this experimental work, specimen of En-8 material of size 55mm*25mm*10mm was machined by high speed CNC vertical milling machine and machining time 1 minute was fixed for each specimen. The CNC face milling was done by MTAB MAX MILL PLUS of specification like spindle power 11kw, range of spindle speed 40-400 rpm, auto tool changer magazine capacity 20 tools, cutting feed rate 1-4000 mm/min, maximum tool diameter 80-125 mm. The CNC machining was conducted in presence of coolant (synthetic oil in water), while for circulating coolant, pump motor of 1.1 kW was used. Spindle speed, feed rate, depth of cut were the face milling parameters, and three levels were assigned for each of them, as presented in table 1.

Table 1: Face Milling Process Parameters and their Levels

Face Milling Parameters/Parametric Levels	Feed Rate (mm/min)	Depth of Cut (mm)	Spindle Speed (RPM)
Level 1	30	0.4	120
Level 2	35	0.5	160
Level 3	40	0.6	200

A full factorial design for three process parameters (of three level each) was used, so 32 experimental runs were performed to obtain optimised parametric setting. For performing each experiment, a new cutting edge was used. In this research, two responses like Material Removal Rate (MRR) and Surface Roughness (SR) were measured. For measuring MRR, initial weight of specimen before machining and final weight of specimen after machining, had measured by UNI BLOC PRECISION BALANCE (of milligram precision), while machining time measured by stopwatch. After this, we have calculated MRR in mm³/min by equation 2.

$$MRR = \left(\frac{W_i - W_f}{\rho \times T} \right) \text{mm}^3/\text{min} \quad (2)$$

Here, W_i = Before machining specimen's weight (in kg)

W_f = After machining specimen's weight (in kg)

T = Machining Time (in min.)

ρ = Density of En-8 steel (7.85×10^{-6} kg/mm³)

Surface Roughness was measured by SURFTEST SJ-210 Mitutoyo. During roughness measurement, we fixed assessment length of 4.00 mm, cut-off length of 0.8 mm, tip angle 600 and measuring force 0.75mN in Roughness tester.

3. RESULTS AND DISCUSSIONS

3.1 Investigation of Milling Performance

The effect of process parameters on responses like MRR & SR were analysed by Design Expert 10.0 software. Multi-objective PSO for optimising process parameters was performed, through MATLAB R2018a (version 9.4).

Figure 1: 3D Plots for MRR (a) Spindle Speed vs Depth of Cut, (b) Spindle Speed vs Feed Rate, (c) Depth of Cut vs Feed Rate (d) Perturbation Plot for MRR.

Figure 2: 3D Plots for SR (a) Spindle Speed vs Feed Rate, (b) Spindle Speed vs Depth of cut (c) Perturbation Plot for SR.

From the 3D plots & perturbation plots of MRR, it is clear that when spindle speed, feed rate and depth of cut increases, so MRR also increases due to high cutting energy. 3 D plots and perturbation plot of surface roughness reveal that at higher spindle speed, lower feed rate and lower depth of cut, we obtain minimum surface roughness. This is because, at higher spindle speed there is less tool-workpiece contact hence surface roughness reduces. Also, when there is low feed rate and lower depth of cut so friction get reduces hence surface quality not deteriorate.

3.2 Analysis of Variance

According to analysis of variance (ANOVA) for MRR, quadratic model is fitted with R-squared value 0.9246. The difference between Adj R-Squared (0.8938) and Pred R-Squared (0.8675) is very less, so it is indicating that quadratic

model is fitted accurately for MRR. Table 2 shows the Analysis of Variance (ANOVA) for MRR. The empirical model fitness for response is judged by F-value. Higher F-value of model indicates good fitness of model. Here, model F-value for MRR is 29.98 and lack of fit F-value is 0.64. Hence quadratic model for MRR is significant and their lack of fit is insignificant.

According to analysis of variance (ANOVA) for SR, quadratic model is fitted with R-squared value 0.996. The difference between Adj R-Squared (0.9943) and Pred R-Squared (0.9909) is very less, so it is indicating that quadratic model is fitted quite good for SR. Table 3 shows the Analysis of Variance (ANOVA) for SR. The empirical model fitness for response is judged by p-value. Lower p-value of model indicates good fitness of model. Here, model p-value for SR is <0.0001. Hence, quadratic model for SR is significant.

Table 2: Analysis of variance for MRR

Source	Sum of Squares	df	Mean Square	F Value	p-Value Prob > F
Model	2.02E+06	9	2.25E+05	29.98	< 0.0001-significant
A-Feed Rate	9.74E+05	1	9.74E+05	129.97	< 0.0001 -significant
B-Depth of Cut	3.698E+005 1	3	3.70E+05	49.35	< 0.0001-significant
C-Spindle Speed	4.96E+05	1	4.96E+05	66.19	< 0.0001
AB	38533.33	1	38533.33	5.14	0.0335
AC	64240.33	1	64240.33	8.57	0.0078
BC	2700	1	2700	0.36	0.5545
A ²	28699.74	1	28699.74	3.83	0.0632
B ²	25321.83	1	25321.83	3.38	0.0796
C ²	29450.03	1	29450.03	3.93	0.0601
Residual	1.65E+05	22	7493.69		
Lack of Fit	1.13E+05	17	6655.36	0.64	0.7740-Significant
Pure Error	51720	5	10344		
Cor Total	2.19E+06	31			

Table 3: Analysis of Variance for SR

Source	Sum of Squares	df	Mean Square	F Value	p-Value prob > F
Model	4.22	9	0.47	601.14	< 0.0001-Significant
A-Feed Rate	0.21	1	0.21	271.93	< 0.0001-Significant
B-Depth of	0.15	1	0.15	191.59	< 0.0001-Significant
C-Spindle Speed	3.73	1	3.73	4778.18	< 0.0001 -significant
AB	0.058	1	0.058	74.41	< 0.0001-Significant
AC	4.72E-03	1	4.72E-03	6.05	0.0223
BC	3.33E-03	1	3.33E-03	4.27	0.0508
A ²	8.12E-04	1	8.12E-04	1.04	0.3191
B ²	3.25E-03	1	3.25E-03	4.16	0.0535
C ²	0.065	1	0.065	83.29	< 0.0001 -significant
Residual	0.017	22	7.81E-04		
Lack of Fit	0.016	17	9.41E-04	3.99	0.0663 -Not Significant
Pure Error	1.18E-03	5	2.36E-04		
Cor Total	4.24	31			

3.3 Regression Analysis

Nonlinear regression models of MRR and SR were generated at 95% confidence level by Design Expert Software 10.0 using analysis of variance method. The Regression equations for MRR and SR, are shown in equation number 3 and

equation number 4. The normal probability plot of residuals indicate normal distribution of errors and linearity in it indicates that fluctuations is consistent for responses.

$$\text{MRR} = -2862.30466 + 339.07061 \times \text{Feed Rate} + 50.53763 \times \text{Depth of Cut} + 5.99691 \times \text{Spindle Speed} - 113.33333 \times \text{Feed Rate} \times \text{Depth of Cut} - 0.36583 \times \text{Feed Rate} \times \text{Spindle Speed} - 3.75000 \times \text{Depth of Cut} \times \text{Spindle Speed} - 2.53355 \times \text{Feed Rate}^2 + 5949.46237 \times \text{Depth of Cut}^2 + 0.040101 \times \text{Spindle Speed}^2. \quad (3)$$

$$\text{SR} = +6.14417 - 0.093549 \times \text{Feed Rate} - 6.75755 \times \text{Depth of Cut} + 2.13378\text{E-}003 \times \text{Spindle Speed} + 0.13917 \times \text{Feed Rate} \times \text{Depth of Cut} + 9.91667\text{E-}005 \times \text{Feed Rate} \times \text{Spindle Speed} + 4.16667\text{E-}003 \times \text{Depth of Cut} \times \text{Spindle Speed} + 4.26022\text{E-}004 \times \text{Feed Rate}^2 + 2.13172 \times \text{Depth of Cut}^2 - 5.95934\text{E-}005 \times \text{Spindle Speed}^2. \quad (4)$$

Figure 3: Normal Probability Plot of Residuals for (a) MRR, (b) SR.

3.4 Single Objective Optimisation

The responses like MRR & SR were optimized by single objective PSO (by varying global variable weightage). In this research, the goal of optimization is to maximize MRR and minimize SR. Convergence curve shows how quickly response is minimize with iterations. Convergence curve for MRR and SR are shown in figure 4. Maximum MRR 5527.92 mm³/min was found at parametric setting of 38.976 mm/min, 0.41 mm & 199 RPM. Minimum SR 2.001 micro meter was found at parametric setting of 30.033 mm/min, 0.422 mm & 191 RPM.

Figure 4: Convergence Curve for (a) MRR, (b) SR.

3.5 Multi-Objective Optimisation

MRR and SR were optimised simultaneously using multi-objective PSO algorithm. Equation 3 and 4 were used as fitness function and by varying global variable w_1 and w_2 value, we can change weightage for MRR and SR, simultaneously. The algorithm handles very smaller number of tuning parameters, so it takes very less computational time to give results. The algorithm parameter settings are shown in table 4. When we gave equal weightage to both the responses, then we found the MRR and SR of 5466.432 mm³/min and 2.579 micro meter respectively. The comparison of multi-objective PSO and single objective PSO is shown in table 5. Pareto Front diagram shows how the responses are correlated with each other. Pareto Front diagram and convergence diagram shown by figure 5 for multi-objective PSO. From Pareto Front diagram, it is clear that when MRR increase so SR also increases with it.

Table 4: Algorithm Tuning Parameters Setting for Multi-Objective PSO

Tuning Parameters	Values
Population size	300
Number of iterations	500
Global variable w_1	0 to 1
Global variable w_2	0 to 1
Phi_01	0.5
Phi_02	0.5

Table 5: Results of Comparison between full Factorial Design, PSO and Multi-Objective PSO

Methods Optimal Parametric Combination		Responses	
		MRR (mm ³ /min)	SR(μm)
Full Factorial	40mm/min, 0.6mm, 200RPM	5520	
Design	30mm/min, 0.4mm, 200RPM		2.023
PSO	38.9mm/min, 0.41mm, 199RPM	5527.9	
	30mm/min, 0.42mm, 191RPM		2.001
Multi-Objective PSO	38.7mm/min., 0.59mm, 189RPM	5466.432	2.579

Figure 5: (a) Pareto-front Diagram, (b) Convergence Curve for Non-Dominated Solutions of MRR and SR.

4. CONCLUSIONS

- During face milling of En8 steel in presence of coolant (emulsion of synthetic oil in water), the Material Removal Rate (MRR) increased on increasing any of the process parameters (i.e. feed rate, depth of cut and spindle speed). Surface Roughness of machined surface reduced on increasing speed but on increasing feed and high depth of cut, Surface Roughness increased.
- Results of ANOVA showed that feed rate is the most significant process parameters for MRR, followed by spindle speed and depth of cut. Most significant process parameter was spindle speed for average Surface Roughness followed by feed rate and depth of cut.
- Second order regression models of MRR and SR were fitted at 95% confidence level, and their adequacy were checked by normal probability plot of residuals.
- Multi-objective PSO gave better results when we require both MRR and SR optimized simultaneously. In this research, single objective PSO was compared with multi-objective PSO. This research reveals that multi-objective PSO can be used as a good choice to solve real world's multi-objective optimization problem.

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