Proceedings of the International Conference on Applied Mechanical Engineering Research (IC-AMER2019)
NIT Warangal, India – May 02-05, 2019
Paper No. XXX (The number assigned when the papaer is accepted)

PERFORMANCE IMPROVEMENT OF NANOFLUID MINIMUM QUANTITY LUBRICATION (NANOFLUID MQL) TECHNIQUE IN SURFACE GRINDING BY OPTIMIZATION USING JAYA ALGORITHM

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The recent industries are more concise about clean, green and sustainable machining process for better quality and productivity. Although the role of cutting fluids in grinding are crucial, but ecological and economic view, the consumption of cutting fluid should be minimum. The conventional cutting fluid is gradually replaced by new technology called nanofluid due to heat transfer and lubricating properties of nanoparticles. The effect of material hardness on grinding performance of EN31 material interms of surface roughness is determined for different cooling environments such as conventional flooded, MQL and Nanofluid MQL. The results show that the surface finish of hard material obtained is better in Nanofluid MQL at 0.30 vol.% concentration in comparison to conventional flooded, MQL and 0.15 vol.% . In present work modeling and optimization of process parameters of soft material is carried out using Jaya algorithm for better process performance. The process parameters such as table speed, depth of cut, dressing depth, coolant flow rate and nanofluid concentration are considered as input parameters for model development which is based on RSM (response surface methodology). The study demonstrates the validity of regression model by comparing the experimental test results with predicted values obtained from Jaya algorithm at optimal feasible values.

***Keywords*:** Cooling environments, Jaya algorithm, Modeling, Surface roughness

1. Introduction

The large amount of heat generates during grinding at contact interface is due to complex material removal mechanism and abrasive workpiece contact for microseconds. It affects on workpiece quality, tool life, consumption of specific energy and finally on machine efficiency. A large usage of cutting fluid to dissipate heat for cooling is harmful to environment, human operator and also it is uneconomical. The different problems related to high consumption of cutting fluid are stated in paper [1]. The minimum quantity lubrication (MQL) technique in which the small amount of cutting fluid penetrates in mist form with compressed air at contact interface. The results are better compared to conventional flooded but lubricating effects is less due to poor lubricating property of soluble oil as cutting fluid. Recently Nanofluid MQL technique is more cost effective, eco and human friendly [2-4]. The features of nanoparticles are large relative surface area, high mobility and better suspension stability [5-6]. The application of nanofluid and nanofluid based MQL technique (Nanofluid MQL) can reduce the friction, cutting forces and temperature in cutting region due to better heat transfer and tribological characteristics of nanoparticles and better penetration of cutting fluid into contact area using MQL approach [7-10]. The influence of workpiece hardness on performance of MQL technique is studied in paper [11].

From literature study it is observed that the traditional method of optimization can use to find the optimal values of process parameters but the accurate guess of initial solution is not possible and may trap into local optima. The problem is more critical in Nanofluid MQL process of grinding where numbers of parameters are involved. To overcome these limitations, Jaya algorithm is used for optimization and more simply execution. It has only one phase and does not require any algorithm specific parameter for optimization [13].

In present study, the performance of EN31 hard and soft steel interms of surface roughness is analysed experimentally using response surface methodology. The main purpose of this work is to study the Nanofluid MQL technique to improve the performance of soft steel by developing the mathematical model. The mathematic model is treated as fitness function evaluation in Jaya algorithm for finding optimal parameters value.

2. Experimental procedure

Experiments were conducted on hard and soft EN31 rectangular plate of size 100* 50* 25 mm using hydraulic surface grinding machine. The grinding wheel of size 350* 50* 75.2 mm having specification A46-3-L5-V8 is used for experimentation. The soluble oil of ratio 1:20 was used as a cutting fluid for conventional/wet and MQL experiments. The water based Al_2O_3 nanofluid of 0.15 and 0.30 vol. % concentrations were used for Nanofluid MQL experimentation. The concentration (0) indicates the experiments are conducted using MQL technique. The average values of responses were considered for analysis. The EN31 steel extensively used to manufacture the drawing dies and moulds for various forming operations. The good tolerance and better surface finish in dies and moulds is basic requirement which is mainly depends on material selection. The parameters and their levels are shown in Table 1. The experiments are conducted as per design matrix obtained by Response Surface Methodology (RSM) using Minitab 17 software. The minimum experimental runs are determined considering the statistical technique called design of experiments [14]. The photograph of experimental setup is shown in Fig. 1.

Table. 1. Levels of process parameters

Level	Table speed (mm/min)	Depth of cut (μm)	Dressing depth (μm)	Coolant flow rate (ml/hr)	Nanofluid concentration (vol. %)
Low	7000	20	10	250	0
Medium	10000	30	20	500	0.15
High	13000	40	30	750	0.30

Fig.1. Experimental setup

The surface finish which determines performance and service life of machine components was measured in terms of Ra value at three points along the grinding direction. The SJ-201 type surface roughness tester is used to measure the surface roughness. The speed and sampling length of SJ-210 tester was 0.5 mm/s and 2 mm respectively.

3. Results and discussion

The tangential force (Ft) and normal force (Fn) generated during grinding significantly affects on machine performance. The tangential force is generated along the reciprocating movement of worktable and increases with increase in friction whereas the normal force is exerted to the work surface and mostly affected by workpiece hardness. The low value of coefficient of friction is obtained in hard material due to less tangential force develops as better effects of cutting fluid at contact zone. The better improvement of surface roughness is observed in hard steel compared to EN31 soft material in Nanofluid MQL technique may be due to better penetration and lubricity of cutting fluid at contact interface. The slurry effect of lubrication occurs under compressed air pressure on the ground surface. It helps to restore the sharpness of grits better than soluble cutting fluid. The material removal is more shearing in hard material whereas in soft material the material removal is more plastic deformation due to ductility nature of material. Thus it is necessity to optimize the machining parameters for improving the surface roughness of soft material.

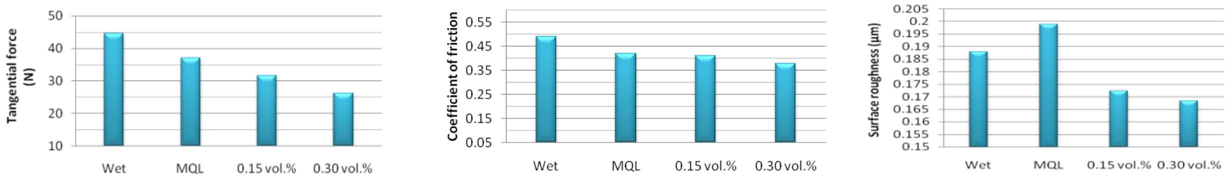

Fig. 2. Grinding parameters under different cutting environments (hard steel): (a)Tangential force (b) coefficient of friction (c) surface roughness

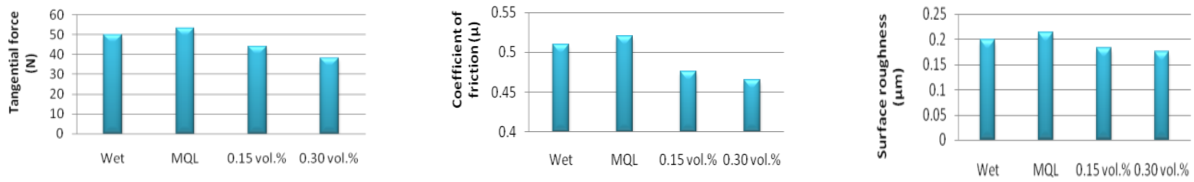

Fig. 3. Grinding parameters under different cutting environments (soft steel): (a)Tangential force (b) coefficient of friction (c) surface roughness

3.1 Development of mathematical model

The quadratic model of surface roughness is developed using RSM. The equation of surface roughness (Ra) in coded form is given in Eq (1). The input factors are coded as table speed (x_1), depth of cut (x_2), dressing depth (x_3), coolant flow rate (x_4) and nanofluid concentration (x_5).

$$Surface\ roughness\ (Ra) = 0.13301 + 0.000009\, x_1 + 0.000628\, x_2 - 0.000424\, x_3 - 0.000049\, x_4 - 0.2187\, x_5 + 0.5461\, x_5 * x_5 - 0.000011\, x_1 * x_5 + 0.000001\, x_3 * x_4 + 0.000078\, x_4 * x_5 \quad (1)$$

The analysis of variance (ANOVA) of response surface quadratic model of surface roughness shows the multiple regression coefficients (R^2) value of 0.9797. The pred R-squared value 0.9605 is also in reasonable agreement with adj R^2 value 0.9715. The value indicates that the model well fitted the data. The P-value of model in ANOVA is less than 0.05, indicates the model terms are significant. The lack of fit is not significant. This shows that the model is adequate to study the relationship between response parameter in concerned with machining process parameters. The papers [15-18] were reviewed on modeling and optimization for determining the optimal machining process parameters.

3.2 Optimization using Jaya algorithm

From literature studies it was observed that all the evolutionary algorithms are probabilistic and requires common controlling parameters like population size and the number of iterations. Beside common control parameters, different algorithms require their own algorithm specific control parameters. The improper tuning of algorithm specific parameters either increases the computational effort or yields local optimal solution. The proposed JAYA algorithm does not have any algorithm specific parameters, simplicity and ability to get optimal solutions with less number of function evaluations [19-22]. The optimal value of process parameters is determined for soft steel using Jaya algorithm.

$$X'_{m,n,i} = X_{m,n,i} + r_{1,m,i}\left(X_{m,best,i} - \left|X_{m,n,i}\right|\right) - r_{2,m,i}\left(X_{m,worst,i} - \left|X_{m,n,i}\right|\right) \quad (2)$$

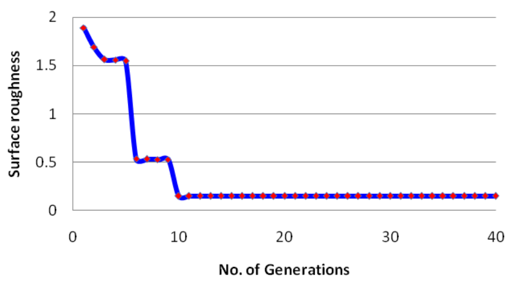

Fig. 4. Convergence curve of surface roughness

where, $r_{1,l,i}$,and $r_{2,l,i}$ are the two random numbers for $'m'$ variable during i^{th} iteration in the range of [0,1]. The term "$r_{1,m,i}\left(X_{m,best,i} - \left|X_{m,n,i}\right|\right)$" indicates the tendency of solution to move closer to the best solution and the term "$r_{2,m,i}\left(X_{m,worst,i} - \left|X_{m,n,i}\right|\right)$" shows the ability of solution to avoid the worst solution. $X'_{m,n,i}$ accepted if it gives a superior function value. All the accepted function values at the end of iteration are considered as input to the next iteration. The algorithm tries to get best optimal solution and rejects the worst solution. The absolute value of $X_{m,n,i}$ is considered in Eq. (2). The objective function is subjected to significant parameter and range constraints such as $7000 \le x_1 \le 13000$; $20 \le x_2 \le 40$, $10 \le x_3 \le 30$; $250 \le x_4 \le 750$ and $0 \le x_5 \le 0.30$. The convergence curve to optimize the surface roughness is shown in Fig.4. The confirmation experiments were conducted at feasible optimal values obtained from Jaya algorithm such as table speed (7000 mm/min), depth of cut (20 µm), dressing depth (10 µm), coolant flow rate (750 ml/hr) and nanofluid concentration (0.22 vol.%). It was also observed that percentage error of surface roughness is 4.51%. The good agreement in result of surface roughness is obtained of predicted value from Jaya algorithm and experimental value.

4. Conclusions

The present work analyzed the modeling and optimization of Nanofluid MQL process of soft steel material to improve the performance in terms of surface roughness using Jaya algorithm. Based on current investigations, the following findings are summarized as follows:

(1) The significant reduction of surface roughness is observed by 14% in Nanofluid MQL at 0.30 vol. % concentration over conventional flooded technique for hard steel. The better cooling and lubrication effect at contact interface and stable nanofluid may be the reasons to obtain better surface quality. In case of soft steel, the surface roughness is worst in comparison to hard steel for

all cutting environments. The higher material deformation due to ductility of material may be the reason for poor value.
(2) The second order quadratic model of surface roughness is developed for significant parameters and its adequacy is checked by analysis of variance to predict the response at 95% confidence interval. The optimal values using jaya algorithm for nanofluid MQL obtained are table speed (7000 mm/min), depth of cut (20 µm), dressing depth (10 µm), coolant flow rate (750 ml/hr) and nanofluid concentration (0.22 vol.%). The convergence speed of Jaya algorithm is very high and optimal surface roughness value obtained in less function evaluations.
(3)The actual experiments were conducted at optimal feasible values obtained from Jaya algorithm to validate the results. The percentage error of 5.49 % is observed of predicted value obtained by Jaya algorithm (0.14933 µm) and experimental value (0.158 µm) for surface roughness.

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