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EFFECT OF MINIMUM QUANTITY LUBRICATION ON SURFACE ROUGHNESS AND TEMPERATURE IN MILLING OF EN31 STEEL FOR DIE MAKING

KEERTHANA Bhosetty[1], VIJAYA KUMAR Gurram[2], ANAND BABU Kumba[3]

[1]*SVU College of Engineering, Department of Mechanical Engineering, Tirupati,517502, Andhrapradesh, India, e-mail:* bubbly.keethu@gmail.com
[2]*SVU College of Engineering, Department of Mechanical Engineering, Tirupati,517502, Andhrapradesh, India, e-mail: vijayluther2003@gmail.com*
[3] *SVU College of Engineering, Department of Mechanical Engineering, Tirupati,517502, Andhrapradesh, India, e-mail: kumba.anand@gmail.com*

Abstract: Minimum Quantity Lubrication has enormous influence on the process parameters in machining. The main aim of the present work is to study the effects of spindle speed, depth of cut, tool material, amount of coolant dispensed and type of coolant on surface roughness and tool temperature in EN31 steel die making including Minimum Quantity Lubrication (MQL) by introducing a self-designed MQL setup and to optimize the responses using fuzzy-logic and Particle Swarm Optimization technique.

KEYWORDS: MQL, EN31 steel die making surface roughness and tool temperature, fuzzy-logic and Particle Swarm Optimization technique

1 INTRODUCTION

Although Non-traditional machining process are playing major role in machining industry, conventional milling process remains its importance as it is flexible in cutting keyways and slots etc.. In other hand Minimum Quantity Lubrication (MQL) refers a small amount (50-5600ml/hr) of lubricant dispensing system which is the substitute for the flood type lubricating system which dispenses 200 L/h of lubricant and causes the soil as well the water contamination. ``Minimum quantity lubrication (MQL) stands to be one of the most suitable techniques for cooling and lubricating the most conventional machining processes like milling, turning etc., In MQL a very small quantity of lubricant directed towards the cutting zone, [1] studied the effects of MQL on surface roughness the full sample set exhibited good surface finish conditions. The STD among the samples was 0.04 μ m and thus concluded that the MQL settings do not have a significant effect on the surface roughness. 900ml/hr of lubrication dispensing is achieved with self-designed MQL setup for end milling, where lubricant and air is mixed by MQL set up which is based on spray gun concept [2]. The effects of MQL on tool wear, job dimension and surface finish in turning AISI-1040 Steel, MQL appeared to be effective in reducing surface roughness. However, it is evident that MQL improves surface finish depending upon the work-tool materials and mainly through controlling the deterioration of the auxiliary cutting edge by abrasion, chipping and built-up edge formation [3]. Taguchi’s orthogonal array is well structured technique for Planning of experiments to study the entire parameter space with a reduced number of experiments [4, 5]. When investigated the Surface Roughness in Drilling of Al 7075/10% - SiCp Composite with uncoated and coated HSS tools under MQL Condition using Fuzzy Logic. Results exhibits that turning with MQL is a good alternative for conventional lubrication [6]. the traditional and non-traditional methods are studied for die making and [7] selected milling for machining of En-24, [8] investigated high speed milling process for die-cast manufacturing and increased quality, accuracy and speed of material processing, also reduced processing costs and saves

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machining time, [9] investigated and obtained a set of optimal machining parameters (i.e., spindle speed, depth of cut and feed rate) for face milling operations in order to minimize the surface roughness and to maximize the material removal rate using response surface methodology and are compared to the experimental results. En 31 steel has high resisting nature against wear and can be used for components which are subjected to severe abrasion, wear or high surface loading, good ductility and shock resisting, high degree of hardness with compressive strength and abrasion resistance, better tensile strength. En 31 steel has better mechanical, physical and thermal when compared to all engineering materials such as En 8, En 24, En 36 etc., [10] conducted experiments on machining of En 31 steel with different electrode materials (copper, brass and graphite) with electric discharge machining (EDM). [11] Focused on the analysis of optimum cutting conditions to get the lowest surface roughness and maximum material removal rate in CNC turning of different grades of EN materials. It shows that positive inserts are better than the negative inserts and EN-31 materials are superior to EN-8 for MRR. [12] carried out experimental work in electrical discharge machining (EDM) on EN31 (air hardened steel) using three different tool materials namely copper, aluminium and EN24, and also the problems involved in using graphite and brass as tool material are investigated. Various methods can be used to study the influences of process parameters on responses such as Response surface Methodology (RSM) Taguchi Based Desirability method, fuzzy based Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) [13, 14, 15, 21]. The developed flexible classification algorithm by applying PSO to inventory classification is utilized as a single objective algorithm for cost minimization, demand correlation maximization, or inventory turnover ratio maximization [16]. Numerical studies were conducted by [17], and the classification performance of the PSO algorithm was comparable to other approaches. [18] Studied the significance of process parameters Pulse on time, pulse off time, peak current and servo voltage by applying ANOVA analysis for both MRR and SR. The optimal response values from RSM and PSO are compared. It is found that, the results of PSO are better than that of RSM, [19] compared genetic algorithms (GA) and simulated annealing (SA), and the proposed algorithm can improve the quality of the solution while speeding up the convergence process. Particle Swarm Optimization Technique is proved to be an efficient optimization algorithm when[20] conducted WEDM experiments on Monel 400 using Ezeecut NXG CNC WEDM and optimize the MRR and SR using PSO. When compared the relative performances of fuzzy based Particle Swarm Optimization (PSO) with Genetic Algorithm (GA), in the results the fuzzy based PSO system exhibits an improved holding ability than GA [21].

2 DESIGN AND WORKING OF MQL SETUP

As there are many setups are existing for maintaining minimum quantity lubrication which are of high cost and consume more space, for this work a setup is designed for maintaining minimum quantity lubrication which is more economical than other systems and is found to be best. The milling experiments are conducted on En-31 material for making die using solid carbide tool and HSS tools under MQL condition and the responses are optimized using particle swarm optimization and fuzzy logic methods and are compared. This prepared setup is tested many times for maintaining the lubricant as minimum as possible and for making the mist lubricant that it reaches the heat affected zone of the milling operations. In accordance to working procedure of the MQL setup, a cyclic timer connect to the compressor, which controls the power supply of compressor starts and stops according to the time that has been set in the cyclic timer i.e., 10sec. The air from compressor comes and lubricant from lubricant chamber comes simultaneously. At the end the air pressures the lubricant to impinge on to the work tool interface through the nozzle. The control valves control the air and coolant to the minimum required level. From this we obtained minimum of lubricant dispensed of 35ml/hr.

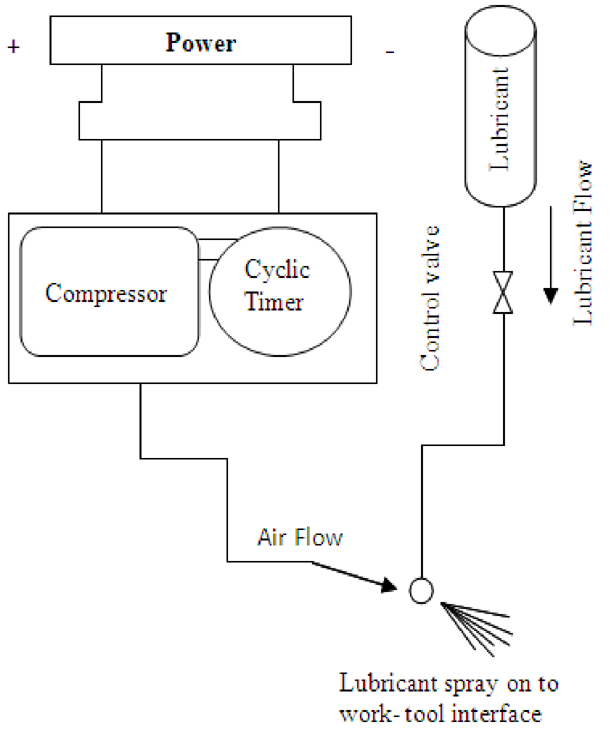

Fig. 1 MQL setup

Fig. 2 I-section machined En 31 material

3 EXPERIMENTAL WORK

For this work, the milling operations were conducted on En 31 material, as per L18 orthogonal array which is designed using Minitab software by considering the parameters and their levels of Table 1 which influence the Milling process. Experiments were performed on 500 x 80x 32mm sized work piece in vertical milling machine. The work material is high hardened alloy steel with high resistance to wear, ductility and tensile strength. For machining of these hard material En 31, solid carbide and High-speed steel (HSS) are used during milling. Chemical composition of En 31 was given in Table2. The Experimental setup of milling process is shown in Fig.1. ASTM 370 Standards are considered for making I- Section and is made on the work material based on orthogonal array L18. The responses: Surface roughness and temperature are recorded in Table 3 by measuring with the help of talysurf and pyrometer for each experimental run.

Table 1: Process Parameters and their Levels

Name of the Parameter	Parameters Levels		
	level 1	level 2	level 3
Tool Material (TM)	HSS	SC	
Speed (S in rpm)	150	185	275
Depth Of Cut (DOC in mm)	0.25	0.5	0.75
Coolant Type (CT)	50%W in SO	60% Win SO	70% Win SO
Amount of Coolant Dispensed (ACD)	50ml/hr	100ml/hr	150ml/hr

*Note: W in SO –Water in Soluble Oil, HSS- High Speed Steel, SC- Solid Carbide

Table 2: Chemical composition of En 31 alloy steel

Steel Material	Chemical Composition in %					
	C	Mn	Si	S	P	Cr
EN 31	0.9	0.3	0.10	0.4	0.4	1.0

Table 3: Experimental design and measured Response values

Experimental design						responses								Fuzzy Grade
						Surface Roughness (μm)				Tool Temp (^{0}C)				
Ex No	TM	S (rpm)	DOC (mm)	CT (W in SO)	ACD ml/hr	Trial 1	Trial 2	Trial 3	Avg.	Trial 1	Trial 2	Trial 3	Avg.	
1	HSS	150	0.25	50%	50	0.75	0.88	0.83	0.82	31.5	32.1	31.5	31.7	0.6344
2	HSS	150	0.5	60%	100	1.15	1.25	1.2	1.2	32.7	33.5	32.8	33	0.2805
3	HSS	150	0.75	70%	150	1.08	1.12	1.22	1.14	34.3	33.7	34.6	34.2	0.2514
4	HSS	185	0.25	50%	100	0.54	0.58	0.56	0.56	32.8	33.5	34.2	33.5	0.5224
5	HSS	185	0.5	60%	150	0.78	0.76	0.86	0.8	31.4	31.8	31.3	31.5	0.696
6	HSS	185	0.75	70%	50	0.24	0.26	0.25	0.25	32.8	34.2	33.5	33.5	0.6677
7	HSS	275	0.25	60%	50	0.62	0.68	0.74	0.68	32.9	34.6	33.9	33.8	0.4208
8	HSS	275	0.5	70%	100	0.25	0.28	0.31	0.28	32.2	32.2	32.2	32.2	0.7464
9	HSS	275	0.75	50%	150	0.42	0.47	0.49	0.46	31.5	32.3	31.3	31.7	0.7371
10	SC	150	0.25	70%	150	0.34	0.39	0.41	0.38	32.8	33.6	33.2	33.2	0.6511
11	SC	150	0.5	50%	50	0.31	0.35	0.3	0.32	32.1	32.2	32.1	32.2	0.7221
12	SC	150	0.75	60%	100	0.38	0.42	0.46	0.42	33.2	33.4	33.6	33.4	0.5917
13	SC	185	0.25	60%	150	0.68	0.72	0.7	0.7	32.8	32.5	33.4	32.9	0.5482
14	SC	185	0.5	70%	50	0.21	0.23	0.25	0.23	32.5	32.7	32.9	32.7	0.7602
15	SC	185	0.75	50%	100	0.27	0.33	0.3	0.3	31.8	32.3	32.8	32.3	0.7291
16	SC	275	0.25	70%	100	0.2	0.26	0.23	0.23	33.8	34.1	34.4	34.1	0.6098
17	SC	275	0.5	50%	150	0.3	0.35	0.31	0.32	32.7	34.2	33.6	33.5	0.6128
18	SC	275	0.75	60%	50	0.38	0.4	0.42	0.4	34.5	34.7	35.2	34.8	0.4052

Table 4. The fuzzy grade for each parameter at each level

Level	TM	S	DOC	CT	ACD
1	0.550744	0.5217	0.56445	0.659483	0.601567
2	0.625467	0.653933	0.636167	0.4904	0.579983
3	0.588683	0.5637	0.614433	0.582767	
Delta	0.074722	0.132233	0.072467	0.169083	0.021583
Rank	3	2	4	1	5

4 OPTIMIZATION OF THE RESPONSES

The experimental responses were optimized using the fuzzy logic technique and particle swarm optimization technique

4.1 Fuzzy logic technique

Responses are optimized using fuzzy-logic technique and fuzzy-logic is performed using mat-lab software. The fuzzy grade is tabulated in the table3 and it is calculated for each parameter at each level as tabulated in table4 and shown in fig.3. From the optimization based on Fuzzy, with reference to thefigure3, the optimal conditions can be noted as

Tool material at level 2 i.e. SC tool,

Speed at level 2 i.e. 185rpm,

Depth Of Cut at level 2, i.e. 0.5mm,

Coolant Type at level 3, i.e. 70% water in soluble oil and

Amount of Coolant Dispensed at level 1, i.e. 50ml/hr.

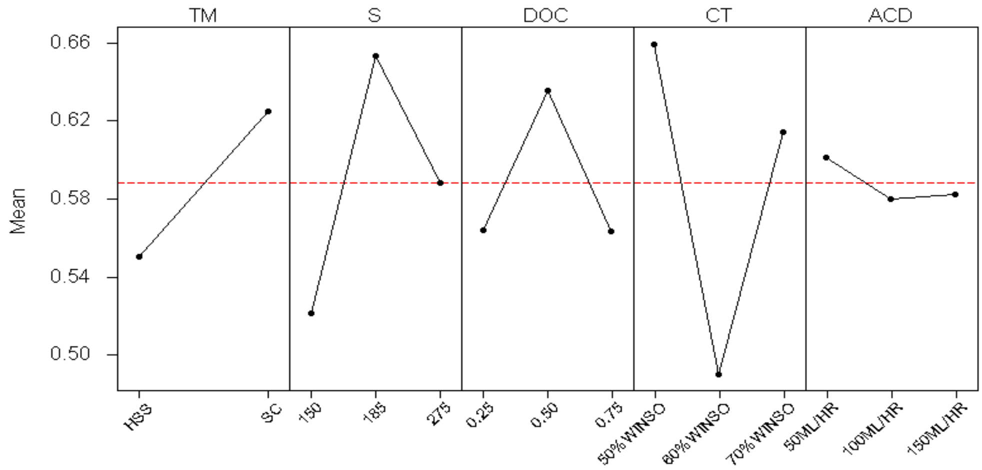

Fig.3. The fuzzy grade for each parameter at each level

*Note: TM: Tool Material, S: Speed, DOC: Depth of Cut, CT: Coolant Type, ACD: Amount of Coolant Dispensed, HSS: High Speed Steel, SC: Solid Carbide W in SO: Water in Soluble Oil.

4.2 Particle swarm optimization

As a foremost step, the mathematical relationship between process parameters and machining outputs is obtained through the method of multiple regressions with the assistance of MINITAB 13.1(Software Package for Statistical Solutions). Quadratic models were developed by using regression analysis to determine the relation of process parameters with Temp, MRR and SR. These models were developed at 95 % confidence level.

Regression model of Surface Roughness

SR = 1.26 - 0.321 TM - 0.159 S - 0.0333 DOC - 0.0225 CT + 0.0917 ACD

Correlation coefficient is 55.3%.

Regression model of Temperature

TEMP = 31.3 + 0.440 TM + 0.203 S + 0.058 DOC + 0.420 CT - 0.142ACD

Correlation coefficient is 100%.

Regression models are used for obtaining the optimization results with PSO algorithm. A single objective optimization normally gives one optimal solution. In practical situations, most of the problems are multi objective; there could be a number of optimal solutions minimizing the objective value that is necessary to determine the optimal process parameters.

We have used an open source MATLAB PSO toolbox. The code was verified and then used for our project. In the code, c_1 = 1.2, c_2=0.012 and w= 0.0004. Maximum number of iterations is taken as 2000 and the population size is 50.

The fitness function used for multi-objective optimization was given by

Min (Z) = w1*SR+TEMP*w2

Where w1 and w2 are equal weights assigned to each equation.

Min (Z) = 16.28+0.0595TM+0.022S+ 0.01235 DOC+0.1987CT-0.02515ACD

Fig 4 shows the convergence of PSO to obtain an optimized trend and the best objective value achieved during each iteration. It describes the efficiency of the algorithms to initially explore through the solution space and converge to a near optimal or best optimal solution towards the termination of the algorithm. The algorithm was executed for several times to make sure the repeatability of the results. Table shows the optimized and experimental results. The error between the experimental and predicted results was reasonably small, i.e. less than 10 %. Results showed that this approach can be effectively used to find the near optimum performance of alloy.

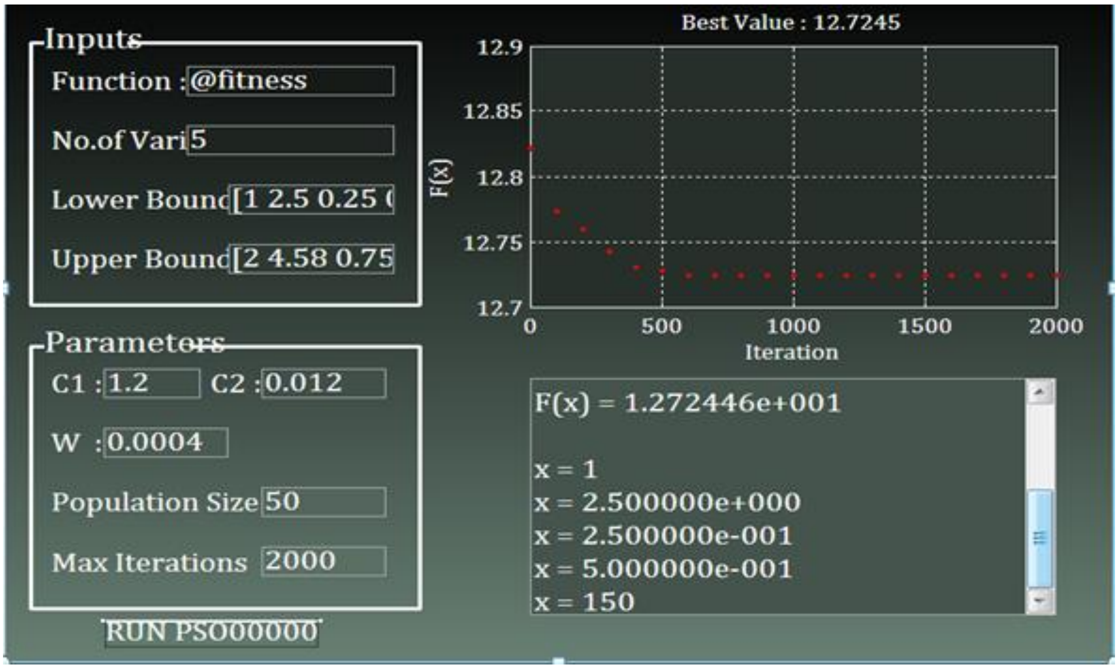

Fig 4. PSO Tool Box

From the optimization based on PSO, with reference to the above PSO tool box, the optimal conditions can be easily noted down as

- Tool material at level 1 i.e., HSS tool,
- Speed at level 1 ie,.150rpm,
- Depth Of Cut at level 1, ie,.0.25mm,
- Coolant Type at level 1, ie,.50% water in soluble oil and
- Amount of Coolant Dispensed at level3, i.e., .150ml/hr.

5 Confirmation experiment

The confirmation tests have been conducted for the obtained optimal combination of process parameters from fuzzy and PSO techniques and results are tabulated in the table 5.

Table 5. The confirmation experimental results

Method	Optimal combination	Confirmation experimental results	
		Surface roughness	Tool temperature
Fuzzy Logic	TM2S2DOC2CT3ACD1	0.21	31.0
PSO	TM1S1DOC1CT1ACD3	0.15	29.0

Conclusions

- From the experimental results, it is revealed that the surface roughness and tool temperature are well optimized using PSO technique.
- From table 4 it is concluded that coolant type most influential parameter in milling for considered responses.
- Tool material has medium effect on responses.
- Depth of cut and Amount of coolant dispensed are least influence the responses.
- Since from confirmation test results, it is concluded that PSO is the best method from optimal combination obtained.

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