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Bi-Objective Optimization of MQL Based Turning Process Using NSGA II

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ABSTRACT:Minimum quantity lubrication (MQL) based machining methods are widely used in industry now-a days as they environment friendly and save cutting fluid costs. In the present work to augment the advantages of MQL in turning, a bi-objective optimization of process parameters in MQL turning is presented. The optimum selection of process parameters in turning has a significant role to ensure quality of product, to reduce the machining cost and to increase the productivity. The two conflicting objectives under investigation in this study are material removal rate and surface roughness subjected to the parameter constraints of cutting speed, feed and depth of cut. A non-dominated solution set within the experimental range has been obtained and reported which provides a wide range of trade-off operating conditions. An appropriate operating combination set can be selected by the decision maker based on norm.

KEYWORDS: turning, optimization, genetic algorithms, empirical modeling.

I. INTRODUCTION

The increasing need for higher productivity, product quality in the manufacturing fields requires higher material removal rate and long life and high stability of the cutting tools. Higher productivity is achieved by increasing the parameters like depth of cut, feed and cutting velocity, but these are associated by high cutting temperature and large amount of heat. This high temperature not only affects the tool life but also destroy the surface integrity of the final product. The conventional coolant application fails to penetrate the chip tool interface, which cannot efficiently remove the heat generated during machining [1]. Moreover this cutting fluid has so many adverse effects too, such as it may pollute water resources and soil affecting the environment. On the shop floor, operators may get affected by skin and breathing issues due to repeated contact with cutting fluids.

In order to minimize this problem a new technique has been developed known as Minimum Quantity Lubrication (MQL). Minimum quantity lubrication (MQL) technique consists of misting or atomizing a very small quantity of lubricant, typical flow rate of 50-500 ml/hour, in an air flow directed towards the cutting zone [2]. This method involves the application of an aerosol of highly compressed air (typical pressure of air = 4-6 bar) and cutting fluid (lubricant) through a specially designed nozzle with hole diameter of magnitude 1-2mm. Lubricant mixed with compressed air to generate a mist or an aerosol. The mist particles provide lubrication and the compressed air helps to reduce the temperature during machining. In this method, as the cutting fluid in the form of small droplets of aerosol comes in contact with the heated cutting zone (aerosol is impinging on tool and work-piece interface point), it evaporates extracting the latent heat from the machining area.

In order to get the optimum settings, it is common practice in industries to resort to trial-and-error method. For this reason, there is a heavy loss of material, time and other resources occurring in the manufacturing industries. In order to optimize the performances of the process, the optimal settings of the process variables need to be found. This raises the need of application of suitable optimization technique.

In the case of MQL turning, the most significant performance indicators are material removal rate and surface roughness. Material removal rate (MRR) indicates the Productivity while surface roughness (Ra) is a measure of surface quality. In MQL turning, because it is a complex stochastic process, it is very difficult to determine the optimal



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machining parameters for the best machining performance. Moreover, the performance measures, namely MRR and *Ra*, are conflicting in nature as it is desirable to have higher MRR with lower value of surface roughness.

II. RELATED WORK

Various investigators have proposed optimization techniques, both traditional and advanced, for optimization of MQL turning process.Sundara Murthyand Rajendran et.al.[3] have usedGA based ANN prediction model proposes to envisage the quality characteristics of surface roughness and tool wear in end milling experiments conducted beneath minimum quantity lubrication. The paper also deals with the multiple objective optimizations with principal component analysis, grey relational analysis and Taguchi method.

El-Hossainy et.al.[4] have performed experimental investigation to study the characteristics of the flow of the MWF in a turning process utilizing the MQL technique and to analyse the effect of the WMF's behavior on cutting force, surface roughness and tool wear. The Response Surface Methodology is used to develop mathematical models that relate the main cutting parameters, the workpiece material properties and the cutting fluid viscosity and flow rate with cutting force, surface roughness and tool wear. Multi-objective optimization problem was formulated with the objectives of minimizing production time and maximizing tool life which was solved using NSGA II. Murat Sarıkaya et.al.[5] have evaluated Surface quality for different combination of cutting conditions. The results are analysed using surface graphs and *S/N* ratios. Taguchi design, RSM and desirability function are conducted for optimization. Mathematical models were developed to formulate the input machining parameters for Ra and Rz. Application of MQL is a good tool in order to decrease of the surface roughness.

Literature review infers considerable researchers conducted distinctive investigations for improving the process performance of MQL turning. Though many research papers have been published on Taguchi method, RSM and ANNs as per the authors' knowledge, very limited research work has been reported pertaining to the literature on multi-objective optimization of MRR surface roughness of MQL turning of steels. Hence, an effort has been made in this paper, which confers the application of evolutionary method for multi-objective optimization of MQL turning process.

III. PROPOSED METHODOLOGY

In the current study, unlike the previous approaches, the optimization problem of MQL turning is explicitly formulated as a Bi-objective optimization problem, as the determination of the optimal machining conditions involves a conflict between maximizing MRR and minimizing the surface roughness. It can be noted that the classical optimization methods (weighted sum methods, goal programming, min–max methods, etc.) are not efficient for handling multi-objective optimization problems because they do not find multiple solutions in a single run, and therefore, it is necessary for them to be applied as many times as the number of desired Pareto optimal solutions [6].

The above-mentioned difficulty of classical optimization methods is eliminated in evolutionary algorithms, as they can find the multiple solutions in a single run. As a result, a most commonly used evolutionary approach, the NSGA-II, is proposed in this paper for multi-objective optimization of laser beam cutting process. GA-based multi-objective optimization methodologies have been widely used in the literature to find Pareto optimal solutions. In particular, NSGAII has proven its effectiveness and efficiency in finding well distributed and well-converged sets of near Pareto optimal solutions [7].

IV. EXPERIMENTAL DETAILS AND EMPIRICAL MODELS

For the experiment AISI D2 Steel of length 150mm and diameter 36mm was used, and turned in precision geared head lathe turnmaster-35 (maker: Mysore kirloskar Ltd). The turning experiment was conducted application of MQL system. The tool used for the experiment is uncoated carbide insert. To conduct the turning experiment using minimum quantity lubrication (MQL) technique set up used (make: Dropsa air- oil lubrication system). The prepared oil-mist mixture is supplied to the cutting zone through a nozzle to target dimensional accuracy.



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MQL turning of AISI D2 steel was carried out under the following experimental conditions as summarized in Table.1. The parameters varied during the machining are cutting speed, feed of cut and depth of cut. MRR was calculated as the ratio of volume of material removed from workpiece to the machining time and *R*a was measured perpendicular to the cutting direction using a Mitutoyo surface roughness tester at a 0.8mm cut-off value and an average of six measurements were taken at six different locations to record the response value for *R*a.

S.No	Control Factor	Symbol	Levels			Units
			-1	0	+1	
1	Speed	<i>x</i> ₁	450	710	1120	RPM
2	Feed	<i>x</i> ₂	0.15	0.20	0.25	mm/min
3	Depth of cut	<i>x</i> ₃	0.5	1.0	1.5	mm

Table.1 the process parameters and their levels

The empirical models were developed by the authors based on the above experiment observations .These models are given below (Eq.s 1 & 2) are utilized for bi-objective optimization of MQL turning.

V. OPTIMIZATION USING NSGA-II

Among the various EAs, GA is having been the most popular heuristic and global alternative approach to multiobjective design and optimization problems. These algorithms have attracted significant attention from the research community over the last two decades because of their inherent advantage in solving nonlinear objective functions. Of these, the NSGA-II developed by Deb *et al.* [8], is a well-known and extensively used algorithm that has been applied successfully to several nonlinear complex optimization problems.

The steps involved in NSGA-II based on the main framework of the algorithm [8] can be stated in the following steps:

- 1. Select control parameters: population size, maximum number of generation, crossover probability and mutation probability (Generation, g = 0)
- 2. Generate randomly a uniformly distributed parent population, M_gof size N based on the feasible ranges and constraints if any.
- 3. Calculate the fitness of individuals based on objective function and sort the population according to the nondomination.
- 4. Allocate each solution a rank equal to its non-domination level.
- 5. Determine the crowding distance of each rank and sort the individuals that have identical rank in ascending order by the crowding distance.
- 6. Apply the binary tournament selection.
- 7. Use the simulated binary crossover operator and polynomial mutation to produce an offspring population N_gof size N.
- 8. Combine the offspring and parent population $P(g) = (M_g \cup N_g)$ to form extended population of size 2N.
- 9. Sort the extended population based on non-domination to create different fronts.
- 10. Fill new population, M_{g+1} of size Nwith the individuals from the sorting fronts starting from the best.
- 11. Invoke the crowding-distance method to ensure diversity if a front can only partially fill the next generation. The crowding-distance method continues diversity in the population and prevents convergence in one direction.
- 12. update the number of generations, g = g + 1
- 13. Repeat the steps (3) to (12) until a stopping criterion is met.



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The two objective functions of the present study are: 1. Minimization of Surface roughness and

2. Maximization of material removal rate.

These are given by Eqs. (1) and (2), respectively. The two objective functions are optimized subject to the feasiblebounds of input variables. The optimization problem is defined as follows:

Objective 1: Maximize (MRR)...... Equation (1) Objective 2: Minimize (Ra)Equation (2)

 $\mathsf{MRR}=(X[2]^*x[1])^*(\mathsf{sqrt}(x[2]/((477+x[2])+(27.42^*x[2]-x[2]^*x[2]^*x[1])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(477+x[2]+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(x[0]^*x[2]-(x[0]/0.775)^*x[2])))+(x[0]^*x[2]-(x[0]/0.775)^*x[2]))))+(x[0]^*x[2]-(x[0]/0.775)^*x[2]))))+(x[0]^*x[2]-(x[0]/0.775)^*x[2]))))+(x[0]^*x[2]-(x[0]/0.775)^*x[2]))))$

(((x[1]*x[1]+sqrt(x[2]*x[1]))+x[0]*x[1])*x[2])....Eq.1

((x[2]/(sqrt((((sqrt(((2*X[2])*sqrt(x[2]))/0.0158))*x[1])-

0.489)/((302/x[0])+0.40))*(sqrt(2x[2]*(sqrt(x[2])))))+((x[0]*x[1])/180))+((x[0]*x[1])/180))))... Eq.2



$450 \text{ rpm} \le x_1 \le 1120 \text{ rpm}$	Eq.3
$0.15 \text{ mm/min} \le x_2 \le 0.25 \text{ mm/min}$.Eq.4
$0.5 \mathrm{mm} \le x_3 \le 1.5 \mathrm{mm}$.Eq.5

 x_1 =spindle speed, RPM x_2 =feed rate, mm/min x_3 = depth of cut, mm



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VI. RESULTS AND DISCUSSIONS

The objective functions were optimized in agreement with the constraints given in Eq.s. (1) & (2). As indicated earlier the NSGA-II algorithm was used for finding the Pareto optimal solutions. The source code for NSGA-II is executed in the VC++ programming language on Windows operating system. The optimization results are subtle to algorithm parameters, typical of heuristic techniques. Hence, it is required to perform repetitive simulations to find commensurate values for the parameters. The best parameters for the NSGA-II, selected through 10 test simulation runs, are listed in Table 2.

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Control Parameter	Value			
Population size (N)	100			
Number of generations (n_{gen})	35			
Crossover probability (p_c)	0.85			
Mutation probability (p_m)	0.15			
Distribution index for crossover	50			
operator (n _c)				
Distribution index for mutation	50			
operator (n _m)				

A population size of 100 was chosen with crossover probability of 0.85and mutation probability of 0.15 along with other control parameters. NSGA-II provided good range results and provided for a well-populated Pareto front of the conflicting objective functions as shown in Fig. 2.



Fig.2 Pareto-Optimal front



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Among the 100 non-dominated optimal solutions at the end of 35 generations, 30 optimal input variables and their corresponding objective function values are presented in Table 3. By analysing the Pareto front, a decision maker can exploit it in realizing specific decisions based on the necessities of the process. For instance at point 1 in Fig. 2, MQL turning may be performed at maximum MRR but the Ra will be a higher value and hence poor surface quality. On the other extreme of the front, i.e. point 2 low Ra with good surface quality may be attained but the MRR is minimum. All the other points on the front are in between cases. As can be perceived from the graph, no solution in the front is totally better than any other as they are non-dominated solutions; hence, any one of them is a suitable solution. The selection of a specific solution has to be made only based on manufacturers necessities.

Spindle feed Depth MRR RA S NO speed 1118.51 0.179769 1.28703 273.422 2.03544 1 2 1118.49 0.187773 1.29577 286.836 2.10996 3 1115.39 0.172892 1.31277 265.909 1.99320 4 1119.62 0.164864 1.34458 258.023 1.94653 5 1119.77 0.152433 1.38126 242.621 1.85761 1.42159 1112.25 0.162148 261.581 1.96989 6 1115.10 0.158027 1.09242 1.70060 7 214.472 8 1119.30 0.159552 1.33589 248.660 1.89266 9 1119.37 0.187261 1.36122 295.255 2.15437 10 1119.30 0.179793 1.33589 280.170 2.07166 11 1118.54 0.155800 1.05439 206.492 1.65295 12 0.182886 288.364 2.11665 1119.37 1.36122 13 1117.24 0.152735 1.21580 223.600 1.74720 14 1119.46 0.162074 1.44285 264.756 1.98645 15 1114.82 0.164444 1.26478 246.819 1.88474 0.160974 254.594 1.92796 16 1116.15 1.37141 267.784 2.00466 17 1119.39 0.162130 1.47050 0.185134 278.426 18 1118.87 1.26467 2.06441 238.713 19 1119.80 0.156307 1.29354 1.83468 20 1119.77 0.179763 1.35623 282.857 2.08619 1119.95 0.151106 1.39688 242.188 1.85534 21 22 1119.64 0.151100 1.30882 232.501 1.79759 23 1119.04 0.153830 1.04675 202.858 1.63025 24 1119.77 0.191548 1.35623 301.380 2.18758 25 1119.89 0.155347 1.09923 212.336 1.68485 26 1120.00 0.155747 1.20986 227.589 1.77092 27 1119.25 0.164922 1.44559 269.674 2.01428 28 0.157859 1.20758 229.954 1116.59 1.78646 29 1119.77 0.183228 1.33531 285.510 2.10112 30 1118.80 0.162190 1.42462 262.868 1.97538

TABLE 3. SOME OPTIMAL SOLUTIONS THROUGH NSGA-II

VII. CONCLUSIONS

In this work, the important performance measures namely surface roughness and metal removal rate of MQL Turning on AISI D2 material are optimized. Empirical models are developed through an efficient modelling technique, genetic programming. Subsequently, these models are used for optimization. Since the effect of machining parameters on the chosen responses are opposite in nature, the problem is formulated as the Bi-objective optimization problem and get it



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solved using an efficient evolutionary approach called non-dominated sorting genetic algorithm. By adopting the proposed methodology, the manufacturing engineer can select the optimal combination of machining parameters depending upon his requirement.

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