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Cutting Temperature and Surface Roughness Optimization in CNC End Milling Using Multi Objective Genetic Algorithm

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***Abstract*—Machining of hard materials at high cutting speeds produces high temperatures in the cutting zone, which affects the surface quality. Thus, developing a model for estimating the cutting parameters and optimizing this model to minimize the cutting temperatures and surface roughness becomes utmost important to avoid any damage to the quality surface. This paper presents the development of new models and optimizing these models of machining parameters to minimize the cutting temperature in end milling process by integrating the genetic algorithm (GA) with the statistical approach. The mathematical models for the cutting temperature and surface roughness parameters have been developed, in terms of cutting speed, feed rate, and axial depth of cut by using Response Methodology Method (RSM). Two objectives have been considered, minimum cutting temperature and minimum arithmetic mean roughness (Ra). Due to complexity of this machining optimization problem, a multi objective genetic algorithm (MOGA) has been applied to resolve the problem, and the results have been analyzed.**

Keywords-; Optimization, MOGA, temperature, surface roughness, AISI H13. End milling

I. INTRODUCTION

High speed cutting of hard materials have many advantages, such as reducing of machining time, increasing the metal removal rate and better surface roughness. However, in high speed machining, the flank wear progress increases rapidly and the tooling cost increases. Thus, developing a model to forecast the different responses of machining process and optimizing this model before machining become an important issue.

Mukherjee and Ray [1] classified the modeling techniques in machining into three main parts: statistical regression (single, multi and multivariate) [2, 3], artificial neural network [4] and fuzzy set theory [5]. All these methods based on experimental data. The poor selection of cutting parameters in the experimental work may lead to excessive tool wear and increased surface roughness of work piece [6]. Thus, optimizing the developed models become utmost important

There are different approaches used to optimize the multiple response problems; conventional or nonconventional. The conventional methods based on the mathematical methods such as linear programming, non linear programming, geometric programming and dynamic programming [7] or the statistical methods such as the response surface methodology RSM [8, 9, 10] and Taguchi method [11, 12]. The non conventional methods usually give a near optimal solution and based on the artificial intelligence methods such as genetic algorithm [13,14, 15], neural network [16, 17, 18], tabu search [19], Particle swarm algorithm [20], ant colony algorithm [21] and simulated annealing [22]. In this research, the genetic algorithm as one of the non conventional methods has been used to determine the optimum cutting parameters to achieve the minimum cutting temperature and minimum arithmetic mean roughness (Ra).

In this research, the genetic algorithm as one of the non conventional methods has been used to determine the optimum cutting parameters to achieve minimum arithmetic mean roughness (Ra) and minimum cutting temperature. Genetic algorithms are a family of computational models inspired by evolution. These algorithms encode a potential solution to a specific problem on a simple chromosome like data structure and apply recombination operators to these structures so as to preserve critical information [23].

Genetic algorithm is one the powerful AI tools that have been used in optimization in machining process. Many researchers have been used this method.

Saravanan and Sachithanandam [24] has been developed Genetic algorithm (GA) based optimization procedure to optimize the surface grinding process using GA multi-objective function model.

Cus and Balic [23] employed the GA to determine the optimal machining parameters that minimize the unit production cost. Tutkun [25] used the Real Coded Genetic Algorithms (RCGA) approach for parameter estimation in mathematical models.

Stoic et al. [26] used the GA in testing of hard materials machinability by high speed turning process and influence of cutting parameters on machinability rates

Shunmugam et al. [27] used the GA in face-milling to determine the optimal parameters such as speed, feed rate and depth of cut in each pass has yielded a minimum total production cost

Determining the levels of the input factor that provide an identification of optimum values in any machining process of one response is useful but not as important as knows the tradeoffs available for several responses such as the surface roughness and cutting temperature. Therefore, developing mathematical models then determining the optimal or near optimal conditions in the machining process become utmost important in high speed machining.

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II. RESEARCH METHODOLGY

In order to achieve the research objective, the following steps have been done:

- Studying the process theoretically and experimentally.
- Experimental work;
- Developing new models for the cutting temperature and the surface roughness statistically.
- Validate the models.
- Optimization the developed models by using GA.

Figure 1concluded the research methodology.

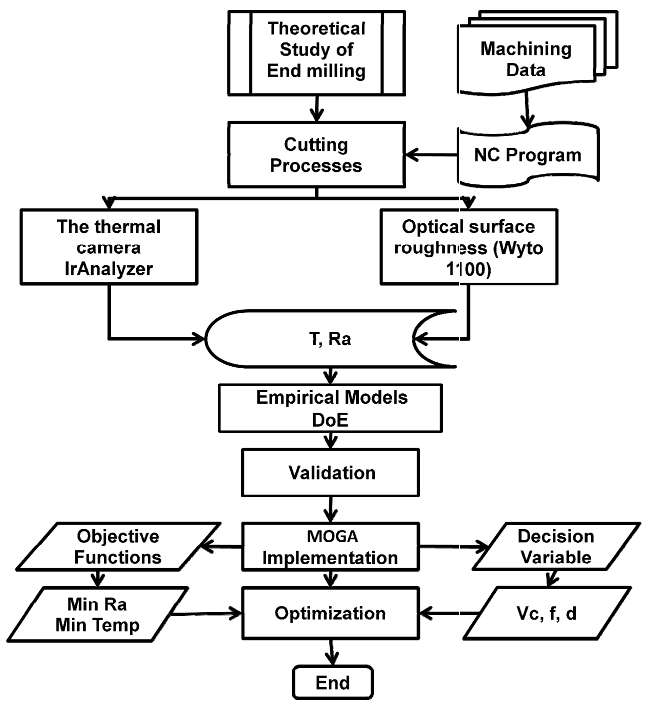

Figure 1. Research Methodology

III. EXPERIMENTAL WORK

The machining has been conducted using a vertical milling centre type MAZAK machine (Model Nexus 410A-II). The machining was under high cutting speed from 150 up to 250 m/ min, low feed rate 0.05-0.15 mm/ rev and low depth of cut 0.1-0.2 mm. The experiments in this research were performed on AISI H13 at hardness of 48 HRC as work material. The thermal camera IrAnalyzer, has been used for monitoring and measuring the temperatures during machining. The experiments for this research were performed on AISI H13 at hardness of 48 HRC as work material. In the experiment, 20 samples of data set have been collected based on five-level of central composite Design (CCD).

All the experiments done by using indexable tool holder Sandvick Coromill R490 and the insert was PVD coated TiAlN carbide. The experimental design concluded in table 1.

Table 1: Cutting conditions in coded factors and actual values

cutting speed (m/min)		**Feed rate (mm/tooth)**		**depth of cut (mm)**	
Actual	***Coded***	***Actual***	***Coded***	***Actual***	***Coded***
250	1	0.050	-1	0.100	-1
250	1	0.150	1	0.100	-1
250	1	0.050	-1	0.200	1
250	1	0.150	1	0.200	1
150	-1	0.050	-1	0.100	-1
150	-1	0.150	1	0.100	-1
150	-1	0.050	-1	0.200	1
150	-1	0.150	1	0.200	1
200	0	0.100	0	0.150	0
200	0	0.100	0	0.150	0
200	0	0.100	0	0.150	0
200	0	0.100	0	0.150	0
200	0	0.100	0	0.150	0
200	0	0.100	0	0.150	0
134.2	-α	0.100	0	0.150	0
265.8	+α	0.100	0	0.150	0
200	0	0.034	-α	0.150	0
200	0	0.166	+α	0.150	0
200	0	0.100	0	0.084	-α
200	0	0.100	0	0.216	+α

The statistical models for the average surface roughness (Ra) and the minimum Root-mean-square roughness (Rq) have been developed by using the Design Expert 8.0.0.6 software. The results show that the models can be used to navigate the design space.e as shown in the following Equations:

$$\begin{aligned} \mathrm{Ra} =& 140.361 - 0.755\,Vc + 1287.83\,f + 612.41\,d \\ & - 1.57765\,Vc\,f - 1.01821\,Vc\,d - 502.10556\,f\,d \\ & + 2.33166\mathrm{E}{-003}\,Vc^{2} - 176.994\,f^{2} - 538.67\,d^{2} \end{aligned} \tag{1}$$

$$\begin{aligned} \mathrm{TEMP} =& -4424.827 + 41.3944\mathrm{Vc} + 6762.162\mathrm{f} \\ & + 1231.3279\mathrm{d} - 13.51414\mathrm{Vcf} - 13.57218\mathrm{Vcd} \\ & - 25751.184\mathrm{fd} - 0.1054\mathrm{Vc}^{2} + 4207.48478\mathrm{f}^{2} \\ & - 20010.081\mathrm{d}^{2} \end{aligned} \tag{2}$$

IV. VALIDATION

A comparision between the theoretical and actual value that comes out from new models of the measured and the predicted values to determine the deviation have been conducted. The results shows different percentage of accuracy, the arithmetic mean roughness (Ra) deviated 7% from the measured values as shown if figure 2 and the cutting temperature model has better predicting results by 9.6 % deviation as shown in figure 3.

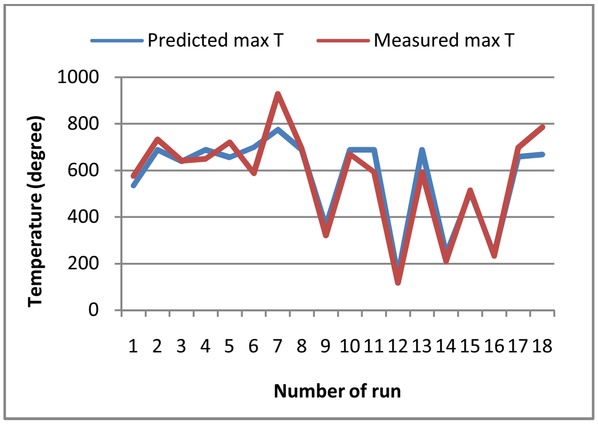

Figure 2. Surface roughness validation

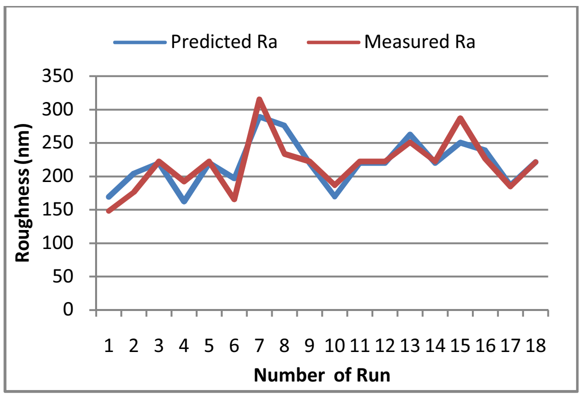

Figure 3. Cutting temerature validation

V. OPTIMIZATION ALGORITHM DESIGN

Four parameters have been used to evaluate the objective variables values and create the population, cutting speed V_c, feed rate f and depth of cut d. Table 2 concluded the objective functions decision variables, constrains and parameters.

Table 2. GA objectives, decision variables, constrains and parameters

Objective Function	**Decision Variables**	**Constraints**
Min Ra Min Temp	Cutting Speed Feed Rate Depth of Cut	$134 \leq Vc \leq 266$ $0.050 \leq f \leq 0.15$ $0.1 \leq d \leq 0.2$
Number of Individuals in Population= 20 Number of generation= 100 Crossover Rate = 35% Mutation Rate = 8		

The chromosome values of each individual are generated randomly from the ranges of these values. The length of the chromosome will be 22 bit to code the values of the four parameters. Bits from 1-9 have been used to code of cutting speed; 10-17 have been used to code feed rate, 18-22 for the depth of cut.

VI. RESULTS AND DISCUSSION

One of the advantages of non conventional optimization methods is the ability to give more than one solution. The results show that both functions have different local optimization solutions as concluded in table.

Table 3. MOGA optimization results

Cutting Speed (m/min)	Feed Rate mm / Tooth	Depth Of Cut (mm)	Ra (nm)	Temp. (Degree)
263	0.077	0.11	335	243
262	0.065	0.19	319	290
263	0.062	0.1	350	144

The table shows that there are different potential areas for the best solution. However, the best that gave the minimum roughness for both, the arithmetic mean roughness (Ra) and cutting temperature (T) was by applying 255 m/min, 0.082 and 0.13 as a cutting speed, feed rate and depth of cut.

VII. CONCLUSIONS

In this paper, the minimum arithmetic mean roughness (Ra) and the cutting temperature have been conducted in CNC milling by using multi objective genetic algorithm optimization (MOGA). The objective functions have been developed using the regression analysis based on experimental work. In the experiment, 20 samples of data set have been collected based on five-level of central composite Design (CCD). The results show that the cutting speed in the range of 263 m/min, feed rate of 0.07 mm/tooth and depth of cut of 0.11mm gave the minimum arithmetic mean roughness (Ra) and minimum cutting temperature in the boundary design of the experiment.

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