A Comparative Study between Genetic Algorithm and Particle Swarm Optimization for the Optimization of Machining Parameters in Milling Process

Ramdas E R

Production Engineering (Mechanical Engineering)
Government Engineering College Thrissur
Thrissur, India

Dr. Manesh K K
Mechanical Engineering
Government Engineering College Thrissur
Thrissur, India

Abstract-Milling is one of the progressive enhancements of miniaturized technologies which have wide range of application in industries and other related areas. Milling like any metal cutting operation is used with an objective of optimizing surface roughness at micro level and economic performance at macro level. In order to optimize the surface finish, the empirical relationships between input and output variables should be established in order to predict the output. Optimization of these predictive models helps us to select appropriate input variables for achieving the best output performance. In this paper, three input variables (speed, feed and depth of cut) are selected and surface roughness and material removal rate are taken as output variables for face milling process. The optimization results obtained from genetic algorithm and particle swarm optimization for surface roughness and material removal rate are compared.

Keywords:- Genetic algorithm; particle swarm optimization; surface roughness; taguchi's orthogonal Array

I. INTRODUCTION

Milling is the most common form of machining, a material removal process, which can create a variety of features on a part by cutting away the unwanted material. Increasing productivity, decreasing costs, and maintaining high product quality at the same time are the main challenges manufacturers face today. The proper selection of machining parameters is an important step towards meeting these goals and thus gaining a competitive advantage in the market [1]. Many researchers have studied the effects of optimal selection of machining parameters of end milling [2]. It can be formulated and solved as a multiple objective optimization problem [3]. In practice, efficient operation of milling operation requires the simultaneous consideration of multiple objectives, including maximum tool-life, desired roughness of the machined surface, target operation productivity, metal removal rate, etc.

Surface roughness is one of the most important parameters to determine the quality of a product. Surface roughness consists of the fine irregularities of the surface texture, including feed marks generated by the machining process. Several factors will influence the final surface roughness in a milling operation such as controllable factors (spindle speed, feed rate and depth of cut) and uncontrollable factors (tool geometry and material properties of both tool and

work piece) [4]. Process optimization means the resources which are utilizing the process should be used effectively and efficiently at minimum cost to produce maximum output. In optimization, the focus is on different parameters which govern the process. In present scenario, it is a matter of great concern in industry to achieve a good quality product at minimum cost. In some instances, parameter settings that are optimal for one defined objective function may not be particularly suited for another objective function. Traditional optimization methods are difficult and the only way is to reduce the set of objectives in to a single objective and handle it accordingly. Therefore evolutionary algorithms such as genetic algorithms (GA) and particle swarm optimization (PSO) are more convenient and usually utilized in multiobjective optimization problems. On number of occasions, it was concluded that non-traditional or soft computing techniques give better results when compared with traditional optimization techniques. Soft computing differs from conventional (hard) computing in the sense that it is tolerant of imprecision, uncertainty, partial truth and approximation [5].

The PSO is an efficient alternative over other stochastic and population-based search algorithms, especially when dealing with multi-objective optimization problems. Face milling is one of the important metal cutting processes used extensively in the finishing operations. Surface finish is the important output responses in the production with respect to quantity and quality respectively. The purpose of present work is to develop a mathematical model using genetic algorithm and particle swarm method for the optimization of machining parameters in face milling operation. Work speed, feed rate, and depth of cut have been chosen as predictors in order to predict surface roughness. Experiments have been conducted in vertical milling machine based on Design of Experiment (three factors*four level orthogonal array design matrix). Surface roughness values are tested by MITUTOYO Surftest SJ-400 surface roughness tester for each experiment. The empirical relationship between input parameters and output parameters has been developed using Minitab commercial software. The regression coefficient developed using Minitab 16 have been used for the development of mathematical model for surface roughness. The experimental values are used to optimize surface

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roughness and material removal rate by the application of genetic algorithm and particle

swarm optimization using Matlab 7.6. In addition to introduction, this paper has relevant literature review in subsection 2. The experimental procedure and optimization is explained in sub-section 3. The results and analysis is explained in sub-section 4. The conclusions are drawn in subsection 5.

II. LITERATURE REVIEW

Researchers gave major emphasis in traditional and nontraditional optimization techniques in process optimization. On number of occasions, it was concluded that non-traditional or soft computing techniques give better results when compared with traditional optimization techniques. Soft computing differs from conventional (hard) computing in the sense that it is tolerant of imprecision, uncertainty, partial truth and approximation.

Vikas Pare, Geeta Agnihotri & C M Krishna [1] compared the optimum values of surface roughness obtained from particle swarm optimization and genetic algorithm in a CNC end milling machine. They used annealed alpha beta titanium alloy Ti-6Al-4V (Ti- 64) as work piece and three types of end mills were used in the experiment which was uncoated carbide and two TiAlN base coated carbide tools. Md. Anavet Ullah Patwari, A K M Nurul Amin, Muammer D Arif [2] predicted the surface finish in end milling of Medium Carbon Steel S45C using coated TiN insert under dry conditions with full immersion and its optimization by coupling the prediction model with genetic algorithm. Milon D Selvam, Dr. A K Shaik Dawood, Dr. G Karuppusami [3] discussed the use of Taguchi technique and Genetic Algorithm (GA) for minimizing the surface roughness in machining mild steel with three zinc coated carbide tools inserted into a face miller of 25 mm diameter. M Farahnakian, M R Razfar, and S Elhami Joosheghan [4] presented an approach for the determination of the optimal cutting parameters (spindle speed, feed rate, depth of cut and engagement) leading to minimum surface roughness in face milling of high silicon stainless steel by coupling neural network (NN) and Electromagnetism-like Algorithm (EM). R Arokiadass1, K Palaniradja, N Alagumoorthi [5] focused on study and analyses of surface quality improvement in end milling operation of Al/SiCp metal matrix composite.

It is important to have a detailed study on previous work done in the area to develop a better knowledge, identify and avoid mistakes and utilize the best of existing path way. Several research works have been done on the field of turning and milling operations regarding the machining performance, optimization, wear analysis, and surface roughness etc.

III. EXPERIMENTAL PROCEDURE AND OPTIMIZATION

The experimental procedure involves four stages viz., (i) Planning for the experiment, (ii) Collection of data by conducting experiments as per the plan, (iii) Establishment of prediction model for the selected output measure, and (iv) Optimization of the predictive model for better results. In the

first stage, face milling operation is selected for study. In the operation of face milling, axis of the milling cutter remains perpendicular to the surface being milled. Cutting action is done by cutting edges of both sides (end and outside) periphery of the milling cutter. Three input variables are selected, as these variables are proved to have significant influence on the output measures such as surface roughness. Surface roughness and material removal rate are the output measure for our case. In the second stage, the data has been referred from the work done in a vertical milling machine. We used mild steel bar as workpiece and tungsten carbide (grade P-30) tip as cutting tool. We conducted experiments using three input variables namely cutting speed, feed and depth of cut. The ranges of three parameters considered are given in table 1.

The limits of the process variable have to be found out after finding the important process variables that are used for experimentation. The limits are known as working range of the experimentation. The upper and lower limits of the process variables have to be found out within which the experiment has to take place. The selection of the limits of the process variables follows with choosing of number of levels within the limits of variables. Usually the upper limits and the number of levels of the process variables are chosen by conducting trail runs by changing one of process variables and keeping the rest constant.

TABLE I. SELECTING INPUT PROCESS PARAMETERS AND THEIR WORKING RANGE

Parameter	Range
Cutting Speed, V (rpm)	130 <v<270< td=""></v<270<>
Feed Rate, f (mm)	0.02 <f<0.08< td=""></f<0.08<>
Depth of Cut, d (mm)	0.5 <d<4< td=""></d<4<>

In the present work, the working ranges of process variables are divided in to four levels:

TABLE II. DIFFERENT LEVELS OF PROCESS PARAMETERS

Parameter	Level 1	Level 2	Level 3	Level 4
Speed	130	170	230	270
Feed	0.02	0.04	0.06	0.08
Depth of Cut	0.5	1	2	4

A method based on "ORTHOGONAL ARRAY" (OA) experiments gives much reduced "variance" for the experiment with "optimum settings" of control parameters. Thus the marriage of Design of Experiments (DOE) with optimization of control parameters to obtain best results is achieved in the Taguchi Method.

Step.1 Selecting the number of parameters and number of levels. In the present work, it is selected that the number of parameter is five and number of level as four.

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Step.2 Finding out the orthogonal array for the same from the array selector, this is presented in table 2.

Step.3 Since the number of parameters as five and number of levels taken as four, then the Orthogonal Array will be L16. Thus 16 experiments have to be done for the prediction of effects of process parameters on the surface roughness and material removal rate. Surface roughness of workpiece is tested by MITUTOYO Surftest SJ-400 which is shown in figure.

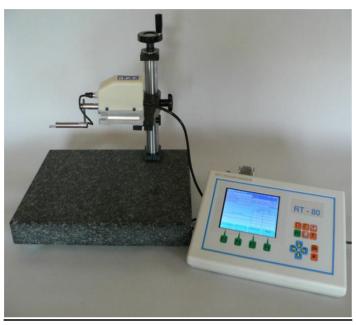


Fig. 1. Surface roughness tester

In this work the values of regression coefficient are calculated using MINITAB 14 statistical analysis software that can be used to create statistical mathematical model. With the help of regression modeling, equation developed for surface roughness and material removal rate is

 $\begin{aligned} R_{carbide} &= 9.20 \text{ - } 0.0261 \text{ x } 1 + 19.2 \text{ x } 2 + 0.114 \text{ x } 3 \\ MRR &= 0.0151 \text{ x } 1 + 500 \text{ x } 2 + 16.7 \text{ x } 3 \text{ - } 24.3 \end{aligned}$

Where x1 refers to cutting speed of the tool, x2 refers to feed of the workpiece and x3 refers to depth of cut.

Regression equations are used to establish a relationship between three selected input variables, such as, speed, feed and depth of cut, and the output variables, surface roughness and material removal rate. This is the mathematical model for both surface roughness and material removal rate. Surface roughness is measured by surface roughness tester and material removal rate is calculated by mathematical formulae for milling.

Material Removal Rate, $MRR = w*d*v (mm^3/s)$

Where w = width of work piece (mm), d = depth of cut (mm), v = linear speed (mm/min)

Linear speed, v = f*N*n (mm/min)

Where f = feed per tooth (mm/tooth), N = cutting speed (rpm), n = number of teeth

In the fourth stage, genetic algorithm and particle swarm optimization are used to optimize the predicted models given above.

GA's are the algorithms based on mechanics of natural selection and natural genetics, which are more robust and more likely to locate global optimum. The cutting conditions are encoded as genes by binary encoding to apply GA in optimization of machining parameters. A set of genes is combined together to form chromosomes, used to perform the basic mechanisms in GA, such as crossover and mutation. Optimum results of cutting conditions are obtained by comparison of values of objective functions among all individuals after a number of iterations. Particle swarm optimization (PSO) is a population based stochastic optimization technique, inspired by social behavior of bird flocking or fish schooling. A population of individuals defined as random guesses of the problem solution is initialized. These individuals are also known as the particles, hence the name particle swarm. Value of the objective function for these individuals represents their positions. An iterative process to improve these positions is then started. The particles iteratively evaluate the positions and remember the location where they had their best success. The individual's best solution is called the particle best or the local best. Each particle makes this information available to their neighbors. They are also able to see where their neighbors have had success. The best solution among all the neighbors is called global best. The algorithm finds initial feasible population and ensures feasibility during the entire optimization process.

In this experiment, we used 10000 number of iteration and used 50 number of particle. We have also tried to increase the number of iterations beyond 10000 but the end result is same. So we selected 10000 iterations. The program code is written in MATALB 7.6 version. The computational time is less than one minute. We can retrieve the result in a very short period of time so it is really very easy to apply and time saving technique.

IV. RESULTS AND DISCUSSION

In this paper, we applied GA for three input parameter case in order to compare the results with PSO. GA and PSO are implemented in MATLAB software by applying several conditions and parameter constraints for surface roughness and material removal rate. Population size and maximum generations selected for GA and PSO is 50 and 10000 respectively. Number of parameters and initial range of parameters are given to GA and PSO. In GA, mutation function selected is uniform and mutation rate selected is 0.2. The selection function in GA is roulette and migration is selected as forward. Then the result obtained by genetic algorithm for surface roughness is given in Table 3.

TABLE III. OPTIMUM VALUES OBTAINED BY GA METHOD

Parameter	Values
Speed (rpm)	170
Feed (mm)	0.025
Depth of cut (mm)	0.5
Surface roughness (µm)	5.38

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The computational time taken for getting optimization values is 1.84 second. In PSO the stall generation limit selected is 30 and boundary constraints as reflection. The result obtained by particle swarm optimization for surface roughness is given in Table 4.

TABLE IV. OPTIMUM VALUES OBTAINED BY PSO METHOD

Parameter	Values
Speed (rpm)	170
Feed (mm)	0.025
Depth of cut (mm)	0.5
Surface roughness (µm)	5.38

The computational time taken for getting optimization values is 0.43 second. The result obtained by genetic algorithm for material removal rate is given in Table 5.

TABLE V. OPTIMUM VALUES OBTAINED BY GA METHOD

Parameter	Values
Speed (rpm)	130
Feed (mm)	0.025
Depth of cut (mm)	0.5
Material removal rate (mm ³ /s)	1.57

The computational time taken for getting optimization values is 1.33 second. The result obtained by particle swarm optimization for material removal rate is given in Table 6. The computational time taken for getting optimization values is 0.41 second. Comparing the optimization techniques i.e., genetic algorithm and particle swarm optimization, they generates same optimization values for surface roughness and material removal rate. The computational time for PSO is faster than GA.

TABLE VI. OPTIMUM VALUES OBTAINED BY PSO METHOD

Parameter	Values
Speed (rpm)	130
Feed (mm)	0.025
Depth of cut (mm)	0.5
Material removal rate (mm ³ /s)	1.57

After predicting the optimization values of surface roughness and material removal rate, the results are validated by conducting three validation experiments. Three experiments are done for getting best values for output parameters. The validation experiment results for surface roughness are shown in table 7.

TABLE VII. VALIDATION EXPERIMENT RESULTS FOR SURFACE ROUGHNESS

	Input parameters			Output	
Expt. No	Speed (rpm)	Feed (mm)	Depth of cut (mm)	Surface roughness (µm)	
1	170	0.025	0.5	5.45	
2	170	0.025	0.5	5.62	
3	170	0.025	0.5	5.21	

Average value of surface roughness (Ra) is 5.43 µm. The validation experiment results for material removal rate are shown in table 8.

TABLE VIII. VALIDATION EXPERIMENT RESULTS FOR MATERIAL REMOVAL RATE

	Input parameters			Output	
Expt. No	Speed (rpm)	Feed (mm)	Depth of cut (mm)	Material removal rate (mm³/s)	
1	130	0.025	0.5	1.68	
2	130	0.025	0.5	1.68	
3	130	0.025	0.5	1.68	

Average value of material removal rate (MRR) is 1.68 mm³/s.

V. CONCLUSIONS

The purpose of this paper is to provide an effective and accurate way to predict surface roughness and material removal rate in conventional milling process. The regression mathematical model was developed to predict the surface roughness and material removal rate. Establishment of empirical relationships between input variables and output variables are done and made a regression mathematical model. Optimization of cutting conditions in milling process is also done by genetic algorithm and particle swarm optimization. The result obtained by using genetic algorithm and particle swarm optimization varies marginally. At the same time, the computation time requires for particle swarm optimization is found to be less compared to that for genetic algorithm. The optimal values predicted by GA and PSO, and experimentation values of surface roughness and material removal rate have some differences. This may be due to some uncertainties in measurement of surface roughness.

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