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A Review Paper for Study of Surface Roughness and MRR Optimization in CNC Milling

S.M. Bhole[1], P.B. Bhise[2]

Department of Mechanical Engineering, Padm. Dr. V. B. Kolte College of Engineering, Malkapur, Maharashtra, India[1]

ABSTRACT

The major goal of this review paper is to determine whether quality is within the desired tolerance level that customers may accept. Using different CNC machining parameters, such as spindle speed (N), feed rate (f), depth of cut (d), and insert nose radius, one may therefore optimize surface roughness and metal removal rate (r). by creating a mathematical model for CNC cutting a specimen made of hard steel. And the Matrix's design was used to create this mathematical model. Also, CNC (Computer Numerical Control), which uses a microcomputer attached to the machine and stores the instructions as a programme. The machine's control logic will also be handled in large part by the computer, making it more versatile than prior hard-wired controllers.This experimental investigation uses response surface methods to determine how different process parameters affect the rate of metal removal and surface roughness. We can then quickly determine which setting will have the biggest impact.

Keyword : -CNCmillingoperation, MRR,RSM, Surfaceroughness

1. INTRODUCTION

The primary issue facing contemporary machining businesses is achieving high quality in terms of work piece dimensional precision and surface finish. In terms of surface roughness, waviness lay, and defects, surface texture refers to the geometric abnormalities of a solid material's surface. Surface irregularities, such as feed marks produced by the machining process, are small imperfections in the surface texture.
In the manufacturing sector, manufacturers prioritized product productivity and quality. Throughout the past few decades, computer numerically controlled machine tools have been used to boost product productivity. One of the most crucial factors in determining a product's quality is the roughness of its surface. Surface roughness is created through a complex, dynamic, and process-dependent mechanism. Many variables, including controllable variables, will affect the ultimate surface roughness in a CNC milling operation (spindle speed, feed rate and depth of cut). To achieve the desired surface roughness, the spindle speed, feed rate, and cut depth should be combined in the best possible way using the principal surface approach.

2. CNCMILLINGPROCESS

By feeding the work piece against a spinning cutter with many cutting edges, milling is the process of machining flat, curved, or uneven surfaces. A reciprocating adjustable worktable that mounts and feeds the work piece is used in the milling process along with a motor-driven spindle that rotates the milling cutter.
A milling machine is a type of machine tool used to cut metal using a milling cutter, which has numerous teeth. The work piece is fed against the rotating milling cutter while being secured to the milling machine table. Cutting teeth on the milling cutter's periphery, side, or both may be present.

2.1 Principal Functions of CNC

The principle functions of CNC are as follows:-

- Machine tool control

- In-process compensation
- Improved programming and operating features
- Diagnostics

2.2 CNC System Elements

A typical CNC system consists of the following six elements:-

- Part program
- Program input device
- Machine control unit
- Drive system
- Machine tool
- Feedback system

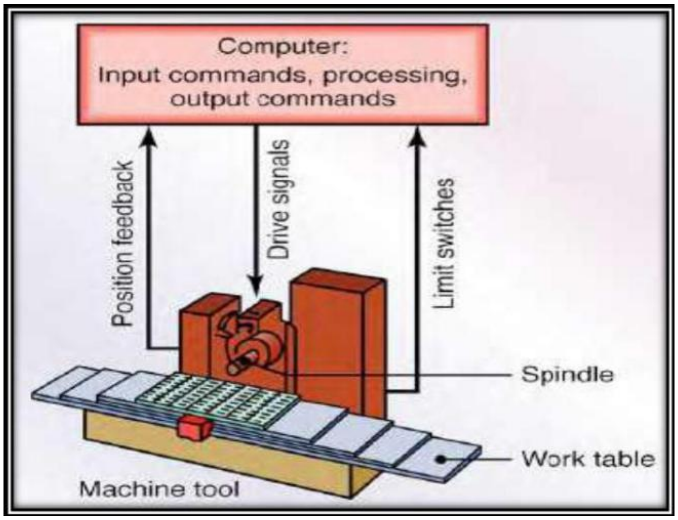

Fig -1: Major components of a numerical control machine tool

3. ADJUSTABLE PROCESS PARAMETERSCutting Speed: Speed (v) is the peripheral speed of the cutter in m/min. Cutting speed (V) =πDN/1000 Where D = cutter diameter, mm N=cutter speed, rpm

The cuttings peed in a milling machine depends on work material, cutter diameter and number of cutter teeth, feed, and depth of cut, width of cutter and use of coolant.

Feed: Feed(f) is defined as the movement of work relative to the cutter axis and is the rate at which the work is being fed to the cutter.

Feed in milling operations expressed in the following three ways:

- Feed per tooth (f_z),mm per tooth of cutter
- Feed per revolution(f_{rev}), mm per revolution of cutter
- Feed per minutes (f_m),mm, per minute

The above three feeds are related as follows: fm = N*frev = fz*Z*N

Where Z = number of teeth in cutter N = cutter speed, rpm

Depth of Cut: Depth of cut is practically self explanatory. It is the thickness of the layer being removed (in a single pass) from the work piece or the distance from the uncut surface of the work to the cut surface, expressed in mm.

Depth Of Cut = D – d

Depth of cut = mm Here, D and d represent initial and final thickness (in mm) of the job respectively.

1. RESPONSE SURFACE METHOD

The response surface methodology (RSM) is a group of statistical and mathematical methods for developing empirical models. The goal of meticulous experiment design is to maximize a response (output variable) that is affected by a number of independent variables (input variables). An experiment is a collection of tests, or runs, in which the input variables are altered in order to determine the causes of variations in the output response.
RSM was initially created to model experimental results before moving on to simulate numerical experiments. The sort of error that the response produces differs. Inaccuracy in physical experiments might arise from measurement mistakes, for instance, whereas numerical noise in computer experiments comes from round-off errors, inadequate convergence of iterative procedures, or the discrete representation of continuous physical events. The faults are thought to be random in RSM.
The design procedure of response surface methodology is as follows:-
1. Creating a sequence of tests that will allow for adequate and accurate measurement of the desired response.
2. Creating the best fitting mathematical model of the second order response surface.
3. Identifying the ideal combination of experimental parameters that results in a maximum or minimum response value.
4. Using two- and three-dimensional charts to illustrate the direct and indirect effects of process factors.

5. LITERATURE SURVEY

In the manufacturing sector, the manufacturers' primary focus is on producing high-quality products. **P.G. Benardos, a researcher from Greece [1]**, has proposed a neural network modeling technique for forecasting surface roughness (Ra) during CNC face milling. The data utilized for training and evaluating the performance of the networks was obtained from experiments carried out on a CNC milling machine, following the principles of Taguchi design of experiments. The experiment considered various factors such as the depth of cut, feed rate per tooth, cutting speed, engagement and wear of the cutting tool, use of cutting fluid, and the three components of the cutting force. By employing a feed-forward ANN trained with the Levenberg-Marquardt algorithm, the model was able to predict surface roughness with a mean squared error of 1.86% and remained consistent across the entire range of values.
P. Franco[2] The impact of radial and axial deviations on the surface roughness during face milling with circular insert cutting tools has been studied. A numerical model has been developed to predict the surface profile and roughness based on these factors. The model includes a random values generation algorithm to determine the variation in roughness caused by tool errors. The study focuses on a 4-tooth tool with a 12mm insert diameter, a 0.5mm depth of cut, a cutting speed of 120m/min, and a feed rate of 0.4-1.4mm/rev. The obtained results are analyse.
Kurbanoglub et al [3] Executed surface roughness estimation for milling using evolutionary programming techniques. CNC milling has emerged as a highly proficient, efficient, and adaptable manufacturing technique for intricate or contoured surfaces. To develop, refine, and construct advanced multi-axis milling centers, it is essential to anticipate their potential manufacturing output. This investigation employed gene expression programming to forecast surface roughness of milling surfaces in relation to cutting parameters. The cutting speed, feed rate, and depth of end milling operations were gathered to anticipate surface roughness..
Babur, Mahmut[4] A researcher originating from Turkey has conducted a study focused on statistical modeling of surface roughness during high-speed flat end milling. Achieving optimal surface roughness is a crucial aspect of the machining process, as it is heavily dependent on tool wear. This study aims to develop a statistical model for estimating surface roughness during high-speed flat end milling under wet cutting conditions. The model utilizes various machining variables such as spindle speed, feed rate, depth of cut, and step over. The study employed experimental results from a rotatable central composite design to develop first- and second-order models, which were evaluated through several statistical tests. The highest coefficient of correlation (Radj 2) of 88% was achieved using a 10-parameter second-order model. To further improve the model's estimation capability, an additional

independent variable was included to account for the effect of tool wear. The total operating time of the tool was deemed the most suitable variable for this purpose. Adding this variable as a linear term increased Radj 2 to 94%, and a good fit was observed between the model predictions and supplementary experimental data.

Julie et al [5] An investigator hailing from Turkey has carried out a research project centered on statistical modeling of surface roughness in the course of high-speed flat end milling. Obtaining an optimum surface roughness is a pivotal constituent of the machining process, given its heavy reliance on tool wear. This investigation endeavors to devise a statistical model for approximating surface roughness during high-speed flat end milling when wet cutting conditions are in place. The model makes use of diverse machining variables such as spindle speed, feed rate, depth of cut, and step over. The probe used experimental outcomes from a rotatable central composite design to establish first- and second-order models, which underwent numerous statistical assessments. The maximum coefficient of correlation (Radj 2) of 88% was attained using a 10-parameter second-order model. To further improve the model's estimation capacity, an additional autonomous variable was incorporated to take into account the impact of tool wear. The total running time of the tool was judged to be the most fitting variable for this purpose. Supplementing this variable as a linear term raised Radj 2 to 94%, and a favorable match was witnessed between the model forecasts and supplementary experimental data.

Tian-Syung Lan [6] Research on CNC milling in a virtual environment and the use of optimal MRR with tool life management is presented. The paper introduces the modeling of dynamic MRR control and optimal solutions with the use of Calculus of Variations to minimize machining costs for individual cutting tools while maximizing expected machining quantity. The feasibility of the optimal MRR control is demonstrated through a real-world CNC machining case from Air TAC in a virtual system, which shows promising results in simulated cutting forces. The dynamic solution is also implemented experimentally on a digital PC-based lathe system and the surface roughness of machined work-pieces is stabilized as the tool is consumed, while meeting recognized standards for finish turning. This study offers an economical solution for virtual machining prior to realization of optimum MRR and advances the realistic implementation of digital PC-based lathe systems in the CNC machining industry with valuable insights.

M.F.F. Ab. Rashid and M.R. Abdul Lani [7] Explored Surface Roughness Estimation for CNC Milling Procedure through Artificial Neural Network. The objective of this study is to construct a mathematical pattern utilizing multiple regressions and artificial neural network model for AI-based approach. Spindle speed, feed rate, and depth of cut were selected as predictors to anticipate surface roughness. FANUC CNC Milling was utilized to run 27 samples and the experiment was conducted utilizing full factorial design. Analysis of variances revealed that the feed rate was the most significant parameter, followed by spindle speed and depth of cut. After obtaining the anticipated surface roughness using both methods, the average percentage error was calculated. The mathematical model created using multiple regression method demonstrated an accuracy of 86.7%, which is dependable for surface roughness prediction. Conversely, the artificial neural network technique demonstrated an accuracy of 93.58%, which is practical and useful in surface roughness prediction. The findings from this study can be applied in the industry to decrease time and cost in surface roughness prediction.

K. Schutzer, et al [8] Enhancement of surface precision and shop floor feed consistency was achieved via an open CNC monitoring system and cutting simulation. When milling intricate work piece shapes, the feed rate often becomes unstable due to the high degree of surface curvature, resulting in the need for rapid acceleration and deceleration of the interpolated axes. This can negatively impact process time and surface accuracy in terms of the form and texture of the manufactured part. Accurate models, developed through a series of experiments, are necessary to simulate the behavior of the real machine and control it effectively. The goal is to improve the HSC milling process of complex surfaces prior to material removal. Experiments presented in this paper demonstrate that it is possible to optimize surface form accuracy and texture through automated feed rate smoothing during the finishing operation on the machine tool itself. The open CNC system monitors the positions of the axes and spindle speeds, which are then used as input for geometric cutting simulations to predict and optimize surface quality.

Toshihiko et al [9] A study conducted in Japan focused on achieving autonomous milling operation through the Surface Roughness Control Based on Digital Copy Milling Concept. The aim was to develop an intelligent machine tool by creating a system called Digital Copy Milling (DCM) that could generate real-time tool paths using the principle of copy milling. The DCM allowed for dynamic control of the cutting tool, enabling it to follow the surface of the CAD model without using any NC program. The study also enhanced the functionality of DCM by incorporating surface roughness control of the finished surface. The DCM selected cutting conditions and generated tool paths dynamically to meet the instructed surface roughness Ra, from rough-cut to semi-finish-cut and finish-cut operations. The experimental verification of the study was successful. Inspired by this study, I am interested in optimizing surface roughness and metal removal rate in CNC end milling using response surface methodology.

6. MATERIAL SELECTION

- Stainless steel (SS-304)
- Dimension for material is 100*50*20 mm metal plate.

Table -1: Chemical Composition

Cr	Mn	Ph	S	Si	C	Ni	N	I
18.00 –20.00	2.00	0.045	0.030	0.75	0.08	8.0 – 10.5	0.10	Bal

Table-2: Mechanical Properties

Properties	Values
Proof Stress	85Mpa
Hardness	80RB
Tensile Strength	655Mpa
Elongation	55pert.

Table-3: Physical Properties

Properties	Values
Yieldstrength	241Mpa
Density	$7.9 * 10^3 Kg/m^3$
Thermal Expansion	$17 * 10^{-6}/K$
Modulus Of Elasticity	200Gpa
Thermal Conductivity	16.2 W/m.K

7. CONCLUSION

By adjusting the cutting parameters, the best cutting conditions for face milling were determined in this study. Experimental runs and choosing the best cutting parameters for surface polish are done with the L9 orthogonal array. The confirmation runs' successful completion of the surface finish under the best cutting parameters revealed the effectiveness of the parameter settings. Response surface technology will be used in this project to mill parts with the best surface roughness possible. Moreover, RSM is a powerful and useful technique for milling surface roughness optimization.

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