A review on Machining Parameters of CNC Milling Process

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Abstract— In any manufacturing process, surface roughness is a common parameter for quality and customer satisfaction. Customers will satisfy based on the physical appearance of a manufactured product. The surface roughness value of the machined product is depend on the different machining parameters like speed, feed, depth of cut (DOC), coolant flow rate etc. Many researchers have done their work in this field to achieve the minimum surface roughness value by optimizing the machining or process parameters in end milling. In this paper presented is the description of feed for milling and the CNC milling process.

Keywords: Cutting, Milling, CNC, ANN

I. Introduction

The machining industry has seen a significant growth in the past five to six years, and it is projected to be a $100B industry by 2025 [1]. This is primarily due to the growing demand for higher-quality products and computer numerical control (CNC) machines, which enable manufacturers to develop these high-quality and high-complexity products at higher speeds. In the milling process, the work piece is stationary, and the tool is rotating. In this machining process, the rotating tool, with multiple cutting edges works across the work piece to generate a plane or straight surface. The direction of the feed is perpendicular to the axis of rotation of the tool.

There are two basic forms of milling, face (vertical) milling and peripheral (horizontal) milling [3]. The tools for milling operation, can also be solid, coated or uncoated, or they can have tool inserts along the cutting edges. These inserts are often coated. These coated tools are considered a necessity on most machining applications.

In manufacturing industries, milling processes have been widely utilized to remove material from work pieces, producing various sizes, shapes, and features. Face milling is one of the most common milling processes, due to its high efficiency and excellent productivity.

In face milling, the cutter is mounted on a spindle, which rotates perpendicular to the machined surface of the work piece, and material is removed along the path parallel to the machined surface. Face milling is widely used in many industries such as machine and machine tool building, the automobile industry, etc. One of the major control parameters in face milling is surface roughness that is considered to be one of the most important quality aspects to determine if machine parts will function properly and can be assembled smoothly.

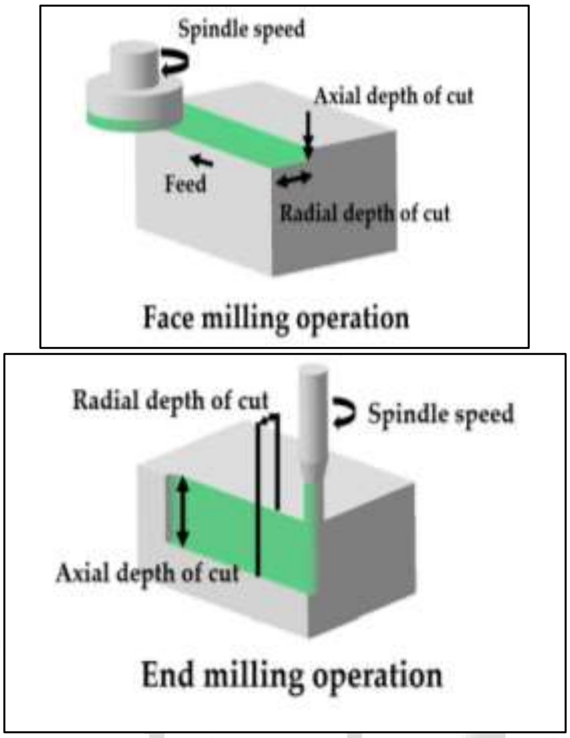

Fig. 1. Milling operations

II. Literature review

1) N.A. Fountas et al. [1] presented the trajectory optimization of three well-known 3-axis surface machining tool-paths available to commercial computer-aided manufacturing systems by means of a genetic algorithm.
2) Ilesanmi Daniyan et al. [2] presented a nnumerical models obtained from the Response Surface Methodology (RSM) and Artificial Neural Network (ANN) techniques for predicting the magnitude of the temperature and surface roughness during the machining operation of titanium alloy (Ti6Al4V). The design of the numerical experiment was carried out using the Response Surface Methodology (RSM) for the combination of the process parameters while the Artificial Neural Network (ANN) with 3 input layers, 10 sigmoid hidden neurons and 3 linear output neurons were employed for the prediction of the values of temperature.
3) Abbas, A.T et al. [3] presented an algorithm using an artificial neural network (ANN) with the Edge worth-Pareto method to optimize the cutting parameter in CNC face-milling operations. The set of parameters are adjusted to improve surface roughness and minimal unit-volume material removal rates, thereby reducing production costs and improving accuracy. An ANN algorithm is designed in Matlab, based on a 3–10-1 Multi-Layer Perceptron (MLP), which predicts the Ra of the workpiece surface to an accuracy of ± 5.78% within

the range of the experimental angular spindle speed, feed rate, and cutting depth.

4) Pimenov DY et al. [4] presented a novel Edge worth–Pareto optimization of an artificial neural network (ANN) for surface roughness (*Ra*) for prediction of one component in computer numerical control (CNC) turning over minimal machining time (T_m) and at prime machining costs (*C*) an magnesium alloys. An ANN is built in the Matlab programming environment, based on a 4-12-3 multi-layer perceptron (MLP), to predict *Ra*, T_m, and *C*, in relation to cutting speed, v_c, depth of cut, a_p, and feed per revolution, f_r.
5) Erdakov IN Abbas et al. [5] presented the effects of cutting speed *V*, feed rate *f*, and depth of cut *t* in turning of high-strength. There is little modern research on machining high-strength steel. The high cost of this material compels us to look for the optimum turning conditions to provide for the specified roughness of surface and the minimum machining time of unit volume. As a result of this study, an artificial neural network was designed in Matlab on the basis of the multilayer perceptron that predicts roughness of surface of the workpiece with ±2.14% accuracy within the range of the experimental cutting speed, depth of cut, and feed rate values.
6) Pooja A. Sutar et al. [6] This paper deals with on the influence of cutting speed, feed, depth of cut (doc) and type of coolant (dry and wet) on the surface roughness on AISI 316L stainless steel material during end milling. The experimental plan was based on Taguchi's technique L18 orthogonal array with four factors and three levels for each variables and studying the contribution of each factor on surface roughness. The ANOVA technique is employed to study the significance of each parameter. The parameters observed are the optimum values for the surface roughness, environment is dry, cutting speed is 1600 rpm, and feed rate is 0.12 mm/min and depth of cut is 0.1mm.
7) Shadab Anwar et al. [7] this paper presents a study that investigates the effect of the end milling machining parameters on the surface roughness of the EN31 steel. The end milling machining parameters considered are rotational speed, feed rate and depth of cut. The feed rate is found to be the most dominant parameter for surface roughness of EN 31 steel. End milling was done by using solid carbide tool. After completion of the experiment they concluded that the optimum parameters that are required to obtain a better surface finish arespeed @ 300rpm, feed rate 500mm/min, depth of cut 0.15mm, and the surface roughness therefore achieved is a minimum of 1.184µm. And to minimize the surface roughness feed rate contributes maximum of 59.84% followed by spindle speed 29.58% and depth of cut 9.162%.
8) Nitin Agrawal et al. [8] The present paper deals with the effect of different process parameters (cutting speed, feed and depth of cut) on surface roughness on Aluminum alloy material on CNC milling machine with HSS milling cutter. They prepared 36 specimens of alloy have been machined on CNC milling machine then SJ 201 surface roughness tester has been used to determine the surface roughness value. They concluded that depth of cut is most significant parameter, followed by feed rate and spindle speed.
9) Ravikumar D Patel et al. [9] this paper, mathematical model can be developed easily for milling process. Number of experiments have been done by using Hy-tech CNC milling machine. Conclusion from Taguchi method, Surface roughness is most influenced by Feed rate followed by spindle speed and lastly depends on depth of cut. Predicted surface roughness has been obtained, average percentage error is calculated by ANN method.
10) Pooja A et al. [10] the present work focused on the influence of cutting speed, feed, depth of cut (doc) and type of coolant (dry and wet) on the surface roughness on AISI 316L stainless steel material during end milling. The experimental plan was based on Taguchi's technique L18 orthogonal array with four factors and three levels for each variables and studying the contribution of each factor on surface roughness.
11) Fatemeh Aghazadeh et al. [11] This paper investigates a robust tool wear monitoring system for milling operation. Recent developments in machine learning, in particular deep learning methods, result in significant improvement in automation of different industries. Therefore, in this research, we employed convolutional neural network (CNN) as a well-established and powerful deep learning algorithm for tool wear estimation.
12) Javad SoltaniRad et al. [12] This paper investigates an online effective method for tool condition monitoring. Acoustic emission signal of a system which is acquired by a sensor mounted to the spindle of the milling machining center is used as the fault indicator because it is easily to be installed, inexpensive and practical for use in industrial environment.
13) P. K. Ambadekar et al. [13] In this work which is first of its kind, the CNN model gives an accuracy of 87.26% to predict the remaining useful life of a cutting tool. In particular, the study exhibits that CNN method gives good response to the data in the form of images, when used as an indicator of tool wear classification in different classes.
14) Achyuth Kothuru et al. [14] this study to generate the saliency maps to visualize the specific features utilized by the CNN model for a given spectrogram of audio signal. Furthermore, the study examines the saliency maps of different tool condition levels to understand the intuition of proposed CNN model in selecting the specific localized features of spectrogram for accurate prediction.
15) Martyna Wiciak-Pikuła et al. [15] In this work, multilayer perceptron (MLP) models were used to predict the tool flank wear VBB and tool corner wear VBC during milling of AMC with 10% SiC content. The signals of vibration acceleration and cutting forces were selected as input to the network, and the tests were carried out with three cutting speeds.
16) Wang J et al. [16] This paper presents a comprehensive survey of commonly used deep learning algorithms and discusses their applications toward making manufacturing "smart". The evolvement of deep learning

technologies and their advantages over traditional machine learning are firstly discussed.

17) Datta A et al. [17] In this paper, a tool condition monitoring technique by analysing turned surface images has been presented. The aim of this work is to apply an image texture analysis technique on turned surface images for quantitative assessment of cutting tool flank wear, progressively.
18) Aghazadeh F et al. [18] This paper investigates a robust tool wear monitoring system for milling operation. Recent developments in machine learning, in particular deep learning methods, result in significant improvement in automation of different industries. Therefore, in this research, we employed convolutional neural network (CNN) as a well-established and powerful deep learning algorithm for tool wear estimation.

III. Feeds for Milling

The rate of feed, or the speed at which the workpiece passes the cutter, determines the time required for cutting a job. In selecting the feed. There are several factors which should be considered. Forces are exerted against the workpiece, the cutter, and their holding devices during the cutting process. The force exerted varies directly with the amount of feed and depth of cut. And in turn are dependent upon the rigidity and power of the machine. Milling machines are limited by the power they can develop to turn the cutter and the amount of vibration they can resist when using coarse feeds and deep cuts. The feed and depth of the cut also depend upon the type of milling cutter being used. For example. Deep cuts or coarse feeds should not be attempted when using a small diameter end milling cutter. Coarse cutters with strong cutting teeth can be fed at a faster rate because the chips maybe washed out more easily by the cutting oil. Coarse feeds and deep cuts should not be used on a frail workpiece if the piece is mounted in such a way that its holding device is not able to prevent springing or bending.

Over speeding may be detected by the occurrence of a squeaking scraping sound. If vibration (referred to as chattering) occurs in the milling machine during the cutting process. The speed should be reduced and the feed increased. Too much cutter clearance. A poorly supported work piece, or a badly worn machine gear are common causes of chattering.

IV. Cutting Oils

The major advantage of using a coolant or cutting oil is that it dissipates heat, giving longer life to the cutting edges of the teeth.

The oil also lubricates the cutter face and flushes away the chips, consequently reducing the possibility of marring the finish.

A. Depth of Cut

When setting the depth of cut, the workpiece should be brought up to just touch the revolving cutter. After a cut has been made from this setting, measurement of the workpiece is taken. At this point, the graduated dial on the traverse feed is locked and used as a guide in determining the depth of cut. When starting the cut, the workpiece should be moved so that the cutter is nearly in contact with its edge, after which the automatic feed may be engaged. When a cut is started by hand, care must be taken to avoid pushing the corner of the workpiece between the teeth of the cutter too quickly, as this may result in cutter tooth breakage. In order to avoid wasting time during the operation, the feed trips should be adjusted to stop the table travel just as the cutter clears the workpiece.

B. Feed rate

The speed of the cutting tool's movement relative to the workpiece as the tool makes a cut. The feed rate is measured in inches per minute (IPM) and is the product of the cutting feed (IPR) and the spindle speed (RPM).

C. Cutting speed

The speed of the workpiece surface relative to the edge of the cutting tool during a cut, measured in surface feet per minute (SFM).

D. Cutting feeds

The distance that the cutting tool or workpiece advances during one revolution of the spindle and tool, measured in inches per revolution (IPR). In some operations the tool feeds into the workpiece and in others the workpiece feeds into the tool. For a multipoint tool, the cutting feed is also equal to the feed per tooth, measured in inches per tooth (IPT), and multiplied by the number of teeth on the cutting tool.

V. CNC Milling Process

Milling is the process of machining flat, curved or irregular surface by feeding the work piece against a rotating cutter containing a number of cutting edges. Milling process consists of a motor driven spindle, which mounts and revolves the milling cutter and a reciprocating adjustable worktable, which mounts and feeds the work piece. Milling machine is a machine toot that cuts metal with multiple-tooth cutting tool called a milling cutter. The work piece is fastened to the milling machine table and is fed against the revolving milling cutter. The milling cutter can have cutting teeth on the periphery or side or both.

A. Principle Functions of CNC

The principle functions of CNC are as follows:-

- Machine tool control
- In-process compensation
- Improved programming and operating features
- Diagnostics

B. 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

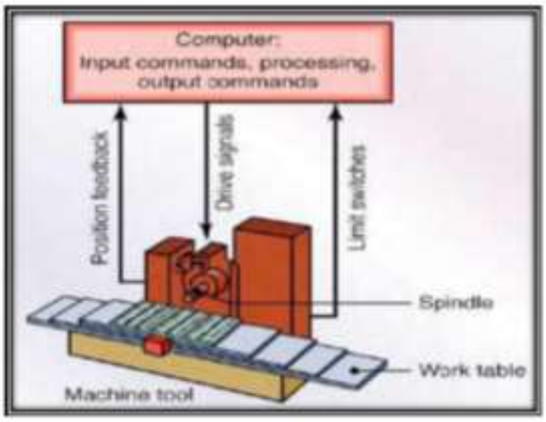

Fig. 2: Major Components of a numerical control machine tool

VI. Conclusion

Assize of data increases the performance of models using classical artificial intelligence increases. There are many machine learning approaches available for tool condition monitoring for the milling process. The shortcomings of machine learning are accuracy, speed, robustness, etc. in this review presented are the feed milling and the cutting oils are depth of cut, cutting speed, cutting feed. The CNC milling process is presented in this review paper.

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