PREDICTION OF CUTTING FORCE IN TURNING USING DESIGN OF EXPERIMENTS AND ARTIFICIAL NEURAL NETWORK

A PROJECT REPORT

Submitted By

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BONAFIDE CERTIFICATE

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Abstract

ABSTRACT

The cutting force has a significant influence on the dimensional accuracy because of tool and workpiece deflection in turning. Force modeling in metal cutting is important for a multitude of purposes, including thermal analysis, tool life estimation, chatter prediction, tool condition monitoring, etc. Cutting force plays a vital role in turning operation. Required surface finish and dimensional accuracy is based only on cutting force. Cutting force in turning is determined by the various machining parameters such as cutting speed, feed, depth of cut, etc. within the operational constraints. Cutting force involves three forces viz. tangential, thrust and radial. But only both tangential and thrust force is significant since it affects the surface finish characteristics and dimensional accuracy If the thrust force is too high or if the machine tool is not sufficiently stiff, the tool will be pushed away from the surface being machined and tangential force is the highest of the three forces and accounts for about 98 percent of the total power required by the operation.

Experiments were conducted in all geared head centre lathe on machining C 45 steel specimens using Carbide tipped cutter using Design of Experiments based on central composite method. Results obtained from the experiment were used to predict the cutting force with the help of mathematical model developed using Quality America software. Using the measured force an Artificial Neural Network (ANN) model was developed using MATLAB 7.0 software. ANN model architecture consists of single hidden layer with 5 hidden neurons and trained by using feed forward back propagation algorithm. In addition, the results obtained by experimental procedure and from ANN model were compared to confirm that the developed ANN is more accurate in prediction.

ஆய்வுச் சுருக்கம்

கடையப்படும் பொருளின் அளவு வேறுபாடானது வெட்டின் விசையை பொருத்து மாறுபடும் ஏனெனில் கடைசலின் போது கடையும் பொருளும் கடையப்படும் பொருளும் ஏற்படுத்தும் திசைமாற்றமே காரணம். உலோக கடைசலுக்கு தரப்படும் விசையை வடிவமைத்தலானது பல்வேறு பயன்பாடுகளை கொண்டுள்ளது. வெப்பத்தின் பகுப்பாய்வு, பொருளின் ஆயுளை மதிப்பிடுதல், கடையும் பொருளின் நிலைமையைக் கண்காணித்தல் போன்ற பயன்பாடுகளை கொண்டுள்ளது.வெட்டின் விசையானது கடைசலில் முக்கிய பங்கு வகிக்கிறது. வெட்டின் விசையை பொருத்து கடையப்படும் பொருளின் மேற்பரப்பு தன்மையும், கடையப் படும் பொருளின் அளவும் வேறுபடும். இயந்திரத்தின் பல்வேறு அளபுருகளான வெட்டின் வேகம், ஊட்டம், வெட்டின் ஆழம் ஆகியவற்றைக் கொண்டு வெட்டின் விசையை கண்டறியலாம். வெட்டின் விசையை மூன்று வகையாக பிரிக்கலாம். அவைகள் தொடு கோட்டு விசை, சுழற்சி விசை, தாக்கு விசைகள் ஆகும். இவற்றுள் தொடு கோட்டு விசை, தாக்கு விசை மட்டுமே கடைப்பொருளின் பண்புகளையும் பொருளின் அளவையும் மாற்றுகிறது. தாக்கு விசை அதிகமாக இருக்கும் பொழுது கடையும் பொருள் கடையப்படும் பொருளின் மேற்பரப்பை விட்டு விலகி விடும். இந்த செயல்பாட்டில் பயன்படுத்தப் படும் மொத்த சக்திகளில் 98% மேலாக தொடுகோட்டு விசை பயன்படுத்தபடுகிறது.

ஆல் கியர்டு ஹெட் சென்டர் லேத்தைக் கொண்டு இந்த ஆராய்ச்சி செய்து முடிக்கப்பட்டுள்ளது. C45 ஸ்டீலை கடைவதற்கு கார்பைடு நுனி கடைப்பொருள் பயன்படுத்தப்பட்டுள்ளது.டிசைன் ஆப் எக்ஸ்பரிமெண்ட்ஸ் (DOE) உதவியுடன் இந்த ஆராய்ச்சி நடத்தப்பட்டது. ஆராய்ச்சியின் முடிவைக் கொண்டு வெட்டின் விசையை நிர்ணயிக்க குவாலிட்டி அமேரிக்கா மென்பொருளின் மூலம் கணித மாதிரி உருவாக்கப்பட்டது. அதே ஆராய்ச்சியின் முடிவைக் கொண்டு மேட்லேப் 7.0 மென்பொருளின் உதவியுடன் வெட்டின் விசைக்கு செயற்கை நரம்பணு வலை (ANN) மாதிரி உருவாக்கப்பட்டது. இந்த ஆய்வில் ANN கட்டமைப்பில் ஒரு மறை அடுக்கில் 5 மறை நரம்பணுக்கள் கொண்டுள்ளது. மேலும் இதை பீடுபார்வார்டு பேக் ப்ரொபகேஷன் மூலம் பயிற்சி செய்யபட்டுள்ளது. மேலும் ஆராய்சியின் முடிவில் கிடைத்த வெட்டின் விசையையும் ANN மாதிரியில் கிடைத்த வெட்டின் விசையையும் ஒப்பிட்டு செய்து, ANN மாதிரியில் கிடைத்த வெட்டின் விசையை சிறந்த்து என்று கணிக்கப்பட்டுள்ளது.

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ANN	-	Artificial Neural Network
DOE	-	Design of Experiments
d	-	Depth of cut (mm)
P	-	Power (kw)
f	-	Feed rate (mm / rev)
F_c	.	Cutting force (N)
α_e	.	Effective rake angle
L	-	Length of the work piece (mm)
i	-	Inclination angle
t_o	-	Depth of cut (mm)
As	-	Shear plane area mm^2
V	-	Cutting speed (m / min)
C	-	Carbon
Mn	-	Manganese
P	-	Phosphorous
S	-	Sulphur
F_x	.	Feed force in x direction.
F_y	.	Cutting force in y direction
F_z	.	Radial force in z direction
Φ	-	Shear angle
α	-	Rake angle
μ	-	Coefficient of friction
β	-	Friction angle
F_s	.	Tangential force (N)
F_n	.	Radial force (N)
F_t	.	Thrust force (N)
α_c	.	Chip flow angle
α_n	.	Normal rake angle

Chapter 1

Introduction

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW OF MACHINING PROCESS:

In terms of annual dollars spent, machining is the most important of the manufacturing processes. Machining can be defined as the process of removing material from a work piece in the form of chips. The term metal cutting is used when the material is metallic. Most machining has very low setup cost compared to forming, molding, and casting processes. However, machining is much more expensive for high volumes. Machining is necessary where tight tolerances on dimensions and finishes are required. The Machining section is divided into five categories: Drilling, turning, milling, and grinding and chip formation.

1.1.1 Turning:

Turning is another of the basic machining processes. Information in this section is organized according to the subcategory links in the menu bar to the left. Turning produces solids of revolution which can be tightly toleranced because of the specialized nature of the operation. Turning is performed on a machine called a lathe in which the tool is stationary and the part is rotated. The figure below illustrates an engine lathe. Lathes are designed solely for turning operations, so that precise control of the cutting results in tight tolerances. The work piece is mounted on the chuck, which rotates relative to the stationary tool.

1.1.2 Drilling:

Drilling is easily the most common machining process. One estimate is that 75% of all metal cutting material removed comes from drilling operations. Drilling involves the creation of holes that are right circular cylinders. This is accomplished most typically by using a twist drill. The chips must exit through the flutes to the outside of the tool. The cutting front is embedded within the work piece, making cooling difficult. The cutting area can be flooded, coolant spray

1.1.3 Milling:

Milling is as fundamental as drilling among powered metal cutting processes. Milling is versatile for a basic machining process, but because the milling set up has so many degrees of freedom, milling is usually less accurate than turning or grinding unless especially rigid fixturing is implemented. For manual machining, milling is essential to fabricate any object that is not axially symmetric. There is a wide range of different milling machines, ranging from manual light duty Bridgeports™ to huge CNC machines for milling parts hundreds of feet long.

1.1.4 Grinding:

Grinding is a finishing process used to improve surface finish, abrade hard materials, and tighten the tolerance on flat and cylindrical surfaces by removing a small amount of material. Information in this section is organized according to the subcategory links in the menu bar to the left. In grinding, an abrasive material rubs against the metal part and removes tiny pieces of material. The abrasive material is typically on the surface of a wheel or belt and abrades material in a way similar to sanding. On a microscopic scale, the chip formation in grinding is the same as that found in other machining processes. The abrasive action of grinding generates excessive heat so that flooding of the cutting area with fluid is necessary.

1.1.5 Chip Formation

Because of the importance of machining for any industrial economy, Machining Theory has been extensively studied. The chip formation process is the same for most machining processes, and it has been researched in order to determine closed form solutions for speeds, feeds, and other parameters which have in the past been determined by the "feel" of the machinist. With CNC machine tools producing parts at everfaster rates, it has become important to provide automatic algorithms for determining speeds and feeds. The information presented in this section are some of the more important aspects of chip formation.

1.2 TURNING PROCESS:

Turning produces solids of revolution that can be tightly toleranced because of the specialized nature of the operation. Turning is performed on a machine called a lathe in which the tool is stationary and the part is rotated. Workpieces, large and small can be machined in one setup through multi-tasking capabilities on single- and multi-spindle machines. For larger workpieces, workhorse engine lathes, vertical turning centres, and a new generation of computer numerical lathes deliver the required power and accuracy. Automation is provided by bar feeders, robots, and pallet delivery systems.

1.3 MECHANICS OF MACHINING

1.3.1 Statics

Orthogonal machining has been defined as a two-force system. Consider Figure 1.1, which shows a free-body diagram of a chip that has been separated at a shear plane. It is assumed that the resultant force *R* acting on the back of the chip is equal and opposite to the resultant force *R'* acting on the shear plane. The resultant *R* is composed of the friction *force F* and the normal force *N* acting on the tool chip interface contact area.

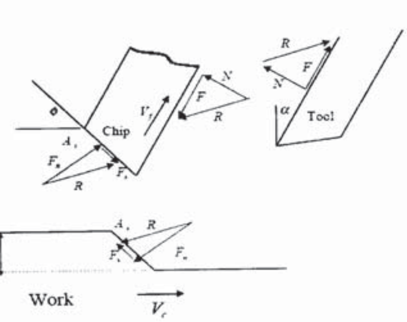


Figure 1.1 Free body diagram of orthogonal chip formation process Showing equilibrium condition between resultant forces R and R'

The resultant force R' is composed of a tangential force F_s and radial force F_n acting on the shear plane area A. Since neither of these two sets of forces can usually be measured, a third set is needed, which can be measured using a dynamometer (force transducer) mounted either in the work holder or the tool holder. Note that this set has resultant R, which is equal in magnitude to all the other resultant forces in the diagram. The resultant force R is composed of a cutting force F_c and a thrust force F_t. Now it is necessary to express the desired forces (F_s, F_n, F, and N) in terms of the measured dynamometer components, F_c and F_t, and appropriate angles.

1.3.2 Dynamics

Machining is a dynamic process of large strain and high strain rates. All the process variables are dependent variables. The process is intrinsically a closed-loop interactive process. Remember that plastic deformation is always preceded by elastic deformation, which behaves like a big spring. The mechanism by which a process dissipates energy is called chatter or vibration. In machining, it has long been observed in practice that rotational speed may greatly influence process stability and chatter. Experienced operators commonly listen to machining noise and interactively modify the speed when optimizing a specific application. In addition, experience demonstrates that the performance of a particular tool may vary significantly based on the machine tool employed and other characteristics such as the workpiece, fixture holder, and the like. Today more than ever, the manufacturing industry is more competitive and responsive, characterized by both high volume and small batch production seeking economies of scale. High productivity is achieved by increased machine and tooling capabilities along with the elimination of all non-value-added activities. Few companies can afford lengthy trial-and-error approaches to machining-process optimization or additional processes to treat the effect of chatter.

In metal cutting, chatter is a self-excited vibration that is caused by the closed loop force-displacement response of the machining process. The process-induced variations in the cutting force may be caused by changes in the cutting velocity, chip cross section (area), tool/chip interface friction, built-up edge, workpiece variation, or most commonly, process modulation resulting in regeneration of vibration

1.4 ORTHOGONAL MACHINING

In order to understand the complex process of oblique cutting, the tool geometry is simplified from the three-dimensional (oblique) geometry, which typifies most processes, to a two-dimensional (orthogonal) geometry. Low speed orthogonal plate machining as shown in Figure 1.2 uses a flat plate setup in a milling machine. The workpiece is moving past the tool at velocity V.

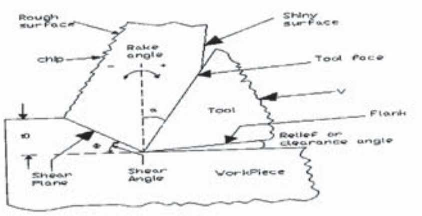


Figure 1.2 Schematic illustration of a two-dimensional cutting process, also called orthogonal cutting

The feed of the tool is now called t_0, the uncut chip thickness. The DOC is the width of the plate w. The cutting edge of the tool is perpendicular to the direction of motion V.The angle that the tool makes with respect to a vertical from the workpiece is called the back rake angle α.

A positive angle is shown in the schematic. The chip is formed by shearing. The onset of shear occurs at an angle Φ with respect to the horizontal. This model is sufficient to allow us to consider the behavior of the work material during chip formation, the influence of the most critical elements of the tool geometry (the edge radius of the cutting tool and the back rake angle α), and the interactions that occur between the tool and the freshly generated surfaces of the chip against the rake face and the new surface as rubbed by the flank of the tool.

Basically, the chip is formed by a localized shear process that takes place over a out of a radial compression zone that travels ahead of the tool as it passes over the workpiece. This radial compression zone has, like all plastic deformations, an elastic compression region that changes into a plastic compression region when the yield strength of the material is exceeded.

1.5 THE MECHANICS OF OBLIQUE CUTTING

The majority of cutting operations involve tool shapes that are three dimensional. As we have seen, in orthogonal cutting the tool edge is perpendicular to the movement of the tool and the chip slides directly up the face of the tool.

1.6 TYPES OF CHIPS

When we observe actual chip formation under different metal-cutting conditions, we find significant deviations from the ideal model. Because the types of chips produced significantly influence the surface finish of the workpiece and the overall cutting operation (for instance tool life, vibration, and chatter), the types of chips are described in the following order.

- Continuous
- Build-up edge
- Serrated or segmented
- Discontinuous

Let's first note that a chip has two surfaces: one that is in contact with the tool face (rake face) and the other from the original surface of the workpiece. The tool side of the chip surface is shiny, or burnished, which is caused by the rubbing of the chip as it moves up the tool face. The other surface of the chip does not come into contact with any solid body. This surface has a jagged, rough appearance (Figure 1.2), which is caused by the shearing mechanism shown in (Figure 1.8)

1.6.1 Continuous chip:

Continuous chips are usually formed with ductile materials at high cutting speeds and/or high rake angles (Figure 1.3). The deformation of the material takes place along a narrow shear zone, the primary shear zone. Continuous chip may, because of friction, develop a secondary shear zone at the tool-chip interface (Figure 1.4).the secondary zone becomes thicker as tool-chip friction increases.

Figure 1.3 Continuous chips with narrow, straight primary zone

In continuous chips, deformation may also take place along a wide primary shear zone with curved boundaries (Figure 1.5). Note that the lower boundary is below the machined surface, subjecting the machined surface to distortion, as depicted by the distorted vertical lines. This situation occurs particularly in machining soft metals at low speeds and low rake angles. It can produce poor surface finish and induce residual surface stresses, which may be detrimental to the properties of the machined part.

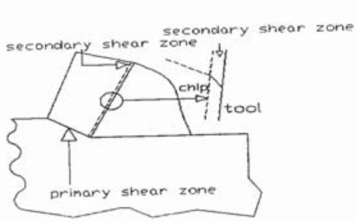


Figure 1.4 Secondary shear zone at the chip-tool face interface

Although they generally produce good surface finish, continuous chips are not always desirable, particularly in the computer-controlled machine tools widely used today. They tend to become tangled around the tool holder, the fixturing, and stopped to clear away the chips. This problem can be alleviated with the chip breakers and by changing machining parameters, such as cutting speed, feed and cutting fluids.

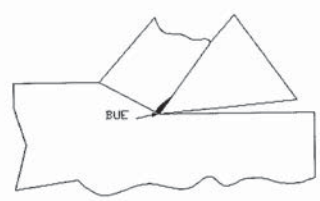


Figure 1.5 Continuous chips with large primary shear zone

1.6.2 Built-up edge chips

A built-up edge, consisting of layers of material from the workpiece that are gradually deposited on the tool (hence the term built-up), may form at the tip of the tool during cutting (Figure 1.6). As it becomes larger, the BUE becomes unstable and eventually breaks up. Part of the BUE material is carried away by the tool side of the chip: the rest is deposited randomly on the workpiece surface. The process of BUE formation and destruction is repeated continuously during the cutting operation, unless measures are taken to eliminate it.

The built-up edge is commonly observed in practice. A built up edge, in effect, changes the geometry of the cutting edge. Note, for example, the large tip radius of the BUE and the rough surface finish produced.

Because of work hardening and deposition of successive layers of material. BUE hardness increases significantly. Although BUE is generally undesirable, a thin, stable BUE is usually regarded as desirable because it reduces wear by protecting the rake face of the tool.

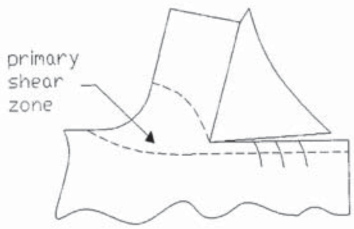


Figure 1.6 Continuous chips with built-up edge

As the cutting speed increases, the size of the BUE decreases; in fact it may not form at all. The tendency for a BUE to form is also reduced by any of the following practices:

a. decreasing the depth of cut
b. increasing the rake angle
c. using a sharp tool, and
d. Using an effective cutting fluid.

In general, the higher the affinity (tendency to form a bond) of the tool and workpiece materials, the greater the tendency for BUE formation. In addition, a cold-worked metal generally has fewer tendencies to form BUE than one that has been annealed.

1.6.3 Serrated chips:

Serrated chips (also called segmented or nonhomogeneous chips) are semi continuous chips with zones of low and high shear strain (Figure 1.8).metals with low thermal conductivity and strength that decreases sharply with temperature, such as titanium, exhibit this behavior. The chips have a saw tooth like appearance.

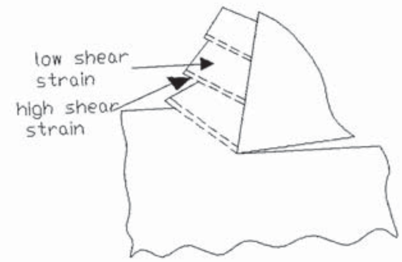


Figure 1.7 Segmented or Nonhomogenous chip

This type of chip should not be confused with the illustration in (Fig 1.8) in which the dimension d is highly exaggerated.

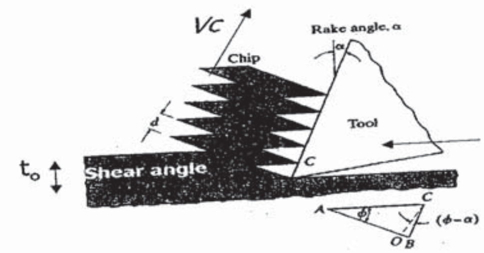


Figure 1.8 Schematic illustration of the basic mechanism of chip formation in metal cutting

1.6.4 Discontinuous chips:

Discontinuous chips consist of segments that may be firmly or loosely attached to each other (Figure 1.9).discontinuous chips usually form under the following condition:

1. Brittle workpiece materials, because they do not have the capacity to undergo ... strains involved in cutting.
2. Workpiece materials that contain hard inclusions and impurities, or have structures such as the graphite flakes in gray cast iron.
3. Very low or very high cutting speeds.
4. Large depths of cut.
5. Low rake angles.
6. Lack of effective cutting fluids.
7. Low stiffness of the machine tools.

Because of the discontinuous nature of chip formation, forces continually vary during cutting. Consequently, the stiffness or rigidity of the cutting-tool holder, the workholding devices, and the machine tool are important in cutting with both discontinuous-chip and serrated chip formation. If it is not stiff enough, the machine tool may begin to vibrate and chatter. This, in turn adversely affects the surface finish and dimensional accuracy of the machined component, and may damage the cutting tool or cause effective wear.

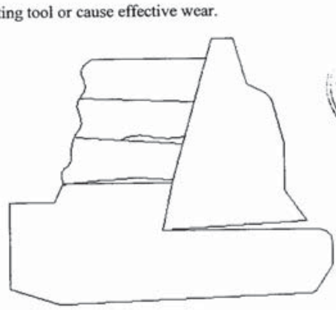


Figure 1.9 Discontinuous chips

1.7 CUTTING FLUIDS

The purposes of using cutting fluids on the lathe are to cool the tool bit and workpiece that are being machined, increase the life of the cutting tool, make a smoother surface finish, deter rust, and wash away chips. Cutting fluids can be sprayed, dripped, wiped, or flooded onto the point where the cutting action is taking place. Generally, cutting fluids should only be used if the speed or cutting action requires the use of cutting fluids. Descriptions of some common cutting fluids used on the lathe follow.

1.7.1 Lard Oil

Pure lard oil is one of the oldest and best cutting oils. It is especially good for thread cutting, tapping, deep hole drilling, and reaming. Lard oil has a high degree of adhesion or oiliness, a relatively high specific heat, and its fluidity changes only slightly with temperature. It is excellent rust preventive and produces a smooth finish on the workpiece. Because lard oil is expensive, it is seldom used in a pure state but is combined with other ingredients to form good cutting oil mixtures.

1.7.2 Mineral Oil

Mineral oils are petroleum-base oils that range in viscosity from kerosene to light paraffin oils. Mineral oil is very stable and does not develop disagreeable odors like lard oil; however, it lacks some of the good qualities of lard oil such as adhesion, oiliness, and high specific heat. Because it is relatively inexpensive, it is commonly mixed with lard oil or other chemicals to provide cutting oils with desirable characteristics. Two mineral oils, kerosene and turpentine, are often used alone for machining aluminum and magnesium. Paraffin oil is used alone or with lard oil for machining copper and brass.

1.7.3 Mineral-Lard Cutting Oil Mixture

Various mixtures of mineral oils and lard oil are used to make cutting oils which combine the good points of both ingredients but prove more economical and often as effective as pure lard oil.

1.7.4 Sulfurized Fatty-Mineral Oil

Most good cutting oils contain mineral oil and lard oil with various amounts of sulfur and chlorine which give the oils good antiweld properties and promote free machining. These oils play an important part in present-day machining because they provide good finishes on most materials and aid the cutting of tough material.

1.7.5 Soluble Cutting Oils

Water is an excellent cooling medium but has little lubricating value and hastens rust and corrosion. Therefore, mineral oils or lard oils which can be mixed with water are often used to form cutting oil. A soluble oil and water mix has lubricating qualities dependent upon the strength of the solution. Generally, soluble oil and water is used for rough cutting where quick dissipation of heat is most important. Borax and trisodium phosphate (TSP) are sometimes added to the solution to improve its corrosion resistance.

1.7.6 Soda-Water Mixtures

Salts such as soda ash and TSP are sometimes added to water to help control rust. This mixture is the cheapest of all coolants and has practically no lubricating value. Lard oil and soap in small quantities are sometimes added to the mixture to improve its lubricating qualities. Generally, soda water is used only where cooling is the prime consideration and lubrication a secondary consideration. It is specially suitable in reaming and threading operations on cast iron where a better finish is desired.

1.7.7 White Lead and Lard Oil Mixture

White lead can be mixed with either lard oil or mineral oil to form cutting oil which is especially suitable for difficult machining of very hard metals.

1.8 CUTTING FORCES AND POWER

1.8.1 Types of cutting force:

The forces acting on a cutting in turning are important in the design of machine tools. The machine tool and its components must be able to withstand these forces without causing significant deflections, vibrations, or chatter during the operation. There are three principal forces during a turning process: tangential force, thrust force and radial force.

(i) Thrust force:

The thrust force acts in the longitudinal direction. It is also called the feed force away from the chuck. a knowledge of the thrust force in cutting is important because the tool holder, the work-holding devices, and the machine tool must be sufficiently stiff to minimize deflection caused by this force.

(ii) Tangential Force:

This acts in a direction tangential to the revolving workpiece and represents the resistance to the rotation of the workpiece. In a normal operation, tangential force is the highest of the three forces and accounts for about 98 percent of the total power required by the operation.

(iii) Radial Force:

Radial force acts in a radial direction from the center line of the workpiece. The radial force is generally the smallest of the three, often about 50 percent as large as longitudinal force. Its effect on power requirements is very small because velocity in the radial direction is negligible

Knowledge of the forces and power involved in cutting operations is important for the following reasons:

1. Power requirements must be known to enable the selection of a machine tool with adequate power.
2. data on cutting forces is required so that:

A. Machine tools can be properly designed to avoid excessive distortion of the machine elements and maintain the desired dimensional tolerances for the finished part, tooling and tool holders, and work holding devices, and

B. It can be determined, in advance of actual production, whether the workpiece is capable of withstanding the cutting forces without excessive distortion.

1.8.2 Merchant's Model

For the purpose of modeling chip formation, assume that the shear process takes place on a single narrow plane rather than on the set of shear fronts that actually comprise a narrow shear zone. Further, assume that the tool's cutting edge is

new surface. The workpiece passes the tool with velocity V, the cutting speed. The uncut chip thickness is t_0. Ignoring the plastic compression, chips having thickness T_c is formed by the shear process. The chip has velocity V_C. The shear process then has velocity Vs and occurs at the onset of shear angle Φ. The tool geometry is given by the back rake angle α and the clearance angle γ.

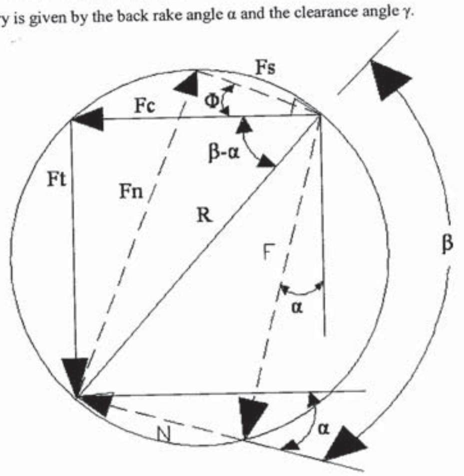


Figure 1.10 Merchant's circle

The forces acting on the tool in orthogonal cutting are shown in the Figure 1.2 the cutting forces F_c acts in the direction of cutting speed, V, and supplies the energy required for cutting. The thrust force, F_t acts in a direction normal to the cutting velocity, that is, perpendicular to the workpiece. These two forces produce the resultant force, R.

Note that the resultant force can be resolved into two components on the tool face: a friction force, F, along the tool-chip interface, and a normal force, N. perpendicular to it. Using Figure 1.10 it can be shown that

Frictional force $F = R\sin\beta$ .... (1.1)

Normal force $N = R\cos\beta$ .... (1.2)

Note also that the resultant force is balanced by an equal and opposite force along the shear plane and is resolved into a shear force F_s, and a normal force, F_n. It can be shown that these forces can be expressed as follows:

Tangential force $F_s = F_c\cos\phi - F_t\sin\phi$ .... (1.3)

Were,

Φ = Shear angle

F_c = cutting force.

Radial force $F_n = F_c\sin\phi + F_t\cos\phi$ .... (1.4)

Were,

F_t = Thrust force

Because we can calculate the area of the shear plane by knowing the shear angle and the depth of cut, we can determine the shear and normal stresses in the shear plane.

The ratio of F to N is the coefficient of friction μ at the tool-chip interface, and the angle β is the friction angle.

It can be expressed as

$$\mu = \frac{F}{N} = \frac{F_t + F\,.\tan(\alpha)}{F_c - F_t.\tan(\alpha)} \quad \text{..............................} \quad (1.5)$$

The coefficient of friction in metal cutting generally ranges from about 0.5 to 2, indicating that the chip encounters considerable frictional resistance while moving up the rake face of the tool.

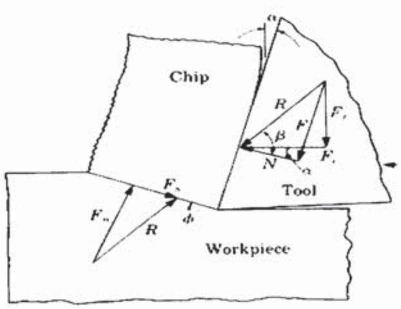


Fig 1.11 Forces acting on a cutting tool in two-dimensional cutting.

Although the magnitude of forces in actual cutting operations is generally on the order of a few hundred newtons, the local stresses in the cutting zone and the pressures on the tool are very high because the contact area are very small. The chip-tool contact length (Fig 1.2), for example, is typically on the order of 1 mm (0.04 in). Thus, the tool is subjected to very high stresses, which lead to wear, and sometimes chipping and fracture of the tool.

Chapter 2

Literature Review

CHAPTER 2

LITERATURE REVIEW

2.1. INTRODUCTION

Recently different methods have been reported in the literature to optimize the machining parameters using various non-conventional methods. A number of researchers have dealt with the prediction of machining parameters. The turning operation was considered by many researchers and starting from graphical methods to geometric programming methods have been used to determine the optimum speed and feed.

2.2. SELECTION OF MACHINING PARAMETERS

These include - A simplified approach to optimum selection of machining parameters, machining economics and industrial data manuals, optimization of the constrained machining economics problem by geometric programming, a probabilistic approach to determination of the optimum cutting conditions and machining parameters as cutting speed, feed and depth of cut with constrains as thrust and tangential cutting force.

2.3. ABOUT RESEARCHERS EXPLANATION

Chen et al. (2000) evaluate the cutting forces generated using CBN tools when cutting steel being hardened to 45–55 HRC. He suggests Radial thrust cutting force was the largest among the three cutting force components and was most sensitive to the changes of cutting edge geometry and tool wear and he also suggests the surface finish produced by CBN tools was compatible with the results of grinding and was affected by cutting speed, tool wear and plastic behavior of the workpiece material.

Li et al. (2001) has used neural network for predicting cutting force-induced errors in real-time based on turning operations based on estimated cutting force. the machine- workpiece-tool system he develops a model of elastic deflection of machine- workpiece-tool system due to the cutting force in turning. He also uses novel radial basis function (RBF) neural network to map the relationship between the cutting force components (radial, axial and tangential) and the consequent dimensional deviation of the finished parts caused by the combined deflections of the machine–workpiece–tool system.

Lei Zhang et al. (2003) In end milling of pockets, variable radial depth of cut is generally encountered as the end mill enters and exits the corner, which has a significant influence on the cutting forces and further affects the contour accuracy of the milled pockets. He explains an approach for predicting the cutting forces in end milling of pockets. He presents a mathematical model to describe the geometric relationship between an end mill and the corner profile. The milling process of corners is discredited into a series of steady-state cutting processes, each with different radial depth of cut determined by the instantaneous position of the end mill relative to the workpiece. He introduces an analytical model for the steady-state machining conditions for the prediction of cutting force for each segmented process with given radial depth of cut. The predicted cutting forces can be calculated in terms of tool/workpiece geometry, cutting parameters and workpiece material properties, as well as the relative position of the tool to workpiece. Experiments of pocket milling are conducted for the verification of the proposed method.

Halil Bil et al. (2004) He studied to compare various simulation models of orthogonal cutting process with each other as well as with the results of various experiments.He compared the estimated cutting and thrust forces, Shear angles, chip thickness and contact lengths on the rake face by three codes with experiments performed in this study and with experiment result supplied in literature. In addition he examined effect of friction factor, different remeshing criteria, and threshold tool penetration value. Finally he found that although individual parameters may match with experimental results, all models failed to achieve a satisfactory correlation with all measured process parameters.

the finish hard turning of AISI H13 were experimentally investigated. He found that cutting edge geometry, workpiece hardness and cutting speed affect the force components. He also found that lower workpiece surface hardness and honed edge geometry results in lower tangential and radial forces.

Kumanan et al. (2006) he proposes the prediction of machining forces using multi-layered perception trained by genetic algorithm then he uses the data obtained from experimental results of a turning process to train the proposed artificial neural networks with three inputs to get machining forces as output. He then computed the optimal ANN weights using GA research.

Palanisamy et al. (2006) has developed a dynamic cutting force model for end milling operation for end milling operation for predicting tangential and thrust cutting force and he has also validated the predicted model with the experimental cutting force during the machining of AISI 1020 steel using a three-axis milling tool dynamometer

Kadirgama (2006) he describes the application of neural network methods to predict the cutting force model in milling 618 stainless steel. He has taken cutting force as a response and cutting speed, feed, axial depth and radial depth as variables. He used design of experiment to reduce number of experiments and provided the optimum experiment condition. He compared the predictive result with the experimented result. Since the value of prediction was closer to the experimental result he accepts the error from the neural network result.

Li et al. (2007) Prediction of cutting force plays an essentially important role in the selection of optimum cutting parameters and investigation of cutting mechanisms. An extended octree is presented to represent the workpiece and tool swept volume to acquire the cutting depth and cutting width with high precision so that the cutting forces can be predicted precisely he describes algorithm of acquisition of cutting width and cutting depth in flat-end milling.

Singh Dilbag et al. (2007) he explores the use of solid lubricants during hard turning while machining bearing steel with mixed ceramic inserts at different increase in surface finish with the use of solid lubricants he also proves that there is a decrease of surface roughness values from 8 to 15% as compared to dry hard turning while using the solid lubricants.

Vishal Sharma (2008) studied machining variables such as cutting forces and surface roughness are measured during turning at different cutting parameters such as approaching angle, speed, feed and depth of cut. He analyzed the data obtained by experimentation and used to construct model using neural networks. He tested the obtained model with the experimental data and he indicates the result.

Closer study of the above works reveals that there has been substantial evidence to support the view that dimensional accuracy and surface finish can be improved by providing the required cutting force. Some researchers predicted machining parameters based on a single variable by considering a single constraint. In the present work, efforts have been made to study the influence of cutting speed, feed and depth of cut on the tangential and thrust force.

Chapter 3

Development of Mathematical Model Using Design of Experiments

CHAPTER 3

DEVELOPMENT OF MATHEMATICAL MODEL USING DESIGN OF EXPERIMENTS

3.1. INTRODUCTION

Design of experiments (DOE) is a statistical technique used to study multiple variables simultaneously. Sir R.A Fisher in England introduces DOE in the early 1920s. His primary goal was to determine the optimum water, rain, sunshine, fertilizer, and soil condition needed to produce the best crop. Using the DOE technique Fisher was to able to lay out all combination of the factors included in the experimental study. The conditions were created using a matrix, which allowed each factor an equal number of test conditions. Methods for analyzing the results of such experiments were also introduced. When the number of combinations possible became too large, schemes were devised to carry out a fraction of total possibilities such that all factors would be evenly present. Fisher devised the first methods that made it possible to analyze the effect of more than one factor at a time. DOE is highly effective wherever and whenever it is suspected that the performance of a part or process is controlled by more than one factor.

3.2. PURPOSE OF EXPERIMENTATION

The purpose of experimentation should be to understand how to reduce and control variation of a product or process; subsequently, decisions must be made concerning which parameters affect the performance of a product or process. The loss function quantifies the need to understand which design factors influence the average and variation of a performance characteristic of a product or process. By properly adjusting the average and reducing variation, the product process, the

3.3. DESIGNED EXPERIMENTS

A designed experiment is the simultaneous evaluation of two or more factors (parameters) for their ability to affect the resultant average or variability of particular product or process characteristics. It is important to note that this is an iterative process; the first round through the DOE process will many times lead to subsequent rounds of experimentation. The beginning round, often referred to as a screening experiment, is used to find the few important, influential factors out of the many possible factors involved with a product or process design. This experiment is typically a small experiment with many factors at two levels. Later rounds of experiments typically involve few factors at more than two levels to determine conditions of further improvement.

3.4. DESIGN OF EXPERIMENTS PROCESS

The DOE process is divided into three main phases, which encompass all experimentation approaches. The three phases are

(1) The planning phase,
(2) The conducting phase, and
(3) The analysis phase.

The planning phase is by far the most important phase for the experiment to provide the expected information. The planning phase is when factors and levels are selected and, therefore, is the most important stage of experimentation. Also, the correct selection of factors and levels is non-statistical in nature and is more dependent upon product and process expertise.

The second most important phase is the conducting phase, when test results are actually collected. If experiments are well planned and conducted, the analysis is actually much easier and more likely to yield positive information about factors and levels.

The analysis phase is when the positive or negative information concerning the

successfully yield positive results. This phase, however, is the most statistical in nature of the three phases of the DOE by a wide margin. Because of the heavier involvement of statistics, the analysis phase is typically the least understood by the product or process expert.

The major steps to complete an effective designed experiment are listed in the following text. The planning phase includes steps 1 through 9, the conducting phase is step 10, and the analysis phase includes steps 11 and 12.

1. State the problem(s) or area(s) of concern.
2. State the objective(s) of the experiment.
3. Select the Quality characteristic(s) and measurement system(s).
4. Select the factors that may influence the selected quality characteristics.
5. Identify limits of factors
6. Select levels for the factors.
7. Select the appropriate design
8. Select interactions that may influence the selected quality characteristics or go back to step 4 (iterative steps).
9. Assign factors to design and locate interactions.
10. Conduct tests described by trials in design.
11. Analyze and interpret results of the experimental trials.
12. Conduct confirmation experiment.

These steps are fundamentally the same regardless of whether one is designing a Taguchi-based experiment or a classical design. All designed experiments require that a certain number of combinations of factors and levels be tested to observe the results of those test conditions. Two or more passes through the process are often utilized; earlier rounds of experimentation provide a growth of knowledge and a basis for later rounds of experimentation.

3.5. RESPONSE SURFACE METHODOLOGY

Experimentation and making inferences are the twin features of general scientific methodology. Statistics as a scientific discipline is mainly designed to achieve

clear and accurate conclusions from the experimental observations, on the basis of which inferences can be made in the best possible manner. The methodology for making inferences has three main aspects. First, it establishes methods for drawing inferences from observations when these are not exact but subject to variation, because inferences are not exact but probabilistic in nature. Second, it specifies methods for collection of data appropriately, so that assumptions for the application of appropriate statistical methods to them are satisfied. The advantages of design of experiments are as follows:

- Number of trials is reduced
- Optimum values of parameters can be determined
- Assessment of experimental error can be made
- Qualitative estimation of parameters can be made
- Inference regarding the effect of parameters on the characteristics of the process can be made

3.6. REGRESSION EQUATION

A statistical technique used to explain or predict the behavior of a dependent variable. A regression equation takes the form of

$Y=a+bx+c$

Where,

Y - Dependent variable
x - Independent variable
c - Regression residual
a & b – constants

3.7. OBJECTIVE FUNCTION

The purpose is to investigate the optimal cutting parameters for minimizing machining time of the turning operation while maintaining material removal rate and stability of the cutting process. The main parameters in machining affecting machining time are cutting speed, feed and depth of cut. The optimal cutting

parameters are subjected to an objective function of minimum machining time with the feasible range of cutting parameters.

3.8. CONSTRAINTS

3.8.1. Surface Roughness

Surface roughness has received serious attentions for many years. It has been an important design feature and quality measure in many situations such as parts subject to fatigue loads, precision fits, fastener holes and esthetic requirements. Furthermore, surface roughness in addition to tolerances imposes one of the most critical constraints for cutting parameter selection in manufacturing process planning.

3.8.2. Tool life

Cutting tool computer programs for analyzing general two-dimensional cutting tool geometries has been developed over a wide range of operating conditions. These programs can be used to predict chip shape and form, cutting forces, tool pressure distribution, and temperatures in the work piece, chip, and tool. This information can be used for further tool analysis, such as calculating tool wear rates, tool stresses, and a tool's chip breaking potential. Tool designers can use these programs to achieve optimal cutting efficiency through the design of proper cutting tool geometries and tool materials. Manufacturing engineers can use the programs to select the best cutting tool for a particular cutting operation. The ultimate result is improved cutting efficiency, work piece quality, and tool performance.

Predicting tool performance

Using the cutting tool programs, a more methodical approach can be taken for designing new high performance cutting tools than trial-and-error approaches used in the past. An engineer can explore the effects of tool geometry changes on cutting tool performance. Tools can be redesigned to achieve lower temperatures, higher cutting speeds, and reduced tool forces, thereby improving cutting is placed on prototype building. Several important variables can be included in a simulation, including workpiece and tool thermal properties, cutting speed, feed rate or depth of cut, and frictional effects.

3.8.3. Cutting forces

There are three cutting forces which are acting on a single point tool and shown in figure 3.1. The F_x is the feed force which is acting on the X direction, the F_y is cutting force acting of on Y direction and F_z is the radial force acting on the Z direction. The vibration will be more in the direction of cutting force F_y than that in the radial direction. with the increase of feed or depth of cut, vibration increase the tool wear when machining at feed of 0.125 mm/ rev. The cutting force F_y was low and almost equal to F_x and F_z and gives better results at higher cutting speed. During machining at 0.16 mm / rev feed force F_x was high and shows increasing trend.

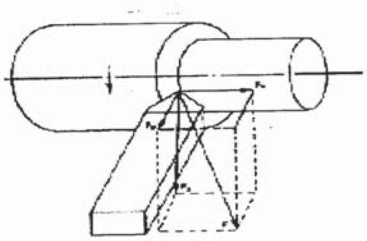


Fig.3.1 Cutting forces acting on a tool.

3.9. CHOSEN INPUT PARAMETERS

The following input parameters were chosen for this study:

- Cutting speed
- Feed
- Depth of cut

3.9.1. Feeds, Speeds & Depth of cut

For all metal cutting processes, "speeds and feeds" are important parameters. The

metal-cutting process. To describe these parameters, we will be using the turning process. The figure below shows the important geometry. The speed is the cutting speed, which is a measure of the part cut surface speed relative to the tool. Speed is a velocity unit, which is typically listed in terms of feet/min, inches/min, meters/second, or meters/min. Feed is the amount of material removed for each revolution or per pass of the tool over the workpiece. Feed is measured in units of length/revolution, length/pass, length/tooth, length/time, or other appropriate unit for the particular process. The depth of cut, DOC represents the third parameter for metal cutting. For turning, DOC is the depth that the tool is plunged into the surface. The DOC is half of the difference in the diameters D_a and D_b, the initial and final diameters, respectively.

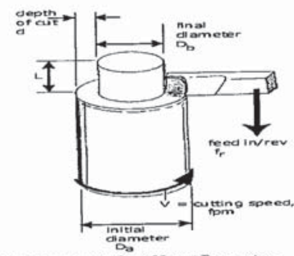


Fig. 3.2 Representation of Input Parameters

3.10. CHOSEN OUTPUT PARAMETERS

The following output parameters were chosen for this study:

- Tangential force
- Thrust force

3.11. EXPERIMENTAL DETAILS & SPECIFICATIONS

Table 3.1 Details of machine, tool and workpiece

Machine	All geared head centre lathe
Work piece material	C45 steel.
[illegible]	Tungsten carbide tip 4035

ALL GEARED HEAD CENTRE LATHE:

Table 3.2 Specification of All geared head centre lathe

Model	Turn master 45
Swing over bed covers	450 mm
Swing over the cross slide	280 mm
Spindle bore	55 mm
Maximum turning length (Between centers)	1500 mm
Height of centres	225 mm
Motor power	415 v, 50 Hz, 3Φ, 5.5 kW
No. of speeds	18
Speed range	40 -2000 RPM

LATHE TOOT DYNAMOMETER:

Table 3.3 Specification of Lathe tool dynamometer

Force direction	x, y and z
Range of force	500 kg in x,y and z direction
Bridge resistance	350 ohms
Bridge voltage(max)	2 volts

3.11.1. C45 steel

Table 3.4 Material property of C45 steel

Density	78000 kg /m^3
Poisson's ratio	0.27-0.30
Modulus of elasticity	215000 N/mm^2
Tensile strength	1780 N/mm^2
Thermal conductivity	54.9 w/m°c
Brinell hardness	180

Table 3.5 Material composition of C45 steel

Element	% weight
C	0.37-0.40
Mn	0.60-0.90
P	0.04 (max)
S	0.05 (max)

3.12. EXPERIMENTAL WORK

The experiments were conducted using all geared head centre Lathe. C45 steel test pieces of size 100 mm length and 35 mm diameter were turned using a tungsten carbide tip - 4035 tool.

3.13. EXPERIMENTAL DESIGN PROCEDURE

The experimental design procedure used for this study is briefly explained below.

3.13.1. Identification of Factors and Responses

The chosen factors were cutting speed (m/min), feed (mm/rev), and depth of cut (mm). The chosen response was surface roughness, cutting force, tool life and power.

3.13.2. Finding the limits of the process variables

The working ranges of all selected factors are fixed by conducting trial runs. This was carried out by varying one of the factors while keeping rest of them at constant values [6]. The upper limit of a factor was coded as +1.682 and the lower limit was coded as -1.682. The chosen levels of the selected process parameters with their units and notations are given in Table 3.3

3.13.3. Development of design matrix

In factorial design, the experiments are conducted for all possible combinations of the parameter levels and these combinations, written in the form of a table where parameters, form a design matrix. The design matrix selected for experiment is a three factor five level central composite rotatable design consisting of 20 sets of coded conditions. The design for the above said models comprises a full replication of 23 (=8) factorial design plus six centre points and six star points; these correspond to the first eight rows, the last six rows and rows nine to fourteen, respectively, in the design matrix.

All process parameter variables at the intermediate (0) level constitute the centre points and the combinations of each of the process parameter variables at either its lowest (−1.682) or highest (+1.682) with two other variables of the intermediate levels constitute the star points. In this matrix, twenty experimental runs provide ten estimates for the effect of three parameters. One estimate for the mean effect of all the three parameters, three linear estimates for main effects, three quadratic estimates due to main effects, and three estimates for the two factor interactions are included. Thus the design matrix has allowed the estimation of linear, quadratic and two-way interactive effects of the selected process parameter variables on cutting force.

Table 3.6 Limits of parameters

Process parameters	Units	Notation	Limits				
			-1.682	-1	0	+1	+1.682
Cutting speed	m/min	V	67.155	82.5	105	127.5	142.84
Feed	mm/rev	f	0.078	0.097	0.125	0.152	0.171
Depth of cut	mm	b	0.131	0.2	0.3	0.4	0.468

3.13.4. Conducting the experiments as per the design matrix

The experiments were conducted at the Lathe shop in Bannari Amman Institute of Technology, Sathyamangalam. In this work, twenty deposits were made using machining condition corresponding to each combination of parameters shown in Table 3.4 at random.

3.13.5. Recording the responses

The responses, Tangential and Thrust force were measured as shown in Table 3.4 and 3.5

3.13.6. Development of a mathematical model

The response function representing any of the machining parameters can be expressed using the equation 3.1

$$Y = f(X1, X_2, X_3) \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (3.1)$$

Where

Y = Response or yield
X_1 = Cutting Speed (v) in m/min
X_2 = Feed (f) in mm/rev
X_3 = Depth of cut (d) in mm

The second order response surface model for the four selected factors is given by the equation 3.2

$$Y = \beta_0 + \sum_{i=1} \beta_i X_i + \sum_{i=1} \beta_{ii} X_i^2 + \sum_{i<j} \beta_{ij} X_i X_j \ldots\ldots\ldots \quad (3.2)$$

The second order response surface model [equation 3.3] could be expressed as follows

$$Y = \beta_0 + \beta_1 v + \beta_2 f + \beta_3 d + \beta_{11} v^2 + \beta_{22} f^2 + \beta_{33} d^2 + \beta_{12} vf + \beta_{13} vd + \beta_{23} fd \ldots\ldots (3.3)$$

Where β_0 is the free term of the regression equation, the coefficients β_1, β_2 and β_3 are linear terms, the coefficients β_{11}, β_{22} and β_{33} are the quadratic terms, and the coefficients β_{12}, β_{13} and β_{23} are the interaction terms. The coefficients were calculated using QA six sigma software (DOE-PCIV).After determining the coefficients, the mathematical model were developed and given below:

Table 3.7 Comparison of Measured and Predicted Tangential force values

Design matrix value and responses (three factors, five levels)						
Design of matrix				Cutting force(tangential)		Percentage error
Ex. no	Cutting speed	Feed	Depth of cut	Measured	Calculated	(%)
1	-1	-1	-1	190	185.80	2.20
2	+1	-1	-1	242.78	246.65	1.59
3	-1	+1	-1	267.52	271.72	1.3
4	+1	+1	-1	315.36	315.57	0.06
5	-1	-1	+1	206.5	210.12	1.75
6	+1	-1	+1	280.72	280.86	0.05
7	-1	+1	+1	303.81	303.77	0.01
8	+1	+1	+1	350	358.03	2.29
9	-1.682	0	0	221.34	221.35	0
10	+1.682	0	0	323.6	318.15	1.68
11	0	-1.682	0	200	199.79	0.10
12	0	+1.682	0	341.75	336.52	1.53
13	0	0	-1.682	247.73	247.44	0.11
14	0	0	+1.682	308.76	303.61	1.66
15	0	0	0	265.87	265.2	0.25
16	0	0	0	267.52	265.2	0.86
17	0	0	0	262.57	265.2	1
18	0	0	0	260.92	265.2	1.64
19	0	0	0	267.52	265.2	0.86
20	0	0	0	265.87	265.2	0.25

The regression mathematical model for the tangential force (Fs) is developed based on the coefficients determined using Six Sigma software:

$$Fs = 265.200 + 28.776V + 40.643\,to + 16.695f + 1.610\,V^2 + 1.046\,to^2 + 3.651f^2 - 4.121\,Vto + 2.474\,Vf + 2.061tof \ldots\ldots\ldots \quad (3.4)$$

Where V is cutting speed in m/min, to is feed in mm/tooth and f is depth of cut in mm.

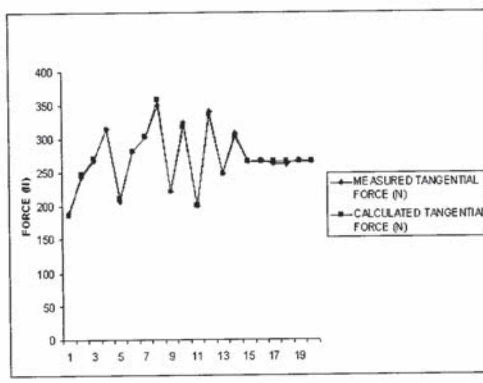


FIGURE 3.3 Comparison of Measured and Predicted Tangential force values

The above graph indicates the amount of deviation of predicted tangential force from the measured tangential force.

TABLE 3.8 Comparison of Measured and Predicted Thrust force values

Design matrix value and responses (three factors, five levels)						
Design of matrix				Cutting force(thrust)		Percentage error (%)
Ex. no	Cutting speed	Feed	Depth of cut	Measured	Calculated	
1	-1	-1	-1	120	116.84	2.62
2	+1	-1	-1	160	162.75	1.72
3	-1	+1	-1	178.14	180.86	1.52
4	+1	+1	-1	214.02	214.19	0.08
5	-1	-1	+1	132.37	135.02	2
6	+1	-1	+1	188.04	188.14	0.057
7	-1	+1	+1	205.36	205.43	0.03
8	+1	+1	+1	240	245.98	2.49
9	-1.682	0	0	143.5	143.49	0
10	+1.682	0	0	220.21	216.21	1.81
11	0	-1.682	0	127.42	127.37	0.033
12	0	+1.682	0	233.81	229.85	1.69
13	0	0	-1.682	163.3	163.17	0.07
14	0	0	+1.682	209.07	205.19	1.85
15	0	0	0	176.9	176.39	0.28
16	0	0	0	178.14	176.39	0.97
17	0	0	0	174.43	176.39	1.12
18	0	0	0	173.19	176.39	1.85
19	0	0	0	178.14	176.39	0.97
20	0	0	0	176.9	176.39	0.28

Similarly the mathematical model for the thrust force (Fs) is developed based on the coefficients determined using Six Sigma software:

$$F_s = 176.397 + 21.615V + 30.462to + 12.49f + 1.222\ V^2 + 0.748\ to^2 + 2.753f^2 - 3.144\ Vto + 1.804\ Vf + 1.599tof \ldots\ldots \quad (3.5)$$

Where V is cutting speed in m/min, to is feed in mm/tooth and f is depth of cut in mm.

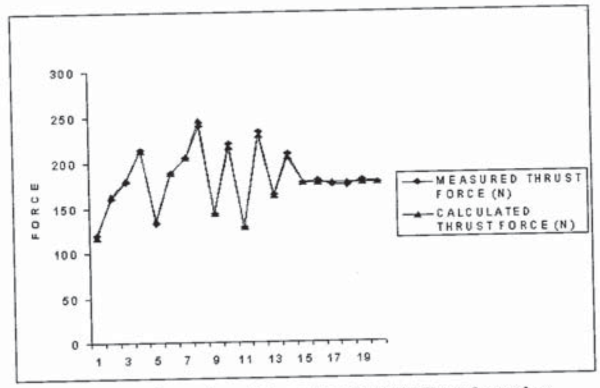


FIGURE 3.4 Comparison of Measured and Predicted Thrust force values

The above graph indicates the amount of deviation of predicted thrust force from the measured thrust force

3.13.7. Checking the adequacy of the developed models

The adequacies of the developed models were tested using the analysis of variance (ANOVA) technique. As per this technique if the calculated F-ratio values for the developed models do not exceed the standard tabulated values for a desired level of confidence (95%) and the calculated R-ratio values of the developed model exceed the standard tabulated values for a desired level of confidence (95%), then the models are said to be adequate within the confidence limit. The conditions were satisfied for the developed model.

3.13.8. Conducting the conformity test

Confirmation tests were conducted in the same experimental setup to confirm the results of the experiment and demonstrate the reliability of the predicted values. The conformity tests show the accuracy of the models developed, which is above 95%.

Chapter 4

Development of Artificial Neural Network Model

CHAPTER 4

DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK MODEL

4.1. INTRODUCTION

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. It is natural proof that some problems that are beyond the scope of current computers are indeed solvable by small energy efficient packages. This brain modeling also promises a less technical way to develop machine solutions. This new approach to computing also provides a more graceful degradation during system overload than its more traditional counterparts.

These biologically inspired methods of computing are thought to be the next major advancement in the computing industry. Even simple animal brains are capable of functions that are currently impossible for computers. Computers do rote things well, like keeping ledgers or performing complex math. But computers have trouble recognizing even simple patterns much less generalizing those patterns of the past into actions of the future.

Now, advances in biological research promise an initial understanding of the natural thinking mechanism. The brains store information as patterns. Some of these patterns are very complicated and allow us the ability to recognize individual faces from many different angles. This process of storing information as patterns, utilizing those patterns, and then solving problems encompasses a new field in computing. This field does not utilize traditional programming but involves the creation of massively parallel networks and the training of those networks to solve specific problems. This field also utilizes words very different from traditional computing.

Artificial neural networks are powerful tools for the identification of systems neural system. Artificial neural networks are massive parallel-interconnected networks that consist of basic computing elements called neurons interconnected via unidirectional signal channels called connection that imitates the human brain. Each processing element has a single output connection that branches into as many collateral connections as desired. The most widely used technique, the feed forward back propagation neural network, is adapted for the prediction of tool wear and surface roughness in the turning operation. It is a gradient descent error-correcting algorithm, which updates the weights in such a way that the network output error is minimized. The feed forward back propagation network consists of an input layer (where the inputs of the problem are received), hidden layers (where the relationship between the inputs and outputs are determined and represented by synaptic weights) and an output layer (which emits the outputs of the problem).

4.2. ANALOGY TO THE BRAIN

The exact workings of the human brain are still a mystery. Yet, some aspects of this amazing processor are known. In particular, the most basic element of the human brain is a specific type of cell which, unlike the rest of the body, doesn't appear to regenerate. Because this type of cell is the only part of the body that isn't slowly replaced, it is assumed that these cells are what provides us with our abilities to remember, think, and apply previous experiences to our every action. These cells, all 100 billion of them, are known as neurons. Each of these neurons can connect with up to 200,000 other neurons, although 1,000 to 10,000 are typical. The power of the human mind comes from the sheer numbers of these basic components and the multiple connections between them. It also comes from genetic programming and learning.

The individual neurons are complicated. They have a myriad of parts, sub-systems, and control mechanisms. They convey information via a host of electrochemical pathways. There are over one hundred different classes of neurons, depending on the classification method used. Together these neurons and their connections form a process which is not binary, not stable, and not synchronous. In short, it is nothing like the currently available electronic

These artificial neural networks try to replicate only the most basic elements of this complicated, versatile, and powerful organism. They do it in a primitive way. But for the software engineer who is trying to solve problems, neural computing was never about replicating human brains. It is about machines and a new way to solve problems.

4.3. ARTIFICIAL NEURONS AND HOW THEY WORK

The fundamental processing element of a neural network is a neuron. This building block of human awareness encompasses a few general capabilities. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then outputs the final result.

Within humans there are many variations on this basic type of neuron, further complicating man's attempts at electrically replicating the process of thinking. Yet, all natural neurons have the same four basic components. These components are known by their biological names - dendrites, soma, axon, and synapses. Dendrites are hair-like extensions of the soma which act like input channels. These input channels receive their input through the synapses of other neurons. The soma then processes these incoming signals over time. The soma then turns that processed value into an output which is sent out to other neurons through the axon and the synapses.

Recent experimental data has provided further evidence that biological neurons are structurally more complex than the simplistic explanation above. They are significantly more complex than the existing artificial neurons that are built into today's artificial neural networks. As biology provides a better understanding of neurons, and as technology advances, network designers can continue to improve their systems by building upon man's understanding of the biological brain.

But currently, the goal of artificial neural networks is not the grandiose recreation of the brain. On the contrary, neural network researchers are seeking an understanding of nature's capabilities for which people can engineer solutions to units of neural networks, the artificial neurons, simulate the four basic functions of natural neurons.

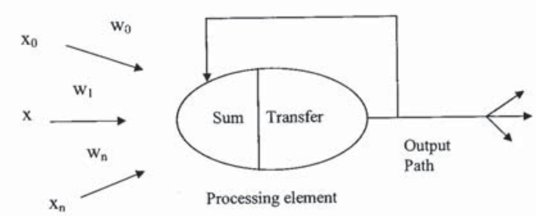


FIGURE 4.1 A Basic Artificial Neuron

Figure 4.1 shows a fundamental representation of an artificial neuron. Various inputs to the network are represented by the mathematical symbol, X (n). Each of these inputs is multiplied by a connection weight. These weights are represented by W (n). In the simplest case, these products are simply summed, fed through a transfer function to generate a result, and then output. This process lends itself to physical implementation on a large scale in a small package. This electronic implementation is still possible with other network structures which utilize different summing functions as well as different transfer functions.

Figure 4.2 shows the simlink model where the cutting speed, feed and depth of cut are input parameters while surface roughness and tool wear are the output parameters of the model. Mug combines several input signals into a vector or bus output signal. It is available in library under 'Signals & Systems'. The Mux block combines its inputs into a single output. Demux extracts and outputs the elements of a bus or vector signal from mux function. It is also available in library under 'Signals & Systems'. The Demux block extracts the components of an input signal and outputs the components as separate signals.

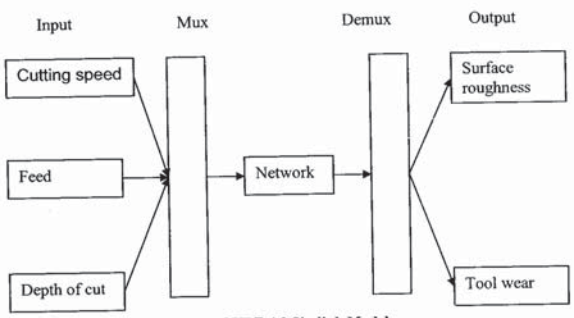


FIGURE 4.2 Simlink Model

4.4. TYPES OF ANN

Basically there are two types of ANN

1. Supervised Networks
2. Unsupervised Networks

4.4.1 Supervised Networks

Supervised neural networks as in Figure 4.3 are trained to produce desired outputs in response to sample inputs, making them particularly well suited to modeling and controlling dynamic systems, classifying noisy data, and predicting future events. Some of the supervised networks available are Feed-forward networks, Radial basis networks, recurrent networks, Learning Vector Quantification (LVQ), etc.

This learning incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required. Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning. Important issue concerning supervised learning is the problem of error-convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of weights, which minimize the error. One well-known method, which is common to many learning paradigms, is the least mean square (LMS) convergence.

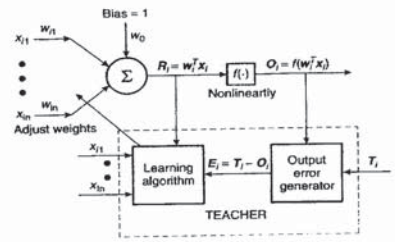


FIGURE 4.3 Supervised Learning Process

4.4.2 Unsupervised Networks

Unsupervised neural networks are trained by letting the network continually adjust itself to new inputs. They find relationships within data and can automatically define classification schemes. Some of the available such type of networks are competitive layers, self-organizing maps, etc.

Generally, the learning process of a back-propagation neural network takes place in two phases. In the forward phase, the output of each neuron in each layer and the errors between the actual output from the outer layer and the target outputs are computed; in the backward phase, weights are modified by the back-propagating errors that occur in each layer of the network.

By knowing some topology and the learning properties of a neural network, one can determine whether a specific neural network, one can determine whether specific neural network architecture is appropriate for a problem. Using the back-propagation learning procedure for GT, the initial weights of connections are generated at random, and an input vector representing the shape or envelope of a standard part propagates forward through the entire network to compute the output of each neuron in the hidden and output layer.

For each neuron in the output layer, its output value is compared with the corresponding target value to calculate the error of each neuron of the output layer. If the output error of the training part geometry is within a predefined tolerance, the training of the network is accomplished; otherwise the learning continues, that is, the weights are modified by calculating and propagating the error of each neuron in the output layer backward through the entire network. A similar computation is performed for the output value of each neuron in a forward phase by the new modified weights. In a target pattern representing a part family only one-neuron value is defined as one and the other values are zero. After the neural network ahs been trained, it assigns an input part in the form of a binary image to a family, even if the shape is incomplete.

4.5. FEED FORWARD BACK PROPAGATION NETWORK

Several ANN topologies have been developed for different applications, the most popular being the Feed Forward Back Propagation Network. It is a gradient descent error-correcting algorithm, which updates the weights in such a way that the network output error is minimized. The way that the neurons are organized forms the structure of the neural network, such as single-layer feed forward networks and multilayer-feed forward networks. A feed forward back propagation network consists of an input layer (where the inputs of the problem are received), hidden layers (where the relationship between the inputs and outputs are determined and represented by synaptic weights) and an output layer (which emits the outputs of the problem).

The network performs two phases of data flow. First the input pattern is propagated from the input layer to the output layer and, as a result of this forward flow of data it produces an output. Then the error signals resulting from the difference between the computed and the actual are back propagated from the output layer to the previous layers for them to update their weights. These have demonstrated their efficacy on many practical problems and have been shown to be relatively easy to use. Hence, this technique is adopted in this study.

4.6. MATLAB SOFTWARE

MATLAB stands for MATrix LABoratory developed by The Mathworks Incorporation, USA and is an interactive system for matrix-based computation designed for scientific and engineering use. It is good for many forms of numeric computation and visualization. Besides dealing with explicit matrices in linear algebra, it can handle differential equations, polynomials, signal processing, and other applications. Results can be made available both numerically and as excellent graphics. It is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation.

Typical uses include:

1. Math and computation
2. Algorithm development
3. Modeling, simulation, and prototyping
4. Data analysis, exploration, and visualization
5. Scientific and engineering graphics
6. Application development, including Graphical User Interface building

In University environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science. In industry, MATLAB is the tool of choice for high-productivity research, development, and analysis. MATLAB has hundreds of built-in functions and can be used to solve problems ranging from the very simple to the sophisticated and complex. It also features a family of application-specific solutions called toolboxes. Very important to most users of MATLAB, toolboxes allow learning and applying specialized technology. Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many others.

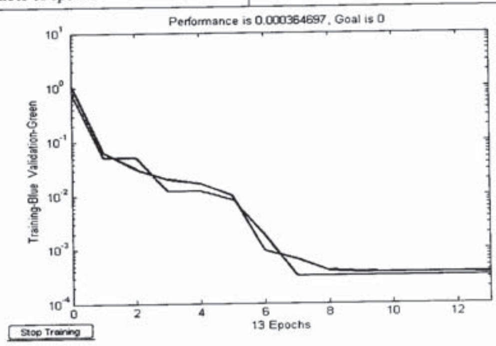
4.7. TRAINING THE NETWORK

MATLAB 7.0 has been used for training the network model for tool wear and surface roughness prediction. There are 20 training patterns considered for prediction of surface finish and tool wear. Each neuron is a processing element, which performs a weighed sum of all input variables that feed it. Depending on the value of weighted sum of the variables, the neuron gives a signal to the neurons in the adjacent layer through a non-linear transfer function. The algorithm used is feed forward backward propagation algorithm.

4.8. RESULTS OF ANN

Table 4.1 Results of ANN

Number of input nodes	3
Number of hidden nodes	5
Number of output nodes	2
Type of learning method	Supervised learning
Algorithm	Feed forward Back propagation
Learning rule	Gradient descent rule
Number of learning patterns used	20
The leaning parameter used	0.5
Number of epochs	1000



ANN training graph for Tangential and thrust force for 27 neurons is given in the figure 4.4. The predicted values of tangential and thrust force by the ANN model are compared with the experimental values for the validation set of experiments.

The below chart and the tabulation indicates the amount of deviations of predicted tangential force from the measured tangential force.

TABLE 4.2 Comparison of Measured and Predicted Tangential force values

Ex no	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Calculated tangential force (N)	Predicted tangential force (N)	% error
1	82.5	0.097	0.2	190	193.24	-1.705
2	127.5	0.097	0.2	242.78	239.84	1.210973
3	82.5	0.152	0.2	267.52	267.38	0.052333
4	127.5	0.152	0.2	315.36	320.44	-1.61086
5	82.5	0.097	0.4	206.5	209.66	-1.53027
6	127.5	0.097	0.4	280.72	281	-0.09974
7	82.5	0.152	0.4	303.81	309.38	-1.83338
8	127.5	0.152	0.4	350	352.72	-0.77714
9	67.154	0.125	0.3	221.34	225.12	-1.70778
10	142.84	0.125	0.3	323.6	323.7	-0.0309
11	105	0.078	0.3	200	197.52	1.24
12	105	0.171	0.3	341.75	346.9	-1.50695
13	105	0.125	0.131	247.73	247.28	0.181649
14	105	0.125	0.468	308.76	309.44	-0.22024
15	105	0.125	0.3	265.87	270.38	-1.69632
16	105	0.125	0.3	267.52	270.38	-1.06908
17	105	0.125	0.3	262.57	270.38	-1.928
18	105	0.125	0.3	260.92	270.38	-1.939
19	105	0.125	0.3	267.52	270.38	1.06908
20	105	0.125	0.3	265.87	270.38	1.69632

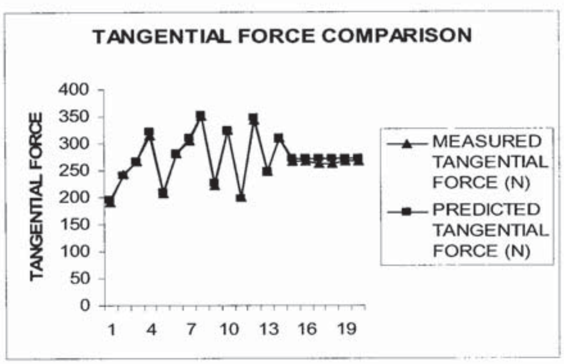


FIGURE 4.5 Comparison of Measured and Predicted Tangential Force Values

The below chart and the tabulation indicates the amount of deviations of predicted thrust force from the measured thrust force.

TABLE 4.3 Comparison of Measured and Predicted Thrust Force Values

Ex no	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Calculated thrust force (N)	Predicted thrust force (N)	% error
1	82.5	0.097	0.2	120	121.93	-1.608
2	127.5	0.097	0.2	160	157.265	1.709
3	82.5	0.152	0.2	178.14	178.215	-0.0421
4	127.5	0.152	0.2	214.02	216.555	-1.18447
5	82.5	0.097	0.4	132.37	134.07	-1.28428
6	127.5	0.097	0.4	188.04	188.55	-0.27122
7	82.5	0.152	0.4	205.36	207.45	-1.017
8	127.5	0.152	0.4	240	242.97	-1.2375
9	67.154	0.125	0.3	143.5	145.26	-1.22648
10	142.84	0.125	0.3	220.21	220.785	-0.26111
11	105	0.078	0.3	127.42	126.02	1.098
12	105	0.171	0.3	233.81	237.195	-1.44776
14	105	0.125	0.468	209.07	210.075	-0.4807
15	105	0.125	0.3	176.9	179.22	-1.31148
16	105	0.125	0.3	178.14	179.22	-0.60626
17	105	0.125	0.3	174.43	179.22	-1.060
18	105	0.125	0.3	173.19	179.22	-1.576
19	105	0.125	0.3	178.14	179.22	-0.60626
20	105	0.125	0.3	176.9	179.22	-1.31148

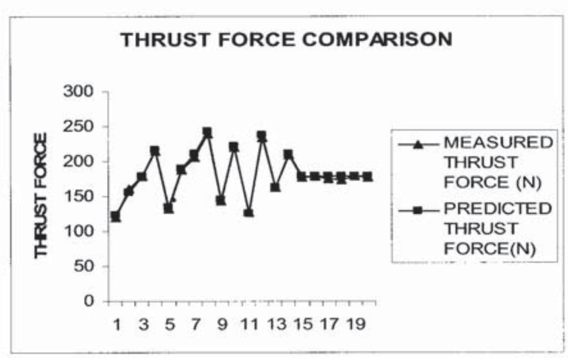


FIGURE 4.6 Comparison of Measured and Predicted Thrust force values

Chapter 5

Results and Discussions

CHAPTER 5

RESULTS AND DISCUSSIONS

- This work dealt with the prediction of tangential and thrust force using mathematical model developed with the help of Design of Experiment (DOE) and Artificial Neural Network (ANN) for the corresponding input parameters viz. cutting speed, feed and depth of cut.

- Based on the DOE, twenty experiments were conducted in all geared head centre lathe on machining C 45 steel specimens using Carbide tipped cutter for the corresponding input parameters.

- Mathematical model was generated for the cutting forces using Quality America software from the experimental results.

- The maximum percentage difference between measured and predicted tangential force using design of experiments is obtained at the experiment no 8. The input parameters, output parameters and the % deviation at the experiment no 8 are given below

  Cutting speed = 127.5 m / min
  Feed = 0.152 mm / rev
  Depth of cut = 0.4 mm
  Measured tangential force value =350 N
  Predicted tangential force value =358.03 N

- The maximum percentage difference between measured and predicted thrust force using design of experiments is obtained at the experiment no 1. The input parameters, output parameters and the % deviation at the experiment no 1 are given below

  Cutting speed = 82.5 m / min
  Feed = 0.097 mm / rev

  Predicted thrust force value =116.84 N
  Percentage deviation =2.63 %

- An Artificial Neural Network (ANN) model was also developed to predict the cutting forces with the help of MATLAB 7.0 software using feed forward back propagation algorithm.

- The results obtained by experimental procedure and from ANN model were compared.

- The maximum percentage difference between measured and predicted tangential force using ANN model is obtained at the experiment no 7. The input parameters, output parameters and the % deviation at the experiment no 7 are given below

  Cutting speed = 82.5 m / min
  Feed = 0.152 mm / rev
  Depth of cut = 0.4 mm
  Measured tangential force value =303.81 N
  Predicted tangential force value =309.38 N
  Percentage deviation =1.833 %

- The maximum percentage difference between measured and predicted thrust force is obtained at the experiment no 2. The input parameters, output parameters and the % deviation at the experiment no 2 are given below

  Cutting speed = 127.5 m / min
  Feed = 0.097 mm / rev
  Depth of cut = 0.2 mm
  Measured thrust force value =160 N
  Predicted thrust force value =157.265 N
  Percentage deviation =1.70 %

- The compared result confirms that the developed ANN model is more accurate in prediction.

References

REFERENCE

1. Halil Bil, Engin Kilic. S and a Erman Tekkaya (2004), "A comparison of orthogonal cutting data from experiments with three different finite element models" *International Journal of machine tool and Manufacture*, Vol. 44, pp.933-944.

2. Hassan Gokkaya and Muammer Nalbant (2005) " The effects of cutting tool coating on the surface roughness of AISI 1015 steel depending on cutting parameters" *Turkish Journal of engineering and environmental science*, Vol. 30, pp.307-316.

3. Kadirgama and Abou-El-Hossein.K A (2006), "Prediction of cutting force model by using Neural Network" *Journal of applied sciences*, Vol. 6, pp.31-34.

4. Kumanan.S,.Nanne Saheb.S.K and Jesuthanam.C.P (2006), "Prediction of machining forces using Neural Networks Trained by a Genetic Algorithm" *Journal of industrial engineering*, Vol. 87, pp.11-15.

5. Lei Zhang and Li Zheng (2004), "Prediction of cutting force in end milling of pockets" *International journal of advanced manufacturing technology*, Vol. 25, pp.281-287.

6. Luke. H. Huang, Joseph C Chen and Tao Chang (1999) "Effect of tool/chip contact length on Orthogonal turning performance" *Journal of Industrial technology*, Vol. 15.

7. Palanisamy. P, Rajendran. I and Sanmugasundram. S (2006), "Prediction of cutting force and temperature rise in the end-milling operation", *Journal of engineering manufacture*, Vol. 220, pp.1577-1587.

8. Palanisamy.P, Rajendran. I and Sanmugasundram.S (2007) "Prediction of tool wear using Regression and ANN models in end-milling operation" *International Journal of Advanced Manufacturing Technology*, DOI 10.1007/s00170-007-0948-5.

9. Serope Kalpakjian and Steven R. Schimid, (2003) "Manufacturing engineering and technology" Pearson education , pp.534-548

10. Tayal Altan, Ibrahim Al-Zkeri and Luca D'Anna "Influence of PCBN Tool edge preparation in Orthogonal hard turning – A finite element analysis" Ohio State University.

11. Thamizhmanii. S and Hasan. S (2006) "Analyses of roughness, forces and wear in turning gray cast iron" *Journal of achievements in materials and manufacturing engineering*, Vol.17,pp. 401-404.

12. Tugrul Ozel, Tsu- Kong Hsu (2004), " Effects of cutting edge geometry, workpiece hardness, feed rate and cutting speed on surface roughness and forces in finishing turning of hardened AISI H13 steel" *International Journal of Advanced Manufacturing Technology*, Vol. 25, pp.262-269.

13. Vishal. S. Sharma, Sures Dhiman, Rakesh Shegal and Sharma. S. K (2008), "Estimation of cutting forces and surface roughness for hard turning using neural networks "*Journal of Intelligent manufacturing*, DOI 10.1007/s10845-008-0097-1.

14. Wuyi Chen, (1997), "Cutting forces and surface finish when machining medium hardness steel using CBN" *International Journal of Machine Tools & Manufacture*, Vol. 40, pp.455-466.

15. Yong Huang and Steven Liang. Y (2003), "Force modeling in shallow cuts with large negative rake angle and large nose radius tools-application to hard turning" *International Journal of Advanced Manufacturing Technology*, Vol. 22, pp.626-632.