OPTIMIZATION OF CUTTING PARAMETERS IN NEAR DRY MACHINING OF HARDENED STEEL

By

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Declaration

It is hereby to declare that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

Nusrat Tarin Chowdhury

This work is dedicated to all of my
Honourable teachers

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a_2	:	Chip thickness
a_1	:	Uncut chip thickness
BUE	:	Built up edge
CBN	:	Cubic boron nitride
d	:	Depth of cut
f	:	Feed rate
G	:	Generation Number
GA	:	Genetic Algorithm
h_m	:	Maximum theoretical roughness
HPC	:	High-pressure coolant
i	:	No of Chromosomes
M	:	No of Cutting Parameters
N	:	No of Population
N_{c_p}	:	No of Crossover Points
MRR	:	Material removal rate
PCBN	:	Poly Crystalline Cubic boron nitride
P_i	:	Probability
P_c	:	Crossover Probability
P_m	:	Mutation Probability
P_Z	:	Tangential component of the cutting force
q_i	:	Cumulative Probability
r	:	Nose radius of the insert
r_i	:	Random Number
R_a	:	Surface roughness
r_c	:	Chip thickness ratio= $\frac{a_1}{a_2}$
RSM	:	Response Surface Methodology
V	:	Cutting velocity
VB	:	Average principal flank wear
VG	:	Viscous Grade

VM	:	Maximum flank wear
VN	:	Flank notch wear
VS	:	Average auxiliary flank wear
VSM	:	Maximum auxiliary flank wear
Ø	:	Diameter of the job
γ	:	Effective rake angle
τ_s	:	Dynamic yield shear strength of the work material
Δ	:	Percentage elongation of the work material
ξ	:	Chip reduction co-efficient
θ	:	Average chip-tool interface temperature
τ_s	:	Shear strength of the work material
φ	:	Principal Cutting Edge Angle

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Abstract

Machining of pre-hardened steel materials, known as hard turning, is gaining more and more attention recently because it offers numerous advantages over traditional grinding in some applications. In addition it differs from conventional turning process since it possesses some special behaviors such as chip breakability and micro structural alteration at the machined surfaces. Typically no cutting fluid is applied during hard turning in order to minimize both cutting forces and environmental impacts. Near dry machining which refers to the use of small amount of cutting fluid addresses itself as a viable alternative for hard machining with respect to tool wear, heat dissertation, cutting force generation and machined surface quality. The present research work is divided into two parts. First of all there is an experimental analysis of the effects of minimum quantity lubrication on cutting zone temperature, main cutting force, chip thickness ratio, tool wear and surface quality of the machined part while turning hardened steel (56 HRC) material with coated carbide insert. The results indicated that the application of near dry machining technique significantly helps to obtain better result in compare to dry condition. The other part of the research work is concentrated to the optimization of cutting parameters (cutting speed, feed rate and depth of cut) while turning hardened medium carbon steel by coated carbide insert under near dry machining condition. Optimization was done using genetic algorithm. The objective function of the optimization process was to determine the cutting parameter that minimizes surface roughness under certain constraints. Statistical models using multiple regression analysis under Response Surface Methodology (RSM) have been developed to establish the objective function and also the constraints for solving the problem. The developed models satisfactorily validate its accuracy by drawing desirable experimental results.

Chapter-1

Introduction

The term manufacturing may refer to a range of human activity, from handicraft to high tech, but is most commonly applied to industrial production, in which raw materials are transformed into finished goods on a large scale. Such finished goods may be used for manufacturing other, more complex products, such as household appliances or automobiles, or sold to wholesalers, who in turn sell them to retailers, who then sell them to end users-the consumers. Among manufacturing processes, metal cutting is unique because it can be used both to create products and to finish products. It is the world's most common manufacturing process, with 10 to 15% of the cost of all goods being attributed to it [**Merchant, 1999**]. Black [**1979**] defined metal cutting as the removal of metal chips from a workpiece in order to obtain a finished product with desired attributes of size, shape, and surface roughness. There are different methods of metal cutting and turning is one of the simplest among these methods. Turning is the process of machining external cylindrical and conical surfaces and it is usually performed on a lathe.

In machining of parts, surface quality is one of the most specified customer requirements where major indication of surface quality on machined parts is surface roughness. Surface roughness is mainly a result of process parameters such as tool geometry (i.e. nose radius, edge geometry, rake angle, etc.) and cutting conditions (feed rate, cutting speed, depth of cut, etc.). In turning operation, tool wear becomes an additional parameter affecting surface quality of finished parts. Tool wear weakens the cutting tool, increases the forces used in cutting and causes a lack of consistency in material removal. Parts and time lost to scrap and rework from tool wear are costly to companies. There are many factors that contribute to the wear of cutting tools: the workpiece properties, cutting tool properties, cutting conditions and machine rigidity.

Temperature on the chip-tool interface is one of the important parameters in the analysis and control of machining process. Due to the high shear and friction energies dissipated during a machining operation the temperature in the primary and secondary shear zones are usually very high, hence affect the shear deformation and tool wear. In a single point cutting, heat is generated at three different zones i.e. primary shear zone, chip tool interface and the tool work-piece interface. The primary shear zone temperature affects the mechanical properties of the work piece-chip material and temperatures at the tool-chip and tool-work piece interfaces influence tool wear at tool face and flank respectively. Total tool wear rate and crater wear on the rake face are strongly influenced by the temperature at chip-tool interface. Therefore, it is desirable to determine the temperatures of the tool and chip interface to analyze or control the process.

High production machining of steel inherently generates high cutting zone temperature. In high speed machining, conventional cutting fluid application fails to penetrate the chip-tool interface and thus cannot remove heat effectively [**Shaw et al., 1951; Paul et al., 2000**]. Addition of extreme pressure additives in the cutting fluids does not ensure penetration of coolant at the chip-tool interface to provide lubrication and cooling [**Cassin and Boothroyd, 1965**]. However, high-pressure jet of soluble oil, when applied at the chip-tool interface, could reduce cutting temperature and improve tool life to some extent [**Mazurkiewicz et al., 1989; Alexander et al., 1998**].

However, a number of negative impacts caused by cutting fluids have offset the benefits they provide. With the large volume of cutting fluid used in traditional machining, misting, skin exposure [**Sokovic and Mijanovic, 2001**] and fluid contamination are problems that must be addressed to assure minimal impact on worker health. When inappropriately handled, cutting fluids may damage soil and water resources, causing serious loss to the environment. Therefore, the handling and disposal of cutting fluids must obey rigid rules of environmental protection.

It has been estimated that the costs related to cutting fluids represent a large amount of the total machining costs. Several research workers [**Klocke and Eisennblatter, 1997; Byrne and Scholta, 1993**] state that the costs related to cutting fluids are frequently higher than those related to cutting tools. Consequently, elimination on the use of cutting fluids, if possible, can be a significant economic incentive. Considering the high cost associated with the use of cutting fluids and projected escalating costs when the stricter environmental laws are enforced, the choice seems obvious. Possibility of controlling high cutting temperature in high production machining by some alternative methods has been reported. Cutting forces and temperature were found to reduce while machining steel with tribologically modified carbide inserts [**Farook et al., 1998**].

In the pursuit of profit, safety and convenience, a number of alternatives to traditional machining are currently under development. Dry machining technologies has been around for as long as traditional machining, but has seen a recent surge in interest as more people are realizing the true cost of cutting fluid. Near dry machining is an obvious, but very intricate balance between dry machining and traditional methods. Other novel cutting fluids, such as utilization of liquid nitrogen, also known as cryogenic machining, are also being explored for their unique properties. Cryogenic machining [**Dhar et al., 2002**] and machining with high pressure coolant jet [**Dhar et al., 2008**] has improved machinability of steel to a certain extent under normal cutting conditions. But it has also been reported that cryogenic machining is costly due to high cost of liquid nitrogen. Liquid nitrogen is also hazardous to workers due to its extremely low temperature. Their exposure can result in mild to extreme frostbite.

Machining without the use of cutting fluids has become a popular option for eliminating the problems associated with cutting fluid. Some researchers meet with success in the field of environmentally friendly manufacturing [**Klocke and Eisennblatter, 1997, Aronson, 1995**]. The advantages of fluidless cutting include cleaner parts, no waste generation and in some cases more precise machining. In addition to these benefits, worker health concerns related to metal working fluid exposure are eliminated. Recycling is simpler because chips generated from this technique have no residual oil on them and can be combined with other scrap metal.

In reality, however, the most prohibitive part of switching to dry machining is that they are sometimes less effective when higher machining efficiency, better surface finish quality and severer cutting conditions are required. For these situations, semi-dry operations utilizing very small amounts of cutting lubricants are expected to become a powerful tool and, in fact, they already play a significant role in a number of practical applications [**Heisel and Lutz, 1994; Wakabayashi, 1998; Sutherland, 2000; Suda, 2001; McCabe and Ostaraff, 2001**].

Near dry machining is also known as semi dry machining is an alternative to traditional use of cutting fluids. As the name implies, near dry machining uses a very small quantity of lubricant delivered precisely to the cutting surface. Often the quantity used is so small that no lubricant is recovered from the piece. Any remaining lubricant may form a film that protects the piece from oxidation or the lubricant may vaporize completely due to the heat of the machining process. With near dry machining the problem of misting and skin exposure is greatly reduced, and fluid does not become contaminated because it is not re-used. The minimization of cutting fluid also leads to economical benefits by way of saving lubricant costs and workpiece- tool- machine cleaning cycle time.

In turning operation, it is an important task to select cutting parameters (speed, feed and depth of cut) for achieving high cutting performance. For efficient use of machine tools, optimum cutting parameters are required. So it is necessary to find a suitable optimization method which can find optimum values of cutting parameters for obtaining better result. The turning process parameter optimization is highly constrained and nonlinear. Usually, the desired cutting parameters are determined based on experience or by use of hand book. But the ranges given these sources are actually starting values and are not the optimal values. However, this does not ensure that the selected cutting parameters have optimal or near optimal cutting performance for a particular machine and environment. Optimization of machining parameters not only increases the utility for machining economics, but also the product quality to a great extent. In this context, an effort has been made to estimate the cutting parameters that will minimize the surface roughness and also keep the cutting zone temperature, cutting force, tool wear as well as chip thickness ratio into satisfactory level using genetic algorithm.

1.1 Hard Turning

Manufacturers around the world constantly strive for lower cost solutions in order to maintain their competitiveness, on machined components and manufactured goods. Technology has played an enormous role in advancing the metal working industry and creating opportunities to reduce costs and improve quality. Technology evolution occurring in the area of hard turning is no less significant. Hard turning is defined as the process of single point cutting of part pieces that have hardness values over 45 RC but more typically are in the 58-68 RC range [**Huddle, 2001**]. Precision hard turning applications have increased drastically in manufacturing industry because it potentially provides an alternative to conventional grinding in machining hardened components. This new technology significantly reduces the production time, tooling costs and the capital investment [**Matsumoto et al., 1986**], especially for low volume production. With grinding, it is typically necessary to rough the material on a lathe then send it to a heat treatment operation and after that it requires several grinding operations to finish it. In hard turning, one can start with a pre-hardened material and machine it. Thus it is possible to skip several steps and actually cut days out of the process.

Researchers are studying to find out the numerous advantages to replacing grinding with hard turning operations. Even though small depths of cut and feed rates are required for hard turning, material removal rates in hard turning can be much higher than grinding for some applications [**Tonshoff et al., 1996**]. It has been estimated that resulting reduction in machining time could be as high as 60% [**Tonshoff et al., 1995**]. This would facilitate flexible manufacturing systems and reduced batch sizes, which are becoming more important in industry. Aside from decreases in machining time, a reduction in the number of required machine tools may also be observed as a result of the increased flexibility of the turning process as compared to grinding [**Konig et al., 1984; Tonshoff et al., 1996**]. The possibility of eliminating cutting coolant is another substantial economic and environmental advantage of hard turning.

It seems obvious that hard turning is an attractive replacement for many grinding operations, but implementation in industry remains relatively low, particularly for critical surfaces. This is because hard turning is a relatively new processing technique, and several questions remain unanswered. Hard turning can influence the workpiece surface microstructure by generating undesirable residual stress patterns and over-hardened surface zones that are referred to as "white layers" [**Konig et al., 1993; Shaw, 1993; Tonshoff et al., 1995; Brinksmeier et al., 1999; Griffiths, 1987**]. The cause and effect of these residual stress patterns and white layer generation are not fully understood.

White layer and residual tensile stresses are expected to reduce fatigue life, but research comparing the fatigue lives of hard turned and ground surfaces found the hard turned surfaces to have increased lives despite the existence of brittle white layers [**Abrao and Aspinwall, 1996**]. In some cases, compressive stresses have been found on hard turned surfaces that improved fatigue life [**Thiele and Melkote, 1999; Liu and Mittal, 1998**]. Because the effects of white layer on the resulting component performance are not well understood, industry remains reluctant to produce critical surfaces by a hard turning process that may contain undesirable conditions.

Cutting tools required for hard turning are relatively expensive, so it is also important to investigate tool life to assure the economic justification for hard turning. Regardless of the attainable dimensional accuracy and surface quality, hard turning will not replace grinding operations if the cost is too high. Poor selection of cutting conditions can lead to excessive tool wear and eliminate any cost savings, while conservative conditions may also increase cost by reducing productivity. Selection of optimal cutting conditions must balance the tradeoff between productivity and tool life, thus the need to study effects of cutting conditions on the wear behavior of different hard turning tool materials.

1.2 Machining under Near Dry Environment

Rapid demand for high production machining creates the need for increasing cutting speed and feed rate, which ultimately refers to the effectiveness of cooling in order to cope with the increase in cutting temperature. In hard turning, Frederick Mason [**2001**] observed in his study that the temperatures generated by the cutting speeds of today's advanced tooling can actually prevent low pressure flood coolant from entering the cutting zone. The majority of the cooling and lubricating aspects of a flood coolant stream are lost as the coolant is vaporized prior to entering the cutting zone.

An experiment was preformed in the area of hard turning AISI 4340 with 2 ml/hr oil in a flow of high pressure air at 20 MPa by Varadarajan et al. [**2002**]. It was found that cutting under near dry lubrication had better performance than that in dry or wet cutting in terms of cutting forces, cutting temperatures, surface roughness, tool life, cutting ratio and tool-chip contact length. Lower cutting forces, lower cutting temperatures, better surface finish, shorter tool-chip contact length, larger cutting ratio and longer tool life were observed in near dry turning compared with those in dry or wet cutting. The method to estimate the cutting temperature was also provided but there was not any comparison between predicted cutting temperatures and measurements.

An experiment was done to investigate the effects of oil-water combined mist on turning stainless steel with the use of 17 ml/hr oil and 150 ml/hr water mixture [**2001**]. The use of oil-water combined mist could prevent the production of built-up edge (BUE) while BUE was observed when cutting dry or with oil mist. Therefore the workpiece surface finish under oil-water combined mist was better than that under dry, oil mist or water soluble oil applications. Lower cutting temperatures were also observed with the use of oil-water combined mist compared to cutting dry or with oil mist.

Many researchers used CBN tool to observe the performance of near dry machining. Among them Diniz et al. [**2003**] applied 10 ml/hr oil in turning AISI 52100 steel while the supplied air pressure was 4.5 bars. According to the experimental data, the following conclusions were drawn. (i) Dry and near dry machining had similar performance in terms of CBN tool flank wear, always better than the tool life under flood cooling. (ii) The workpiece surface roughness measured in near dry cutting was close to that obtained from dry cutting.

When turning AISI 1040 steel the influence of near dry lubrication on cutting temperature, chip formation and dimensional accuracy was investigated by Dhar et al. [**2006**]. The lubricant was supplied at 60 ml/hr through an external nozzle in a flow of compressed air (7 bar). Based on the machining tests, the authors found that near dry lubrication resulted in lower cutting temperatures compared with dry and flood cooling. The dimensional accuracy under near dry lubrication presented a notable benefit of controlling the increase of the workpiece diameter when the machining time elapsed where tool wear was observed. Dimensional accuracy was improved with the use of near dry lubrication due to the diminution of tool wear and damage.

Dhar et al. [**2008**] investigate the effects of near dry machining by different types of cutting fluids (emulsion cutting fluid, vegetable oil and cutting oil) on the cutting performance of hard turned part (56 HRC) as compared to completely dry cutting with respect to cutting temperature, chip thickness ratio, tool wear and surface roughness. In this study, the minimum quantity lubrication was provided with a spray of air and cutting fluids at a pressure 25 bars and coolant flow rate of 120 ml/hr. During each test, cutting temperature, chip thickness ratio, tool wear and machined surface quality were measured and compared. The results indicated that the use of near dry machining by cutting oil (VG-68) leads to reduced surface roughness, delayed tool wear and lowered cutting temperature significantly in compare to other environments.

The effects of cutting fluid on tool wear in high speed milling were studied by Lopez et al. [**2006**]. Both near dry lubrication and flood cooling were applied when cutting aluminum alloys. In addition to experiments, they also performed computational fluid dynamics (CFD) simulations for estimating the penetration of the cutting fluid to the cutting zone. The experiment was conducted at the oil flow rates of 0.04 and 0.06 ml/min and the air pressure of 10 bars. The results showed that (i) with the help of compressed air, the oil mist could penetrated the cutting zone and provide cooling and lubricating while the CFD simulation showed that the flood coolant was not able to reach the tool teeth; (ii) the nozzle position relative to feed direction was very important for oil flow penetration optimization. Sasahara et al. [**2003**] reported that in the case of helical feed milling for boring aluminum alloy, cutting forces, cutting temperature and dimension accuracy under near dry lubrication were close to those under flood cooling condition.

Rahman et al. [**2001, 2002**] carried on their research in end milling with the use of lubricant at 8.5 ml/hr oil flow rate which was supplied by the compressed air at 0.52 MPa. The workpiece material was ASSAB 718HH steel. The experimental results showed that tool wear under near dry lubrication was comparable to that under flood cooling when cutting at low feed rates, low speeds and low depth of cuts. In addition to this the surface finish generated by near dry machining was comparable to that under flood cooling and cutting forces were close in both near dry machining and flood cooling. They also observed that fewer burrs formed during near dry machining compared to dry cutting and flood cooling application. Moreover the tool-chip interface temperature under near dry lubrication was lower than in dry cutting but higher than that in flood cooling.

The effect of near dry machining on tool life when drilling carbon steels with high speed steel twist drills was investigated by Heinemann et al. [**2006**]. The cutting fluid flow rate was 18 ml/hr. It was found that a continuous supply of near dry machining conveyed a longer tool life while a discontinuous supply of lubricant resulted in a reduction of tool life. A low-viscous and high cooling-capable lubricant provided a longer tool life when different lubricants were used for an external near dry machining supply in the tests.

Hafenbraedl and Malkin [**2000**] applied near dry lubrication technique on cylindrical grinding tests. They used ester oil with a flow rate of 12 ml/hr mixing with 69 kPa compressed air and their work material was AISI 5200 hardened steel. The experimental results showed that the application of near dry lubrication leads to lower cutting energy, better surface finish and higher G-ratio were observed when comparing with cutting completely dry or under flood cooling. However the elevated bulk temperature was observed as well as thermal distortion of the workpiece for near dry grinding. This indicated that the cooling from the mixture of ester oil and cold air was not sufficient.

Brinksmeier et al. [**1997**] implemented minimum quantity lubrication with oil flow rate of 0.5 ml/min and air pressure of 6 bar in grinding operation. Two different work materials such as hardened steel (16MnCr5) and tempered steel (42CrMo4V) were used. The results of this study indicate that both dry and near dry grinding would cause thermal damage on the hardened material with the creep feed grinding operation. The experimental results also showed that acceptable surface finish was obtained under near dry machining condition if the material removal rate is low. It was also noticed that the type of lubricant used in near dry machining had a significant impact on the surface finish.

Chapter-2

Literature Review

2.1 Introduction

Optimization of process parameters in machining operations has been an area of interest for many researchers since1950 when Gilbert presented an analytical procedure for determining the optimum cutting speed in a single pass turning operation. The selection of optimal cutting parameters in machining is a difficult task which involves the development of machining models, and optimization algorithms able to handle those models. The problem of the optimal machining condition selection has been analyzed by many researches. Some of the authors [**Wu, 1966; Katsundu, 1989**] analyzed the optimum cutting speed that satisfies the basic manufacturing criterions. Basically, this optimization procedure, whenever carried out, involves partial differentiation for the minimization of the unit cost, maximization of production rate or maximization of profit rate. These manufacturing criterions are expressed as a function of cutting speed. Then the optimum cutting speed is determined by equating the partial differentiation of the expressed function to zero. This is not an ideal approach to the problem to obtain an economical metal cutting. The other cutting variables, particularly feed rate, have also important effect on machining economics. Therefore, it is necessary to optimize cutting speed feed rate and depth of cut simultaneously in order to obtain an economical metal cutting conditions.

The optimization of cutting parameters is the key component in planning of machining processes. However, deep analysis of cutting involves certain costs, particularly in case of small series. In case of individual machining it is particularly necessary to shorten as much as possible the procedure for determination of the optimum cutting parameters, otherwise the cost of analysis might exceed the economic efficiency which could be reached if working with optimum conditions.

2.2 Effect of Cutting Parameters on Cutting Temperature

Temperature plays an important role in machining. Thermal damage due to the high cutting temperature leads to a geometrical inaccuracy of the finished part and reduces the tool life. People have been writing about the part that heat plays in machining metal since the second half of the 19th century. One of the earliest was Taylor, who wrote his paper "On the art of cutting metals" in 1907 [**Taylor, 1907**]. If cutting temperatures rise too high, tool wear increases and damage can be caused to the workpiece and stresses can build up in the finished article. Also, it has been shown that work surface integrity and the machining precision are all directly affected by cutting temperature.

During the machining process, a considerable amount of the machine energy is transferred into heat through plastic deformation of the workpiece surface, the friction of the chip on the tool face and the friction between the tool and the workpiece. Trent and Wright [**2000**] suggest that 99 per cent of the work done is converted into heat. This results in an increase in the tool and workpiece temperatures.

Studies that have been done by many researchers verify the relation between the cutting speed and temperature. Shaw [**1957**], Mari and Gonseth [**1993**], Ay et al. [**1994**], Kitagawa et al. [**1997**], Choudhury and Bartarya [**2003**] all presented in their work that the increase in cutting speed causes an increase in temperature and this increase will result in wear. With increase of cutting speed, friction increases which is responsible for the increase in temperature in the cutting zone. Ay et al. [**1994**] presented that feed rate increase causes steadily increase in temperature of the tool. With the increase in feed rate, section of chip increases and consequently friction increases as reported by Shaw [**1984**]. The temperature distribution depends on the heat conductivity and specific heat capacity of the tool and the workpiece and finally the amount of heat loss based on radiation and convection. However the maximum temperatures occur in the contact zone between the chip and the tool [**Muller-Hummel and Lahres, 1996**].

Ginting and Nouari [**2006**] showed the dependence of the cutting temperature on the cutting speed in their study while dry milling of aerospace material. According to them when the cutting speed is increased from 60 m/min (680 8C) to 150 m/min (1020 8C), the temperature approaches several hundred degrees. For the other cutting parameters, increasing the feed rate entails an increase in the cutting temperature. However, as expected, the effect of the feed rate is not as significant as the effect of the cutting speed.

Federico et al. [**2008**] also investigated the influence of cutting parameters (cutting speed, feed rate and depth of cut) on tool temperature when machining hardened steel with multilayer coated carbide tools. A standard K-type of thermocouple inserted near the rake face of the tool was used to measure the interface temperatures. They concluded that the temperature near the rake face increases significantly when the depth of cut changes from 0.2 to 0.4 mm. The increase in contact length between chip and rake face could be responsible, since it grows, together with uncut chip cross-section.

There are three main sources of heat generation during the process of cutting metal with a machine tool which are:

- Heat is produced in the primary shear zone as the workpiece is subjected to large irreversible plastic deformation.
- Heat produced by friction and shear on the tool rake face, or secondary shear zone. The chip material is further deformed and some adheres to the tool face. In this region the last layer of atoms of the chip material are stationary. The velocity of the adjacent layers gradually increases until the bulk chip velocity is attained. Thus there are both sticking and sliding friction sections. This combined shear and friction action produces heat [**Trent and Wright, 2000**].
- Heat produced at the tool-work interface, where the tool flank runs along the workpiece surface and generates heat through friction. Under normal cutting conditions, a thin layer of workpiece material is extruded below the cutting edge, thus establishing contact with the clearance face for a distance of approximately 0.2 mm below the cutting edge of a sharp tool with a flank angle of 68. This is a part of the third heat source that can be thought of as a part of the total heat pattern [**Chu and Wallbank, 1998**].

As the cutting action proceeds and the heat has been generated most of the heat is dissipated in the following manners:

- The discarded chip carrying away the heat. The temperature decays along the length of the chip. Also, due to heat convection and radiation at the outer surface of the chip, the temperature gradient is higher across the chip cross section than along the length of the chip [**Wang et al., 1996**].
- The workpiece acts as a heat sink.
- The cutting tool acts as a heat sink.
- Coolant, where used, will help to draw away heat from all areas.

2.3 Effect of Cutting Parameters on Cutting Forces

Cutting force is one of the important index of machinability because it governs productivity, product quality and overall economy in machining. Generally cutting force decreases with the increase in cutting speed. However it has been found by many researchers that the cutting force highly affected by feed rate and slightly by cutting speed [**Choudhury and El-Baradie, 1999 ; Kadirgama and Abou-El-Hossein, 2005**].

It is a general tendency that at constant feeds and depths of cut, an increase in cutting speed does not necessarily increase the material removal rate (MRR). In fact it reduces the MRR, thus resulting in reduced cutting forces. As the feed rate is increased, the amount of material engaging to the tool increases – this implies an increased tool-work contact length. Due to this, cutting forces also increase. The same effect occurs as the depth of cut is increased. In addition to increased contact length, the force resisting deflection is high because of the amount of material engaging the tool. This also contributes to an increase in the cutting forces.

Several studies have been performed by scientists all over the world in order to investigate the influence of cutting parameters on main cutting force. Sabberwal [**1961**] and Oxley [**1963**] had shown that the dependence of the specific cutting energy on the chip thickness and cutting velocity by experimental investigation and they have described this dependency by a power law relationship. When turning hardened 52100 bearing steel, the effect of velocity is ignored herein because of the experimental observation that the forces do not change with velocity within the recommended cutting velocity range (1–3 m/s). Chou and Evans [**1999**] also reported that cutting forces had little variation with cutting speed when turning hardened 52100 steel, but Davies et al. [**1996**] observed that the specific cutting energy decreased significantly with speed using relatively large negative rake angle tools. Even an opposite trend in hard turning has been mentioned by Konig et al. [**1984**] that the forces tended to decrease somewhat with a decrease in cutting speed in milling of 42CrMo4 and turning of high speed steels, but no such a conclusion in turning hardened 52100 steel. Apparently, a further study needs to include the effect of cutting speed in modeling the forces. To simplify the model, this study ignores the force dependence on cutting speed based on the experimental observations and the result of Chou and Evans [**1999**]. However, the effect of depth of cut on specific cutting energy cannot be ignored since the depth of cut is only slightly greater than the feed rate and the condition of plane strain is no longer warranted under hard turning conditions.

2.4 Effect of Cutting Parameters on Surface Roughness

Surface roughness which is the major indication of product quality is an important factor in predicting the machining performances of any machining operation [**Mital and**

Metha, 1988; Boothroyd and Knight, 1989]. The surface roughness is known to be significantly affected by different cutting parameters like the depth of cut, spindle speed and feed rate [**Shaw, 1984**]. Besides cutting parameters work material characteristics, work hardness, unstable built-up edge, cutting time, tool nose radius and tool cutting edge angles, stability of machine tool and workpiece setup, chatter, and use of cutting fluids are also responsible to influence surface roughness in varying amounts. Therefore, the surface roughness will be optimized if the appropriate cutting conditions are selected.

Surface roughness has received serious attention for many years. It has formulated an important design feature in many situations such as parts subject to fatigue loads, precision fits, fastener holes, and aesthetic requirements. In addition to tolerances, surface roughness imposes one of the most critical constraints for the selection of machines and cutting parameters in process planning. A considerable number of studies have investigated the general effects of the speed, feed, and depth of cut on the surface roughness.

The impact of three factors, the feed rate, nose radius and cutting edge angles, on surface roughness is depicted [**Groover, 1996; Ozel and Karpat, 2005**]. In the past various methods have been used to quantify the impact of machining parameters on part finish quality. Thiele et al. [**1999**] used a three factor full factorial design to determine the effects of workpiece hardness and tool edge geometry on surface roughness in finish hard turning using CBN tools. After completion of the experiments, an Analysis of Variance (ANOVA) was conducted to predict the effect of edge geometry and feed rate on surface quality. Chou et al. [**2002**] conducted experiments for hard turning of AISI 52100 steel using CBN tools to predict the effect of CBN content on surface roughness. In their experiments, two factor- three level fractional factorial design was used and the effects of cutting edge geometry, workpiece hardness, feed rate and cutting speed on surface roughness were experimentally investigated. In another study, Ozel et al. [**2005**] performed experiments on hard turning of various steels using CBN tools and identified the factors affecting the surface roughness, tool wear, cutting forces and surface integrity.

Kopac and Bahor [**1999**], who studied the changes in surface roughness depending on the process conditions in tempered AISI 1060 and 4140 steels, found speed to be the most dominant factor if the operating parameters were chosen randomly. They also reported that, for both steel types, the cutting tools with greater radius cause smaller surface roughness values. Similar studies were published by Yuan et al. [**1996**], Eriksen [**1998**] and Ozses [**2002**].

Gökkaya et al. [**2004**] investigated the effect of cutting tool coating material, cutting speed and feed rate on the surface roughness of AISI 1040 steel. In their study, the lowest average surface roughness was obtained using cutting tool with coated TiN. A 176% improvement in surface roughness was provided by reducing feed rate by 80% and a 13% improvement in surface roughness was provided by increasing the cutting speed by 200%.

2.5 Effect of Cutting Parameters on Tool Wear

The wear mechanism of tungsten coated and uncoated carbide tools were investigated at various combination of cutting speed, feed rate, and depth of cut for turning of hardened tool steel. Hence at low speed, feed rate and depth of cut, SEM (scanning electron microscope) investigation has shown that both inserts experience uniform and gradual ware on the flank face, and diffusion and oxidation have also been observed [**Ghani, 2004**]. Performance of P10 Tin coated carbide tool when end milling AISI H13 tool steel at high cutting speed, feed rate, and depth of cut on the tool life ware studied experimentally. Hence the result shows that the tool life is highly affected by the feed rate and depth of cut [**Ghani, 2004**]. Effect of cutting speed on tool performance in milling of B4Cp reinforced aluminum metal matrix composites was investigated with the help of five different cutting speed at constant feed rate of 0.26 mm/rev were used in order to determine the effect of cutting speed on tool wear and tool wear mechanism [**Geels, 1996**]. Comparison between constant force and constant rate of feed in material graphic cut-off machines, surface quality in relation to cutting speed, force and rate of feed has been studied where this study shows that when cutting work piece of varying shape, the most uniform surface is obtained by using a constant rate of feed and this combined with high cutting speed will produce surface with the least and most uniformed information [**Geels, 1996**]. The influence of feed rate and cutting speed on the cutting forces, surface roughness and tool chip constant length during face milling has been studied where in the study, three component of the cutting forces developed during face milling AISI 1020 and AISI 1040 steel work piece were measured [**Korkut, 2007**].

The uncut chip thickness or the cutting feed has a direct influence on the quality, productivity, and efficiency of machining. It is believed that the tool life decreases (and thus, tool wear increases) with increasing cutting feed [**Childs et al., 2000; Zorev, 1966; Kronenberg, 1966; Gorczyca, 1987**]. Such a conclusion follows from the generally adopted equation for tool life. For example, generalizing the experimental data, Gorczyca proposed Eq. 2.1 in [**1987**] the following relation:

$$T = \frac{48.36 \times 10^{6}}{v^{4} f^{1.6} d^{0.48}} \quad \text{(2.1)}$$

If the cutting speed v and the depth of cut d are both constant, then it follows from Eq. 2.1 that tool life decreases when the cutting feed f is increased.

A great body of data to support the discussed point and, thus, the structure of Eq. 2.1 can be found in the literature on metal cutting, although many researches, starting with Taylor [**1907**], did not include the cutting feed in their tool life equations because they did not consider this parameter as having a significant influence on tool life, while others found that the experimentally obtained relation "tool wear - cutting feed" has a distinctive minimum. Such a great variation in the experimental results can be explained by the fact that the cutting tests were carried out under variable cutting speeds, which resulted in different cutting temperatures.

Makaraw [**1976**] considered some factors while studying the influence of the cutting feed on the tool wear. According to him when the cutting feed increases (and v is constant), the length of the tool path decreases (for a given length of the workpiece), the cutting (contact) time decreases, as well as the corresponding tool wear. Therefore, the relative surface wear decreases. He also suggested that any change in the cutting feed leads to a corresponding change in the cutting temperature, so the cutting feed should influence the tool wear rate. In his study he also found that increasing the cutting feed leads to a corresponding increase in the normal contact stress at the tool–chip interface and in the tool–chip contact area (length) [**Astakhov, 2004**]. However, the contact area increases at much smaller rate compared to the normal contact stress [**Makaraw, 1976**]. When the level of the normal contact stress reaches a certain tool-material specific limit, the chipping of the cutting edge takes place, which eventually leads to tool breakage. Such a limit can be referred to as the breaking feed. Normally, the cutting feed used in machining common work materials is below the breaking feed. However, in hard turning, an operation that is attracting more and more attention in the automotive and aerospace industries, the breaking feed is normally well below those allowed by the surface finish of machined parts and by the power of the machine tools used, so the working cutting feed can be in close proximity of the breaking feed. Often, the intensity of the vibrations that take place in machining reduces with the cutting feed. When this happens, the tool wear rate reduces. Moreover, increasing the cutting feed changes the ratio of the radial and the axial forces that increases the dynamic rigidity of the machine tool.

2.6 Models used to Predict Temperature and Cutting Force

Researchers have been developed a large number of models for the prediction of cutting temperature and cutting force during machining for the last 60 years. The cutting temperature is a key factor which directly affects cutting tool wear, workpiece surface integrity and machining precision according to the relative motion between the tool and work piece [**Ming et al., 2003**]. The amount of heat generated varies with the type of material being machined and cutting parameters especially cutting speed which had the most influence on the temperature [**Liu et al., 2002**]. Several attempts have been made to predict the temperatures involved in the process as a function of many parameters. Da Silva and Wallbank [**1999**] presented a review for cutting temperature prediction and measurement methods. Additionally, many experimental methods to measure temperature directly, only a few systems have as yet been used this temperature as an indicator for machine performance monitoring and for industrial application. Therefore, design and develop control system to control the temperature lead to better surface finish as machine performance parameter.

There has been significant research reported in modeling the cutting force during machining. A series of papers by Kline et al. [**1982**] presented a mechanistic model which considers the tangential cutting force to be proportional to the chip load and the radial force to be proportional to the tangential force. The size effect is captured by the nonlinear empirical relationship between specific energy and uncut chip thickness. Altintas [**2000**] presented a linear edge effect model in which the tangential force is split into a cutting component and a parasitic component (also known as an edge, rubbing or plowing force). In this model, cutting forces are linearly proportional to both chip thickness and contact area. Both models have been shown to be reasonably accurate at force prediction when model coefficients are properly calibrated [**Fussell et al., 1992, 2001, 2003**].

There are several empirical and analytical analysis exists in the literature for the prediction of both cutting temperature and cutting force. Merhant [**1945**] develops analytical model to predict cutting force. Kienzle [**1952**] develops an empirical model based on a large number of experiments. Within recent years mainly Finite Element Methods are used to simulate cutting force and temperature [**Massilimani and Chessa, 2006; Olovsson, 1999**]. Improvement in manufacturing technologies such as metal cutting requires better modeling and analysis. Numerical methods became recently an efficient tool for investigation of the cutting force and temperature that is generated in the cutting zone. Now a days many researchers are using Response Surface Methodology to predict cutting force during turning operation. The RSM is practical, economical and relatively easy for use and it was used by lot of researchers for modeling machining processes [**Baradie, 1993; Hasegawa et al., 1976; Sundaram and Lambert, 1981**]. Cutting force models however can play an important role in setting cutting conditions that are safe, efficient and produce parts of the desired quality.

2.7 Models used to Predict Surface Roughness and Tool Wear

Process modeling and optimization are the two important issues in manufacturing products. The manufacturing processes are characterized by a multiplicity of dynamically interacting process variables [**Azouzi and Guillot, 1998; Liao and Chen, 1998**]. A greater attention is given to accuracy and surface roughness of product by the industry these days.. Surface roughness and dimensional accuracy are the important factors required to predict machining performances of any machining operations [**Mital and Mehta 1988**]. The predictive modeling of machining operations requires detailed prediction of the boundary conditions for stable machining [**Motghare, 1998, Van Luttervelt, 1998**]. The number of surface roughness prediction models available in literature is very limited [**Mital and Mehta, 1988; Van Luttervelt, 1998**]. Most surface roughness prediction models are empirical and are generally based on experiments in the laboratory. In addition it is very difficult in practice, to keep all factors under control as required to obtain reproducible results [**Van Luttervelt, 1998**]. Generally these models have a complex relationship between surface roughness and operational parameters, work materials and chip-breaker types. Optimization of machining parameters not only increases the utility for machining economics, but also the product quality increases to a great extent [**Azouzi and Guillot, 1998**].

Bernados and Vosniakos [**2002**] reported that there are statistical prediction methods used to model surface roughness in the machining process to achieve the desired levels of machining parameters. Among these techniques are the response surface methodology (RSM) and Taguchi's orthogonal array. Taraman [**1974**] first used Response Surface Methodology (RSM) for predicting surface roughness of different materials. A family of mathematical models for tool life, surface roughness and cutting forces were developed in terms of cutting speed, feed, and depth of cut. Hasegawa et al. [**1976**] conducted 3^4 factorial designs to conduct experiments for the surface roughness prediction model. They found that the surface rough increased with an increase in cutting speed. Sundaram and Lambert [**1981**] considered six variables i.e speed, feed, and depth of cut, time of cut, nose radius and type of tool to monitor surface roughness.

Davim [**2001**] studied the influence of velocity, feed rate and depth of cut on the surface roughness using Taguchi design. Kopac, Bahor and Sokovic [**2002**] conducted a study regarding the influence of machining parameters, i.e., cutting parameters, workpiece material, cutting tool geometry and cutting tool material, on the surface roughness. The experimental study selected was based on Taguchi's orthogonal array L16. The turning process of raw workpieces of low-carbon steel with low cold predeformation was conducted to achieve the desired surface roughness. Nalbant et al. [**2007**] also utilized the Taguchi method to achieve the optimal cutting parameters for minimizing surface roughness in turning. The orthogonal array, signal-to-noise ratio and analysis of variance

(ANOVA) were deployed to study the effects of the three cutting parameters, insert radius, feed rate and depth of cut, in turning operations of AISI 1030 steel bars using TiN coated tools.

Arbizu and Luis Perez [**2003**] used a 23 factorial design to construct a first order model to predict the surface roughness in a turning process of workpieces following the ISO 4287 norm based on spindle speed, feed rate and cutting depth. Following this study, Noordin et al. [**2004**] conducted an experiment on the turning process of AISI 1045 steel. The effects of cutting speed, feed rate and side cutting angle on the multiple-responses (tangential force and surface roughness) were investigated using the CCD, and the second order regression model was built to predict these two responses. Later Sahin and Motorcu [**2005**] utilized RSM to construct a surface roughness model for the turning process of AISI 1040 mild steel coated with TiN. Recently Kandananond [**2009**] used 9SMnPb28k (DIN) steel to develop a model for predicting the surface roughness in order to optimize the cutting conditions. Three machining parameters, depth of cut, cutting speed and feed rate, were included in his predicted model, and the central composite design (CCD) was selected as the design of RSM for his study.

Lin and Lee [**2001**] formulized the experimental results of surface roughness and cutting forces by regression analysis, and modeled the effects of them using S55C steel. Similar investigations were conducted by Ghani and Choudhury [**2002**], Petropoulos et al. [**1972**], Feng and Wang [**2002**], Sekulic [**2002**], Gadelmavla and Koura [**2002**] and Risbood and Dixit [**2003**].

Chao et al. [**1995**] performed a study on turning process by using a Taguchi-based methodology. Major concerns of investigation are tool life and surface roughness. In this study five factors (cutting speed, feed rate, depth of cut, material type, rake angle) with two levels are included. An L16 orthogonal array design, and analysis of variance (ANOVA) is used to for the experiment. Cutting speed, feed rate and depth of cut contributions to surface finish and tool life turn out to be significant rather than the two-factor interactions. Chao et al. concluded that the tool life is sensitive to those three cutting parameters.

Iakovou et al. [**1996**] proposed analytical models and numerical procedures for simultaneously determining the optimal cutting speed and tool replacement policy in machining economics problems with stochastic tool lives. Their model is an unconstrained optimization model and is based upon the basic Taylor tool life equation. Jianqiang and Keow [**1997**] used a lognormal distribution to fit the tool life data by wear and derived a model for determining optimal tool replacement intervals coupled with a forecasting tool replacement strategy.

Choudhury and Appa [**1999**] presented the role of temperature and surface finish to predict tool wear. Doing this study, design of experiments and neural network methods are employed. In the design of experiments three cutting parameters are used. Using all surface finish, temperature and flank wear as response values, regression equations are formed. Following that, both temperature and surface finish are fitted against wear, and then the actual and fitted values compared and average error values are obtained.

Shabatay and Kaspi [**2003**] presented models for calculating the optimal cutting feed rate, spindle speed, and age of preventive tool replacement for a standalone cutting machine. The optimal cutting conditions are determined and analyzed for three different objective functions: minimum expected cycle time, minimum expected cost per unit, and maximum expected profit-rate, under the Age Replacement Strategy (ARS) and assuming that the tool-life distribution function is Normal. They showed that the first two objective functions are separable, and present an efficient one dimension search procedure for the optimization.

A study on the performance of machinability of Inconel 718 showed that the tool life of the silicon nitride based material was mainly dependent on flank wear, whereas for the silicon carbide whisker-reinforced alumina, the tool life criterion was depth of cut notch wear [**Wayne and Buljan, 1990**]. Two types of coated cemented cardide inserts were used. Various combinations of side cutting edge angles (SCEAs), cutting speeds and feedrates were tested at a constant depth of cut. Cutting results indicate the SCEA, together with cutting speed and federate, do play a significant role in determining the tool life of an insert when machining Inconel 718 [**Rahman et al., 1997**].

Ultrasonic vibrations have been extensively adopted in manufacturing processes. Weber [**Weber et al., 1984**] et al. used high-frequency vibrations (20KHz) in radial directions to cut steel materials and found that this approach could increase tool life. Moreover, Wang and Zhao [**1987**] applied high-frequency vibrations (16KHz) to improve surface roughness, reduce microcracks on the workpiece surface and increase cutting stability. Additionally, Liu et al. [**2002**] proposed using ultrasonic-aided vibrations to cut SiCp/Al thin-wall parts for precision processing Compared with conventional cutting, this method is lower in cutting force and does not produce BUE.

2.8 Optimization of Cutting Parameters

Optimization of metal cutting operations means determination of the optimal set of operating conditions to satisfy an economic objective within the operation constraints. An optimization problem consists of optimizing one or multiple objectives function while satisfying several constraints. Those objectives are often conflicting and incomparable. For example, let us suppose the operation of turning where the following objectives are taken in account: we want either to minimize the cost of the operation, to maximize rate of production, to maximize the cutting quality or a suitable combination of these three options [**Duffua, 1993**]. The increase of rate of feeding brings about the growth of the production rate, but also increases the cost of the operation due to excessive tool wear and decreases the surface quality because of greater roughness.

Taylor [**1907**] built the first experimental models in a seminal study. Following his work, many researchers developed different models and optimization algorithms. Iwata et al. [**1972**] used chance constrained programming for solving a problem with a model having uncertainties. Wang et al. [**2002**] used evolutionary algorithms for solving a problem with highly non-linear models. Finite-element simulations avoid the need for experiments, but require a complex material model and are quite time consuming when high precision is required. Ivester et al. [**2006**] showed that machining models have significant uncertainties that may strongly affect the selection of optimal cutting parameters.

Various optimization techniques for selecting process variables were developed. Ermer and Kromodihardjv [**1981**], Ermer [**1971**]; and Gopalkrishnan and Al-Khayyal

[**1991**] considered the single and multipass turning operations based upon some practical constraints (speed, feed, cutting tool life, cutting force and surface roughness) based on the minimum production cost or the minimum production time criteria. Several researchers have also considered an individual rough or finish pass using several techniques [**Chang et al., 1998, Hitomi, 1996; Lee et al., 1999**]. The various methods so far used for determining the optimum cutting parameters are discussed below.

2.8.1 Taguchi Method

Taguchi and Analysis Of Variance (ANOVA) can conveniently optimize the cutting parameters with several experimental runs well designed. Taguchi parameter design can optimize the performance characteristics through the settings of design parameters and reduce the sensitivity of the system performance to source of variation [**Berger and Maurer, 2002; Ryan, 2000**]. On the other hand, Analysis Of Variance ANOVA used to identify the most significant variables and interaction effects [**Henderson, 2006; Ryan, 2000**]. Kwak [**2005**] presented the Taguchi and response method to determine the robust condition for minimization of out of roundness error of workpieces for the center less grinding process. Yang and Tarng [**1998**] employed Taguchi method and optimal cutting parameters of S45C steel bars for turning operations were obtained.

Determination of optimal cutting conditions for surface finish obtained in turning using the techniques of Taguchi and a correlation between cutting velocity, feed and depth of cut with the roughness evaluating parameters R_a and R_t was established using multiple linear regression by Davim [**2001**]. John et al. [**2001**] demonstrated a systematic procedure of using Taguchi parameter design in process control in order to identify the optimum surface roughness performance with a particular combination of cutting parameters in an end milling operation. Kopac et al. [**2002**] described the machining parameters influence and levels that provide sufficient robustness of the machining process towards the achievement of the desired surface roughness for cold pre-formed steel workpieces in fine turning.

2.8.2 Ant Colony System Method

Vijayakumar et al. [**2002**] use the ant colony algorithm for solving multi-pass turning optimization problems. The cutting process has roughing and finishing stages. The machining parameters are determined by minimizing the unit production cost, subject to various practical machining constraints.

It has been established from this research that the ACO algorithm can obtain a near-optimal solution in an extremely large solution space within a reasonable computation time. The effectiveness of the ACO algorithm has been proved through an example. The ACO algorithm is completely generalized and problem independent so that it can be easily modified to optimize this turning operation under various economic criteria, and numerous practical constraints; and the algorithm can also be extended to other machining problems, such as milling operations and threading operations.

2.8.3 A Grey and Fuzzy Logic Method

Tarng et al. [**1995**] present an optimal fuzzy logic controller design using efficient robust optimization techniques called genetic algorithms. It is shown that the developed fuzzy logic controller can achieve an automatic adjustment of feed rate to optimize the production rate with a constant cutting force in turning operations.

From this research it has been found that the design cycle time for the fuzzy control system in turning operations can be greatly reduced from hours to minutes. Computational simulations and experimental cutting tests are performed to confirm the proposed method.

Lee et al. [**1999**] developed a fuzzy non-linear programming model to optimize machining operations. That system can be used to select the tool holder, insert and cutting conditions (feed, speed and depth of cut. Modelling by fuzzy logic opens up a new way to optimize cutting conditions and also tool selection.

2.8.4 Geometric Programming

A number of authors used geometric programming to determine the optimum cutting speed and feed rate under different constraints which satisfy minimum cost of single pass turning operations [**Lambert and Walwaker, 1970; Emer, 1971; Petropopoulos , 1972**]. The developed models and programs can be used to determine the optimum cutting parameters that satisfy minimum production cost or maximum production rate in turning operations under different machining constraints. Later Kolomas [**1991**] utilized Geometric programming model for simultaneous determination of the optimal machining conditions (cutting speed and feed) and the optimal tool replacement policy in the constrained machining economics problem.

Prased et al. [**1997**] have used a combination of geometric and linear programming techniques for solving the multipass turning optimisation problem as part of a PC-based generative CAPP system. The work piece materials considered in their study include steels, cast iron, aluminium, copper and brass and tool materials include HSS and carbide. The minimization of production time is taken as the basis for formulating the objective function. The constraints considered in this study include power, surface finish, tolerance, work piece rigidity, range of cutting speed, maximum and minimum depths of cut and total depth of cut. Improved mathematical models are formulated by modifying the tolerance and work piece rigidity constraints for multi-pass turning operations.

2.8.5 Simulated Annealing

Saravanan et al. [**2003**] applied simulated annealing (SA) and genetic algorithm (GA) to determine the optimal machining parameters for continuous profile machining with respect to the minimum production cost, subject to a set of practical constraints. The constraints considered in this problem are cutting force, power constraint and tool tip temperature. It was shown that SA has performed slightly better than GA. Chen et al. [**1998**] have developed an optimization model for a continuous profile using a simulated annealing approach.

Kolahan and Abachizadeh [**2008**] also developed a simulated annealing algorithm to optimize machining parameters in turning operation on cylindrical workpieces. The turning operation usually includes several passes of rough machining and a final pass of finishing. Seven different constraints are considered in a non-linear model where the goal is to achieve minimum total cost. The weighted total cost consists of machining cost, tool cost and tool replacement cost. Their computational results show that the proposed optimization procedure has considerably improved total operation cost by optimally determining machining parameters.

Khan et al. [**1997**] also applied Simulated Annealing as optimization method for solving machining optimization problems. In this work some benchmark machining models are evaluated for optimal machining conditions. An extension of the Simulated Annealing algorithm, Continuous Simulated Annealing is also used. The results are evaluated and compared with each other as well as with previously published results which used gradient based methods, such as, SUMT (Sequential Unconstrained Minimization Technique), Box's Complex Search, Hill Algorithm (Sequential search technique), GRG (Generalized Reduced Gradient), etc. They have concluded that Simulated Annealing and the Continuous Simulated Annealing which are non-gradient based optimization techniques are reliable and accurate for solving machining optimization problems and offer certain advantages over gradient based methods.

2.8.6 Genetic Algorithm

GA was considered as a suitable algorithm for solving any type of machining process optimization problem [**Saravanan et al., 2001**]. As GA is being used successfully for optimization of turning parameters, Onwubolu et al. [**2001**] have used the genetic algorithm for optimizing the multi-pass turning operation. Srikanth and Kamala [**2008**] proposed a real coded genetic algorithm (RCGA) to find optimum cutting parameters. They explained various issues of RCGA and its advantages over the existing approach of binary coded genetic algorithm. The results obtained, conclude that RCGA is reliable and accurate for solving the cutting parameter optimization.

Ahmad et al. [**2005**] have implemented GA based strategy for milling operation, which is also a constrained optimization problem. They have applied Self Organizing Adaptive Penalty (SOAP) strategy with GA for rapid convergence to the optimum value. Minimum production time, which is a popular economic criterion, is used as the objective functions in this single pass milling parameter optimization problem.

There have been some works regarding optimization of cutting parameters of end milling operation [**Wang et al., 2002; Tandon et al., 1996; Zheng et al., 1996**] for different situations. Saha [**2009**] used genetic algorithm (GA) to obtain the optimum cutting parameters by minimizing the unit production cost for a given amount of material removal for the multi-pass face milling process. Multi-objective formulation is a realistic model for the optimization of cutting conditions in several machining processes. Bouzakis et al. [**2008**] presents a multi-objective optimization procedure, based on genetic algorithms to obtain the optimum cutting conditions (cutting depth, feed rate and cutting speed) in milling. Objectives functions, like machining cost and machining time and several technological constrains are simultaneously taking into consideration. Optimum machining parameters obtained from this procedure can be intended for use by commercial CAD-CAM systems or directly by CNC machines.

2.8.7 Artificial Neural Network (ANN)

The new approach which ensures efficient and fast selection of the optimum cutting conditions and processing of available technological data are the artificial neural networks (ANN). Zuperl and Cus [**2000**] utilized the modified neural algorithm for optimization of turning parameters and their experimental results show an improved performance in terms of maximizing the extend of production, reducing the manufacturing costs and improving the product quality. They have concluded that their proposed approach is more advantageous than interactive approaches, specially for job shop production systems, where products mix is diverse and dynamic.

Wang [**1993**] presents a neural network approach to multiple-objective cutting parameter optimization for planning turning operations. Productivity, operation cost, and cutting quality are considered as criteria for optimizing machining operations. A feed forward neural network and a dynamic training procedure are proposed for modeling manufacturers' preferences using sampled fuzzy preferential data.

2.8.8 Deterministic Approach Method

Wang et al. [**2002**] shown that the deterministic optimization approach involving mathematical analyses of constrained economic trends and graphical representation on the feed-speed domain provides a clearly defined strategy that not only provides a unique global optimum solution, but also the software that is suitable for on line CAM applications. A numerical study has verified the developed optimization strategies and software and has shown the economic benefits of using optimization. This optimization study is based on the criteria typified by the minimum production time per component while allowing for the many practical constraints. It has also shown the substantial benefits in production time and cost per component that can be achieved when using the optimized cutting conditions rather than handbook recommendations.

Al-Ahmari [**2001**] presented a mathematical programming model for optimizing the process parameters and subdivisions of depth of cut in multipass turning operations. The model is a direct non-linear mathematical model that solves the optimization problem of multipass turning operations providing all decision variables (cutting speed, federate, depth cut, subdivision of depth of cut, and number of passes) for both finishing and rough cutting, in a single run.

2.8.9 Dynamic and Integer Programming

Shin and Joo [**1992**] presented a model for the multipass turning operation using a fixed machining interval. They used dynamic programming for the selection of depth of cut for individual passes. The final finish pass is fixed based on the minimum allowable depth of cut and the remaining depth of cut is divided into a number of rough passes of equal sizes to obtain the minimum total cost.

Gupta et al. [**1995**] considered the optimal subdivisions of depth of cut in machining economic problem using two steps. The first step is the minimization cost for rough and finish passes for various fixed depth of cut. In the second step, an optimal combination of depths of cut for rough passes and the finish pass, the optimal number of passes and the minimum total cost are determined using an integer programming model.

Cemal et al. [**1998**] have also developed a graphical model of machining conditions in multi-pass turning operation using a dynamic programming technique under the constraints of maximum and minimum federates and speeds available , cutting power, tool life, deflection of work piece, axial load and surface roughness. They have used a search method to determine values of machining variables with the objective of minimum production cost.

2.8.10 Multiple Performance Characteristic Method

Nian et al. [**1998**] present the Taguchi method with multiple performance characteristics is proposed in this paper. The orthogonal array, multi-response signal-to-noise ratio, and analysis of variance are employed to study the performance characteristics in turning operations. Three cutting parameters namely, cutting speed, feed rate, and depth of cut, are optimized with considerations of multiple performance characteristics including tool life, cutting force, and surface finish.

This research finding that the parameter design of the Taguchi method provides a simple, systematic, and efficient methodology for the optimization of the cutting parameters. Therefore, a useful technical tool for the quality optimization of manufacturing systems with considerations of multiple performance characteristics has been proposed and verified in this study.

2.8.11 Multiple Criteria Simulation Method

Hae et al. [**1996**] present the multiple criteria simulation optimization problem is developed and tested with a turning operation. The goal of the problem is to find the optimum cutting conditions for the turning process with minimum processing time and good surface texture.

This research work proves that the proposed method has produced better results in numerical experiments than other useful methods, except for the required number of interactions during the execution of the algorithm. The proposed method also shows good results with the turning process model on the lathe. The algorithm is capable of dealing with non-analytical representations of the feasible region.

2.8.12 Machining Theory Method

Meng et al. [**2000**] described machining theory method for calculating the optimum cutting conditions in turning for objective criteria such as minimum cost or maximum production rate.

This research finding that the approach used should greatly reduce the experimental work needed in collecting tool life data as it allows variations in work material properties and tool geometry to be allowed for independently of experiments. It was also shown that, in determining the optimum cutting conditions for economic criteria such as minimum cost and maximum production rate.

Yellowley and Gunn [**1989**] shown that the optimal widths of cut for both turning and milling operations can be determined without knowledge of the relevant tool life equation. The exception to this finding occurs when either cutting power or torque constraint is active. However, surface finish constraint has been left out.

2.8.13 Adaptive Control of the Machining

It is obvious that variations during the machining process due to tool wear, temperature changes, vibrations and other disturbances make inefficient any off-line optimization methodology, especially in high quality machining operations where product quality specifications are very restrictive. Therefore, to assure the quality of machining products, reduce costs and increase machining efficiency, cutting parameters must be optimized in real-time according to the actual state of the process. This optimization process in real-time is conducted through an adaptive control of the machining process. The adaptive control applied in machining systems is classified as [**Liang et al., 2004; Ulsoy and Koren, 1989**]: Adaptive Control with Constraints (ACC), Geometric Adaptive Control (GAC), and Adaptive Control with Optimization (ACO).

In the ACC systems, process parameters are manipulated in real time to maintain a specific process variable, such as force or power, at a constraint value. Typically, ACC systems are utilized in roughing operations where material removal rate is maximized by maintaining the cutting forces at the highest possible cutting force such that the tool is not in danger of breaking [**Zuperl et al., 2005**]. In the GAC systems, the economic process optimization problem is dominated by the need to maintain product quality such as dimensional accuracy and/or surface finish [**Coker and Shin, 1996**]. GAC systems are typically used in finishing operations with the objective of maintaining a specific part quality despite structural deflections and tool wear. In the ACO systems, machine settings are selected to optimize a performance index such as production time, unit cost, etc. Traditionally, ACO systems have dealt with adjusting cutting parameters (feed-rate, spindle speed and depth of cut) to maximize material removal rate subject to constraints such as surface roughness, power consumption, cutting forces, etc [**Venu Gopal and Venkateswara Rao, 2003**].

2.8.14 Other Methods of Optimization

Goal programming [**Sundaram, 1978**], Probabilistic approach [**Iwata et al., 1972; Hati and Rao, 1975; Iwata et al., 1976**], Particle Swarm Optimization (PSO) [**Li ei al., 2008**], Feasible Directions [**Tolouei-Rad and Bidhendi, 1997**], Memetic Algorithm [**Baskar et al., 2005**], Tribes Algorithm [**Godfrey and Onwubolu, 2006**], Hybrid Immune-Hill Climbing Algorithm [**Yildiz, 2009**] and Computer Aided Graphical Technique [**kilic et al., 1993**] were also used for the optimization of cutting variables in this aspect. Subsequently, Agapiou [**1992**] used a dynamic programming model for determining the optimum value of objective functions (weighted sum of production cost and time) and Mesquita et al. [**1995**] used a Hook-jeevs search method for finding the optimum operating parameters.

Saravanan et al. [**2001**] have used the Nelder mead simplex, boundary, search procedure for optimizing the CNC turning process, but the work was limited to straight turning only. Contour profile was not considered in this work.

The direct search procedure was used by Arsecularatne et al. [**1992**] to determine the optimum cutting parameters. The turning operation considered in this work was limited to rightand left-hand turning, boring and facing.

2.9 Summary of the Review

From the literature review it is clear that there are many variables that affect the generation of chip tool interface temperature, main cutting force, the tool life and therefore affect the surface roughness [**Lee et al., 1989**]. These factors are cutting conditions (cutting speed, feed rate and depth of cut), tool geometry, cutting fluid (dry, oil etc.), work piece material (hardness, composition etc.), tool material (high speed steel , ceramic etc.), and those factors may influence tool life and surface roughness either independently or interrelatedly [**Chao and Hwang, 1995**]. Thus optimization of these process parameters is one of the foremost targets of Manufacturing Systems. Numbers of research works are performed for generating optimum process parameters. There are many parameters that can be considered in optimize turning operation. The few parameters were reported include depth of cut, feed rate, depth of cut, nose radius, work piece speed, cutting force, cutting speed, number of passes, tool diameter and tool length. The most three parameter that uses by literature is depth of cut, feed rate and cutting speed.

Many works have so far been done to optimize these parameters by using different optimization techniques like goal programming [**Sundaram, 1978**], multistage dynamic programming [**Cemal et al., 1998**], linear programming, geometric programming [**Prased et al., 1997**], integer programming, simulated annealing [**Khan et al., 1997**], artificial neural network [**Zuperl and Cus, 2000**], taguchi method [**Yang and Tarng, 1998**], fuzzy logic [**Lee et al., 1999**] etc. But all of them face great difficulties when the number of variables increases, because the problem becomes combinatorially explosive and hence computationally complex.

Direct search methods include function evaluation and comparisons only. Gradient search methods need values of function and its derivatives, and their computerizations are also problematic. Derivative-based mathematical optimizations are not manageable for optimizing functions of discrete variables. Dynamic programming that may be applied to problems whose solution involves a multistage decision process, can handle both continuous and discrete variables. Contrary to many other optimization methods it can yield a global optimum solution. However, if the optimization problem involves a large number of independent parameters with a wide range of values (as in the case of optimization of cutting parameters), the use of dynamic programming is limited.

Geometric programming is a useful method that can be used for solving nonlinear problems subject to nonlinear constraints, especially if the objective function to be optimized is a polynomial with fractional and negative exponents, while the constraints may be incorporated in the solution techniques. However, if the degree of difficulty increases, the formulated problem might be more complicated than the original problem. Geometric programming can only handle continuous variables.

Genetic Algorithms (GAs) are robust search algorithms that are based on the mechanics of natural selection and natural genetics. They combine the idea of "survival of the fittest" with some of the mechanics of genetics to form a highly effective search algorithm. Genetic algorithms belong to a class of stochastic optimization techniques known as evolutionary algorithms. Among the three major types of evolutionary algorithms (genetic algorithms, evolutionary programming, and evolution strategies) genetic algorithms are the mostly widely used. GAs are most often used for optimization of various systems, especially complex problems such as those involving manufacturing systems analysis.

In the present research work, genetic algorithm is employed for optimization as it normally exhibits fast convergence and straightforward implementation. Genetic algorithm is different from traditional optimizations in the following ways.

- GA goes through solution space starting from a group of points and not from a single point.
- GA search from a population of points and not a single point.
- GA use information of a fitness function, not derivatives or other auxiliary knowledge.
- GA use probabilistic transitions rules, not deterministic rules.
- It is very likely that the expected GA solution will be a global solution.

GA optimization methodology is based on machining performance prediction models developed from a comprehensive system of theoretical analysis, experimental database and numerical methods. The GA parameters along with relevant objective functions and set of machining performance constraints are imposed on GA optimization methodology to provide optimum cutting conditions. Moreover GA has been used to optimize cutting parameters that minimizes surface roughness in dry condition and has not been applied for predicting optimum cutting parameters in near dry machining condition. For all these reasons GA has been chosen for solving the optimization problem in this thesis.

2.10 Scope of the Thesis

The thesis is subdivided into eight chapters including this one and the relevant chapters are organized in the following manner:

Chapter 1 presents the general requirements in machining industries, problems associated with high cutting temperature and conventional cooling practices, recent techniques in machining, benefits of hard-turning over grinding process and expected role of near dry machining in turning of hardened steel.

Chapter 2 describes the survey of previous works. The effect of cutting parameters on various machining responses and the models so far used to predict these machining responses by the researchers all over the world have been presented in this chapter. A short review of several optimization techniques so far used for determining the optimum machining parameters is included in this chapter. It also contains a brief summary of the review as well as the scope of the present work.

Chapter 3 deals with the objective of the present work and also outline the methods that have been followed to draw effective results that commensurate with the goals of the thesis.

Chapter 4 presents the experimental conditions of the machining experiments and detailed procedure for experimental set-up. Besides this chapter contains the experimental results obtained during turning hardened medium carbon steel by using coated carbide tool (SNMG TN 4000) in terms of average chip-tool interface temperature, main cutting force, chip thickness ratio, tool wear and surface roughness under both dry and near dry machining condition.

Chapter 5 illustrates development of statistical models for the objective function as well as for the constraint equations in terms of cutting speed, feed rate and depth of cut. Besides model validation has also been carried out. Then optimization of cutting parameters using Genetic Algorithm is presented in this chapter.

Chapter 6 narrates the discussion on results that have been found through experimental investigation. Relation between cutting forces and chip thickness ratio, auxiliary tool wear and surface roughness has also been discussed.

Chapter 7 contains the concluding remarks with some recommendations for future works. Lastly references are included and appendices are given at the end.

Chapter-3

Objectives of the Present Work

3.1 Objectives of the Present Work

Optimal machining conditions are the key to economical machining operations. Optimization of metal cutting operations means determination of the optimal set of operating conditions to satisfy an economic objective within the operation constraints. In this work genetic algorithm will be used for optimization. From the literature review it has been found that genetic algorithm (GA) has been used to optimize cutting parameters that minimizes surface roughness in dry condition. But other responses like temperature, tool wear and chip thickness ratio are not considered yet. Moreover GA has not been applied for predicting optimum cutting parameters in near dry machining condition. However, the objectives of the present study are

i. Experimental analysis of the effects of minimum quantity lubrication on cutting zone temperature, main cutting force, chip thickness ratio, tool wear and surface quality of the machined part while turning hardened steel (56 HRC) material with coated carbide insert.

ii. Optimization of cutting parameters (cutting speed, feed rate and depth of cut) while turning hardened medium carbon steel by coated carbide insert under near dry machining condition. The objective function of the optimization process is to determine the cutting parameter that minimizes surface roughness under certain constraints. Response Surface Methodology has been utilized to establish the objective function and also the constraints for solving the problem. RSM is a combination of experimental and regression analysis and statistical interferences.

iii. Model validation by comparing the predicted values of the machining responses for the test cutting conditions with the experimental data.

3.2 Methodology

The present research work is divided into two parts. First of all there is an experimental analysis of the effects of minimum quantity lubrication on cutting zone temperature, main cutting force, chip thickness ratio tool wear and surface quality of the machined part while turning hardened steel (56 HRC) material with coated carbide insert. The other part of the research work is concentrated to the optimization of cutting parameters (cutting speed, feed rate and depth of cut) while turning hardened medium carbon steel by coated carbide insert under near dry machining condition. The methodology would be as follows:

i. A nozzle for application of near dry lubricant jet has been fabricated for controlling the spray pattern, covering area and coolant flow rate.

ii. Chip shape, chip color and chip thickness ratio under both dry and near dry machining conditions have been studied to explore the nature of chip tool interaction.

iii. A tool-work thermocouple technique has been developed and used to measure the average chip-tool interface temperature under both dry and near dry machining environment. A tool work thermocouple calibration has been carried out for using to measure the interface temperature. The chips will be collected to measure the thickness and hence chip thickness ratio will be evaluated.

iv. Main cutting force under both the environments has been recorded with the help of lathe tool dynamometer, charge amplifier and computer. Here computer was used to monitor the profile of the cutting force during machining under both the environments.

v. The cutting insert has been withdrawn at regular intervals to examine the pattern and extent of wear on main and auxiliary flanks for all the trials. The average height of the principal flank wear and auxiliary flank wear has been measured using the metallurgical microscope.

vi. The surface roughness has been monitored by a Talysurf to study the effect of near dry machining on machined surface.

vii. Optimization of cutting parameters has been done by using genetic algorithm (GA). The required data was collected from the experiment of the turning process applied on hardened steel at different cutting speeds, feeds and depth of cuts under both dry and near dry machining condition. The objective function of the optimization process was to determine the cutting parameter that minimizes surface roughness under certain constraints. Statistical models have been developed to establish the objective function and also the constraints for solving the problem.

viii. The proposed models have been verified by experimental data of turning hardened medium carbon steel by coated carbide (SNMG) insert under near dry machining condition.

Chapter-4

Experimental Investigations

4.1 Introduction

The medium carbon was heat treated to produce desired hardness as well as great variety of microstructures and properties. The whole process was done in an inert environment by using continuous flow of argon gas. Generally, heat treatment uses phase transformation during heating and cooling to change a microstructure in a solid state. In heat treatment of specimen, the processing was most often entirely thermal and modifies only structure. Thermo-mechanical treatments, which modify component shape and structure, and thermo-chemical treatments which modify surface chemistry and structure, are also important processing approaches which fall into the domain of heat treatment.

The high cutting temperature generated during machining of hardened steel not only reduces tool life but also impairs the product quality. The temperature becomes more intensive when cutting velocity and feed are increased for higher MRR and the work materials are relatively difficult to machine for their high strength, harden-ability and lesser thermal conductivity. Cutting fluids are widely used to reduce the cutting temperature. But there are some major problems associated with the use of conventional methods. It has already been observed through previous research that proper application of near dry machining may play vital role in providing not only environment friendliness but also some techno-economical benefits.

4.2 Material Hardening

The material used in the thesis was medium carbon steel. It was a long solid bar which had been sliced in small pieces with the help of band saw to fit into the electric furnace. The working length of the pieces was 500 mm with diameter of 120 mm as shown in Fig.4.1. To make provision for pulling the red hot metal pieces from furnace, hook had to be facilitated. Using drilling and boring tools a through hole was created in the solid shaft in radial direction. A triangular hook of mild steel was attached to the work piece so that the work-piece can be pulled out from the furnace with the help of a tong.

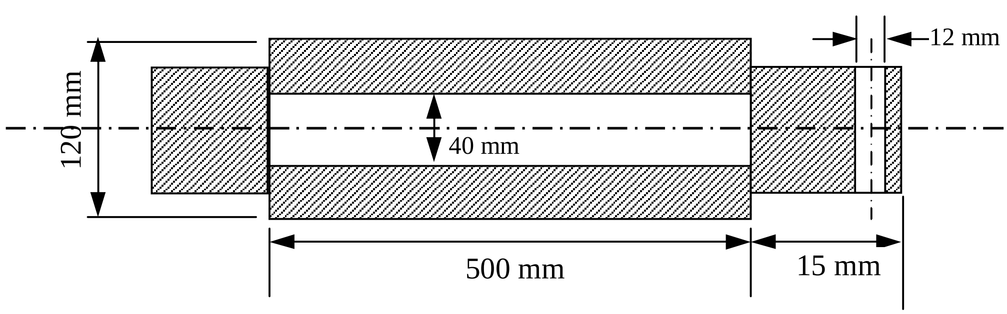


Fig. 4.1 Work material for hardening

Electric furnace of high heating element was used for heat treatment. Before loading the work piece and the test sample, the furnace had to be made oxygen free to avoid oxidation because a scale was formed on the surface of the work material during hardening. Due to scale forming, carbon quickly deposited from the work piece. In this circumstance, two ceramic pipes of internal diameters of 3 mm and 4.5 mm were connected with the furnace inlet and outlet respectively. The other end of the ceramic pipe with 3 mm internal diameter was connected to an argon gas cylinder with the help of a hose pipe. The door of the electric furnace was sealed and isolated from the atmosphere by an asbestos sheet. Argon gas was passed through the furnace chamber to drive out air as well as oxygen. It was done by high flow rate of argon gas of about 7 liters per minute at a pressure of 130 bars. After two minutes, the flow rate was slowed down and held it at 5.5 liters per minute. At this point the furnace was turned on with 5 amperes current rating. It took three hours to raise the temperature to 900°C and held the work material at that temperature for one hour.

A quench tank having capacity 140 liters was set up on the floor of heat treatment lab. 10 kilograms ice and 10 kilograms of sodium chloride was mixed with 120 liters of water to prepare a 10% brine solution. This mixture reduced the absorption of atmospheric gases that, in turn reduced the amount of bubbles. As a result, brine wetted the metal surface and cooled it more rapidly than water. In addition to rapid and uniform cooling, the brine removed a large percentage of any scale that may be present. The work piece was pulled quickly but carefully out from the furnace using a tong and was immersed it vertically into the brine solution. The solution was stirred vigorously for about 10 minutes and was continued the quench until the specimen was cool enough to handle using bare hands. Heat transfer was not so fast through the steam layer. On the other hand the very act of transforming the water into steam means the water has to take in enormous amounts of energy to transform the water from liquid state to gaseous state (steam). Moving the part and re-circulating the water aids in getting the best quench. The test sample was also quenched in the same solution following same manner.

Quenched carbon steels always required to temper because of steels are often more harder than needed and too brittle for most practical uses. Also, several internal stresses like residual stresses are set up during the rapid cooling from the hardening temperature. As a result, to relieve the internal stresses and reduce brittleness, tempering was done. The procedure of tempering is the re-heating of specimen below its re-crystallization temperature (160°C). Holding the specimen at that temperature for a one hour then cooled it usually in still air. The resultant strength, hardness, and ductility depend on the temperature to which the specimen is heated during the tempering process. The purpose of tempering was also to produce definite physical properties within the specimen.

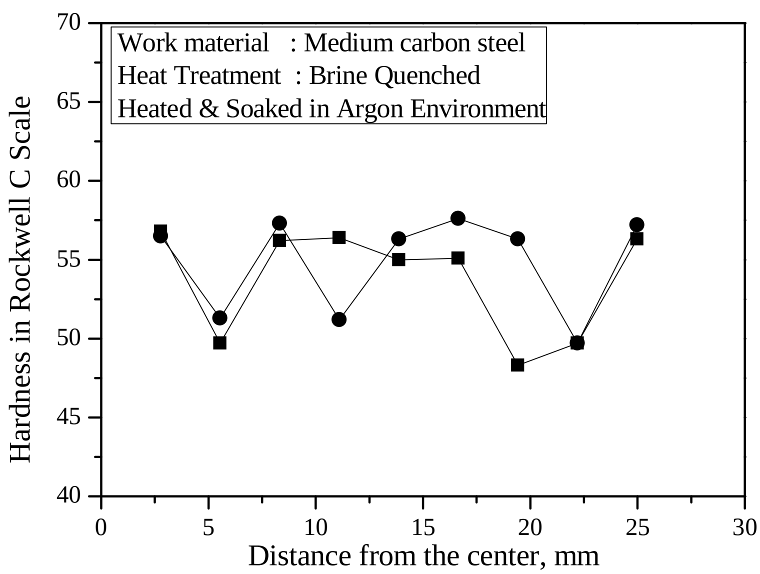


Fig.4.2 Hardness distribution curve of sample

A section about 4 mm was taken off of the stock using wire cut EDM in order to perform a hardness test. The material for the hardness test was taken from the same billet as the stock material being tested. The end of the stock material was faced to create a flat surface on the end of the work piece. The hardness test started at 12.7 mm from the outside of the stock and moved toward the center by 12.7 mm increments. The hardness test was repeated on the material at 180° from the original test line as shown in Fig4.2. The hardness values were averaged and the hardness of the stock piece was 56 HRC.

4.3 Experimental Procedure and Conditions

External longitudinal turning was performed in a powerful rigid lathe (7.5 KW) lathe of excellent operational condition at different cutting velocities (V) and feed rates (f) under dry and near dry machining condition at different depth of cut (d). Fig. 4.3(a) shows the photographic view of the experimental set-up with the near dry lubrication applicator. The coolant used was straight run cutting oil (VG 68) at a flow rate of 60 ml/hr. The oil pressure was set at 20 bar and the air pressure was 15 bar. The workpiece material was medium carbon steel (Outer dia 120mm, inner dia 40mm and length 250mm) hardened to 56~57 HRC. The cutting tool used was coated tungsten carbide tool (SNMG TN 4000 WIDIA) having tool geometry of -6°,-6°,6°,15°,75°,0.8 mm. The insert has been clamped in a PSBNR 2525 M12 type tool holder.

The conditions under which the machining tests have been carried out are briefly given in Table 4.1. A number of cutting velocity, feed and depth of cut have been taken over relatively wider ranges keeping in view the industrial recommendations for the tool-work materials undertaken and evaluation of role of variation in these cutting parameters on the effectiveness of near dry machining technique.

Effectiveness of cooling and the related benefits depend on how closely the near dry machining jet can reach the chip-tool and work-tool interfaces where, apart from the primary shear zone, heat is generated. The nozzle tip orientation regarding the cutting insert has been settling after a few trials and fixing an inclined metal stripe to the insert holder and nozzle tip attaching on it. The thin but high velocity stream of near dry lubricant jet has been heading for along the auxiliary cutting edge of the insert, so that the coolant reaches as close to the chip-tool and work-tool interfaces as possible and cools the above mentioned interfaces and both the principal and auxiliary flanks effectively as well. Fig. 4.3(c) shows the nozzle position.

Table 4.1 Experimental conditions

Machine tool	:	Lathe Machine(China), 7.5 kW
Work materials	:	Hardened medium carbon steel
Hardness (HRC)	:	56~57
Size	:	Outer dia 120mm, inner dia 40mm and length 250mm
Cutting tool	:	Coated Carbide, SNMG-TN 4000, Widia 
Coating	:	TiCN
Geometry	:	-6°,-6°,6°,6°,15°,75°,0.8 mm
Tool holder	:	PSBNR 2525 M12 (ISO specification), Widia
Process parameters		
Cutting velocity, V	:	88, 126, 177 and 252 m/min
Feed rate, f	:	0.10, 0.12 and 0.14 mm/rev
Depth of cut, d	:	0.4, 0.8 and 1.2 mm
Near dry lubricant supply	:	Flow Rate 60 ml/hr, Air Pressure 15 bar, Oil Pressure 20 bar
Environment	:	i. Dry ii. Near dry environment (VG 68 cutting oil)

(b) Surface roughness measuring technique

(a) Near dry machining applicator (c) Nozzle position

Fig. 4.3 Photographic view of the experimental set-up

The Near dry machining system needs to be properly designed for achieving substantial technological and economical benefit in addition to environmental friendliness. Following factors should be considered during the effective design of the near dry machining system:

i. effective cooling by enabling near dry machining jet reach as close to the actual hot zones as possible

ii. avoidance of bulk cooling of the tool and the job, which may cause unfavorable metallurgical changes

iii. minimum consumption of cutting fluids by pin-pointed impingement and only during chip formation

iv. pressure and flow rate of the near dry machining should be maintained at an optimum level and constant throughout the cut

Near dry machining system using cutting fluid and compressed air essentially consists of

- compressor for compressing and delivering compressed air at the desired pressure
- mixing chamber for mixing cutting fluid and compressed air
- suitable nozzle to impinge lubricant to the cutting zone
- pressure and flow control valves for effective economical use of cutting fluid

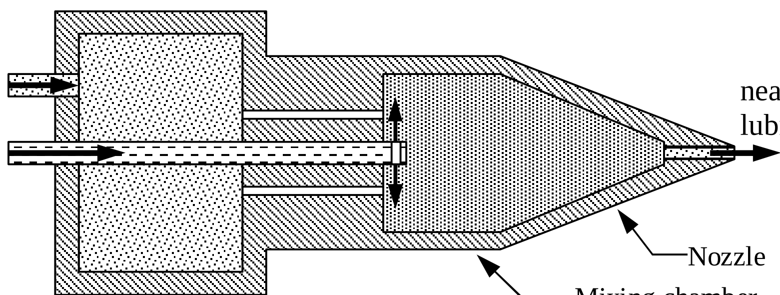


Fig. 4.4 Schematic view of the mixing chamber along with nozzle

For the improvement of cutting performance, the knowledge of temperature at the chip-tool interface with good accuracy is essential. Several experimental and analytical techniques have been developed for the measurement of temperatures generated in cutting zone. The average chip-tool interface cutting temperature was measured under dry and near dry machining conditions undertaken by simple but reliable tool-work thermocouple technique with proper calibration. Thermocouples have always become a popular tool to be used in temperature measurements during metal cutting. This method is very useful to indicate the effects of the cutting speed, feed rate and cutting parameters on the temperature. Thermocouples are conductive, rugged and inexpensive and can operate over a wide temperature range. But proper functioning of this technique needs care about parasitic emf generation.

The set-up of the calibration technique employed for the tool-work thermocouple used in the present investigation has been prepared to be mounted on a precision lathe. The coated carbide SNMG insert has been mounted in the screw type tool holder. To avoid generation of parasitic emf, a long carbide rod has been used to extend the insert. The workpiece was hardened steel. Tool and workpiece have been insulated from the machine tool. A digital multi-meter (Rish Multi, India) has been used to record emf as milivolt. For thermocouple, one end of multi-meter has been connected to the workpiece and other end to the tool. During machining, the emf as milivolt has been recorded from multi-meter under dry and near dry machining conditions. So, to know the chip tool interface temperature we need to calibrate the emf with temperature. Calibration was done using flame heating technique. For calibration, tool-work has been brazed together and the insulated thermocouple has been inserted in sensitive hole in a copper plate. A thermometer has been placed in another hole of the copper plate. Heating has been done by the means of oxy-acetylene welding torch. Due to the heating, thermoelectric emf is generated between the tool and the workpiece. This emf has been recorded by multi-meter at the same time the junction temperature measured by the reference thermocouple has been recorded using a digital temperature readout meter (Eurotherm, UK). Temperature and milivolt data are recorded, analyzed through polynomial regression and equation for temperature is derived. The calibration equation for hardened medium carbon steel is given below.

$$\theta = 40.7668 + 99.4951\ mV - 8.81343\ mV^2 + 0.654631\ mV^3 \quad \text{........} \quad (4.1)$$

The photographic view of calibration by tool-workpiece thermocouple technique and variation of temperature with different emf (mV) has been shown in Fig.4.5 and Fig.4.6 respectively.

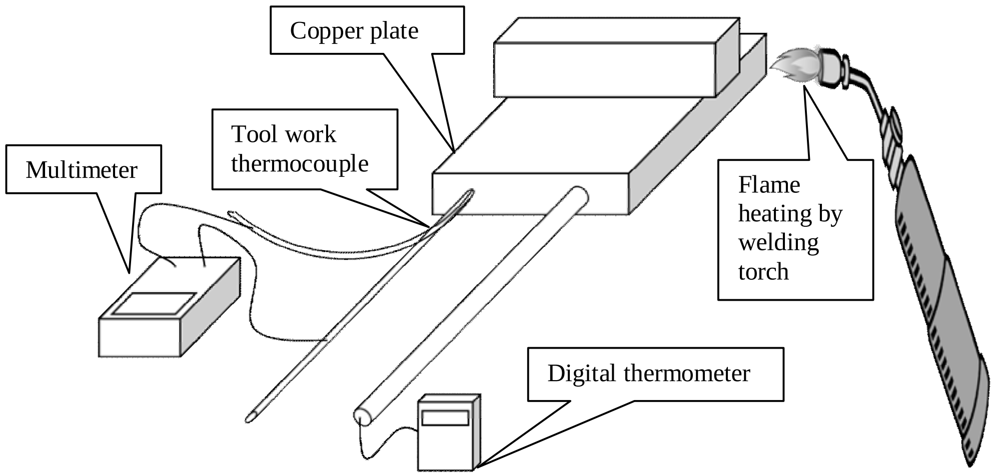


Fig. 4.5 Schematic view of tool-work thermocouple calibration set up

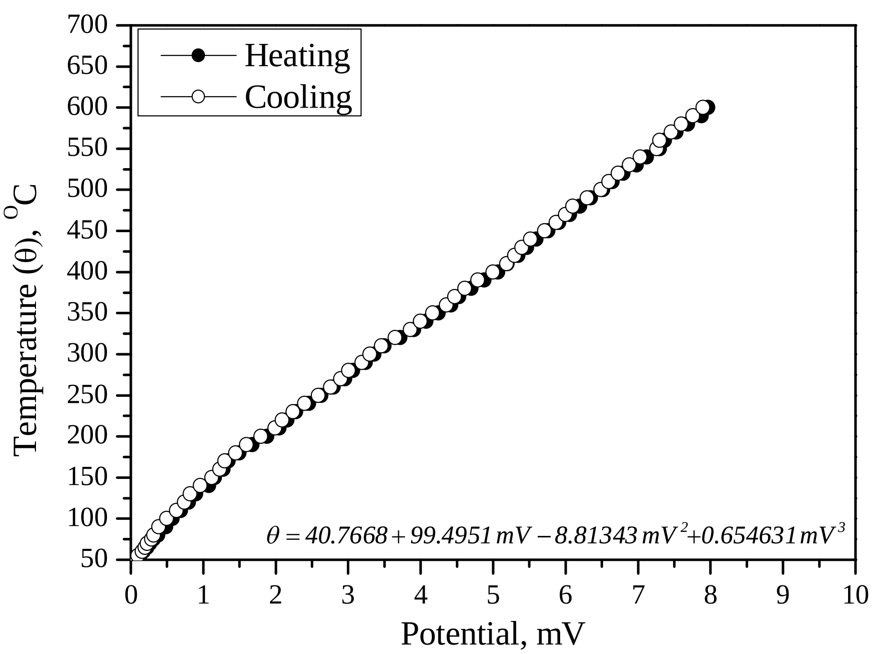


Fig. 4.6 Temperature calibration curve for carbide and hardened medium carbon steel

4.4 Experimental Results

4.4.1 Cutting Temperature

Machining is inherently characterized by generation of heat and high cutting temperature. At such elevated temperature the cutting tool if not enough hot hard may lose their form stability quickly or wear out rapidly resulting in increased cutting forces, dimensional inaccuracy of the product and shorter tool life. The magnitude of this cutting temperature increases, though in different degree, with the increase of cutting velocity, feed and depth of cut, as a result, high production machining is constrained by rise in temperature. This problem increases further with the increase in strength and hardness of the work material.

In the present work, the average chip tool interface temperature has been measured under both dry and near dry machining conditions by tool-work thermocouple techniques during turning of the hardened medium carbon steel by coated carbide insert at different cutting velocities, feed rates and depth of cuts. The evaluated role of near dry machining on average chip-tool interface temperature has been shown in Fig. 4.7, 4.8 and 4.9.

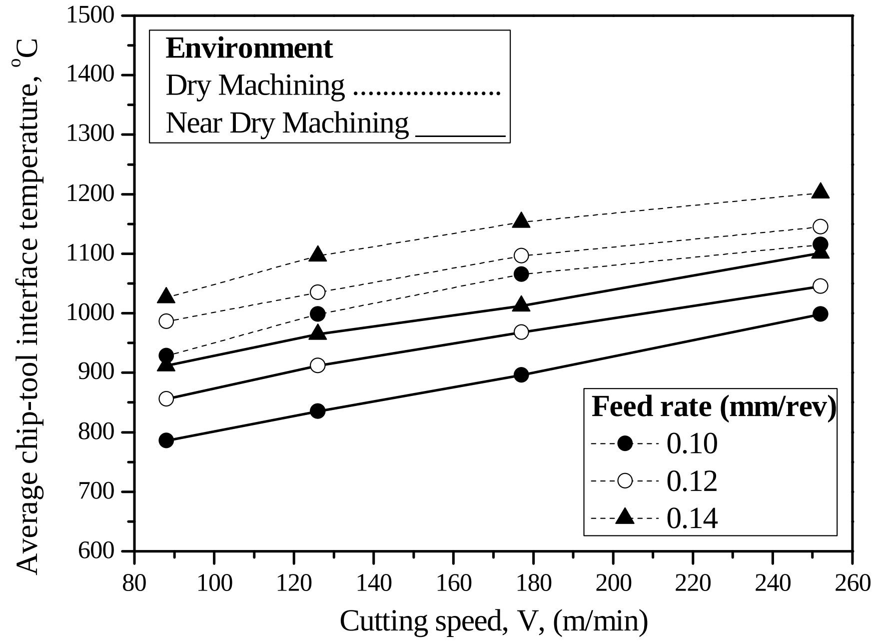


Fig. 4.7 Variation of average chip-tool interface temperature, θ_{avg} with cutting speeds for different feed rates at a depth of cut 0.4mm under dry and near dry machining environments

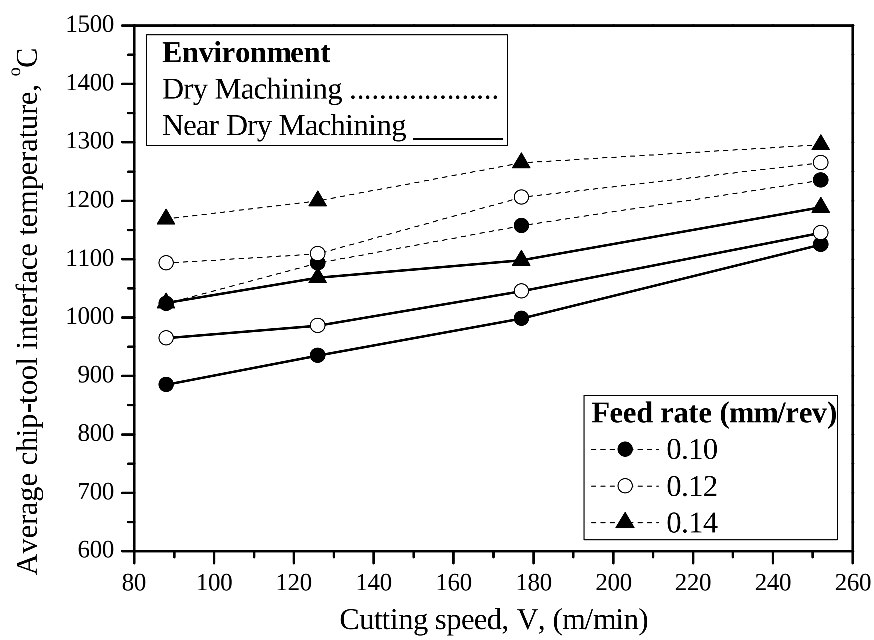


Fig. 4.8 Variation of average chip-tool interface temperature, θ_{avg} with cutting speeds for different feed rates at a depth of cut 0.8mm under dry and near dry machining environments

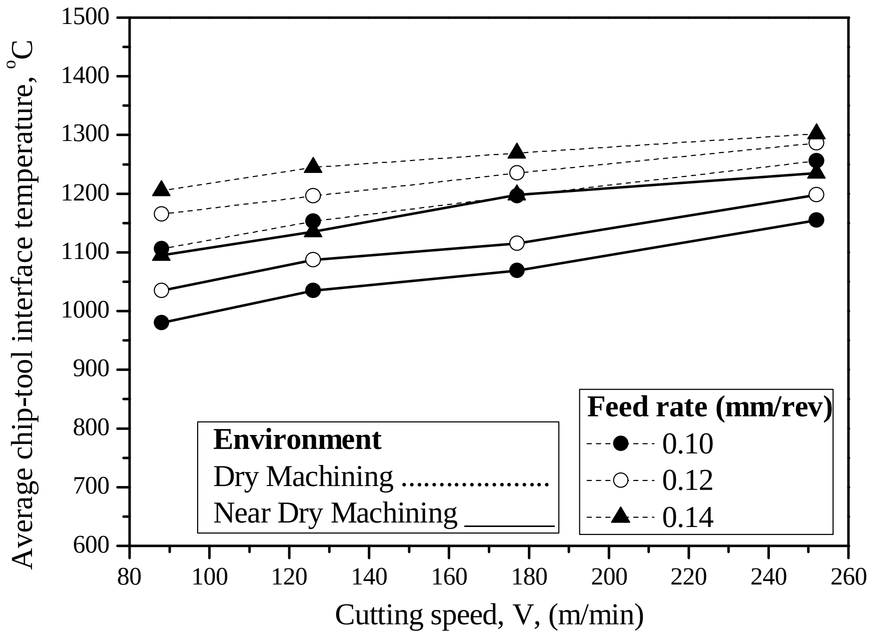


Fig 4.9 Variation of average chip-tool interface temperature, θ_{avg} with cutting speeds for different feed rates at a depth of cut 1.2mm under dry and near dry machining environments

4.4.2 Machining Chips

Chip thickness ratio, r_c (ratio of chip thickness before and after cut) is another important machinability index. For given tool geometry and cutting conditions, the value of r_c depends upon the nature of chip-tool interaction, chip contact length, curl radius and chip form, all of which are expected to be influenced by near dry machining in addition to the levels of V, f and d. The machining chips were collected during all the treatments for studying their shape, color and nature of interaction with the cutting insert at its rake surface. Chips have been visually inspected and the results have been shown in table 4.2. The thickness of the chips was repeatedly measured by a slide caliper to determine the value of chip thickness ratio (ratio of chip thickness before and after cut). The variation in value of r_c with change in V, f and d under both the machining environments evaluated for hardened steel have been plotted and shown in Fig. 4.10, 4.11 and 4.12.

Table 4.2 Shape and color of chips produced during machining

Feed rate, f, mm/rev	Cutting speed, V, m/min	Environment											
		Dry		Near dry machining		Dry		Near dry machining		Dry		Near dry machining	
		Depth of cut (mm)											
		0.4				0.8				1.2			
0.10	88	snarled ribbon	blue	snarled ribbon	metallic	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden
	126	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden
	170	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden
	252	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden
0.12	88	snarled tubular	blue	snarled ribbon	metallic	snarled tubular	blue	snarled ribbon	golden	snarled tubular	blue	snarled ribbon	golden
	126	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden
	170	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden
	252	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden
0.14	88	snarled ribbon	blue	long tubular	golden	snarled ribbon	blue	long tubular	golden	snarled ribbon	blue	snarled ribbon	golden
	126	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden
	170	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	burnt blue	snarled ribbon	golden
	252	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	blue	snarled ribbon	golden	snarled ribbon	burnt blue	snarled ribbon	golden

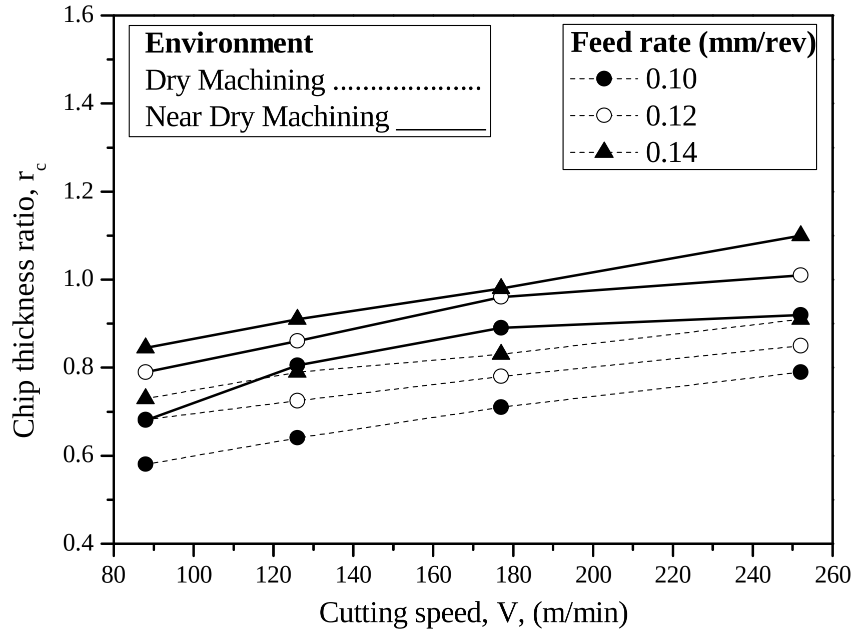


Fig. 4.10 Variation of chip thickness ratio, $r_{c,}$ with cutting speeds for different feed rates at a depth of cut 0.4mm under dry and near dry machining environments

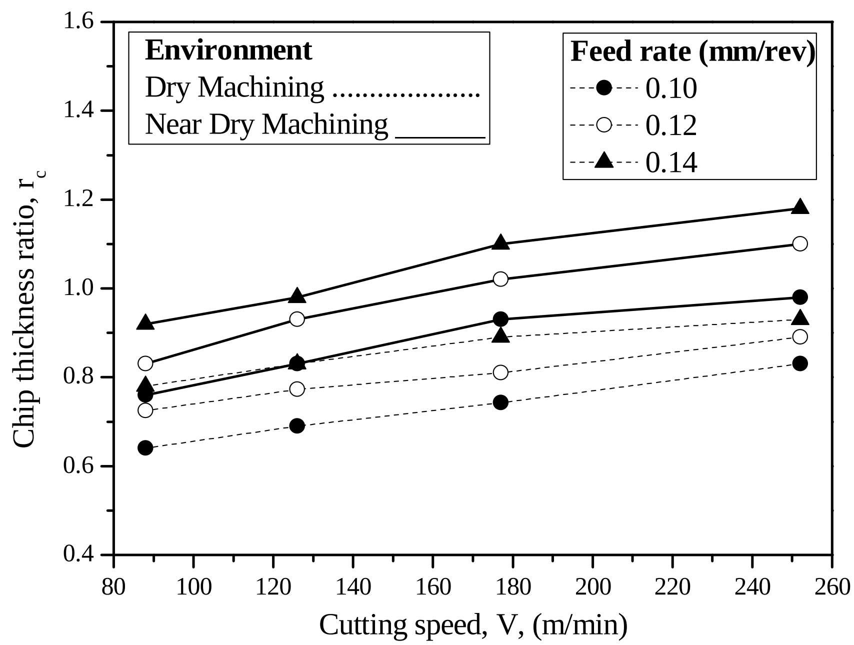


Fig. 4.11 Variation of chip thickness ratio, $r_{c,}$ with cutting speeds for different feed rates at a depth of cut 0.8mm under dry and near dry machining environments

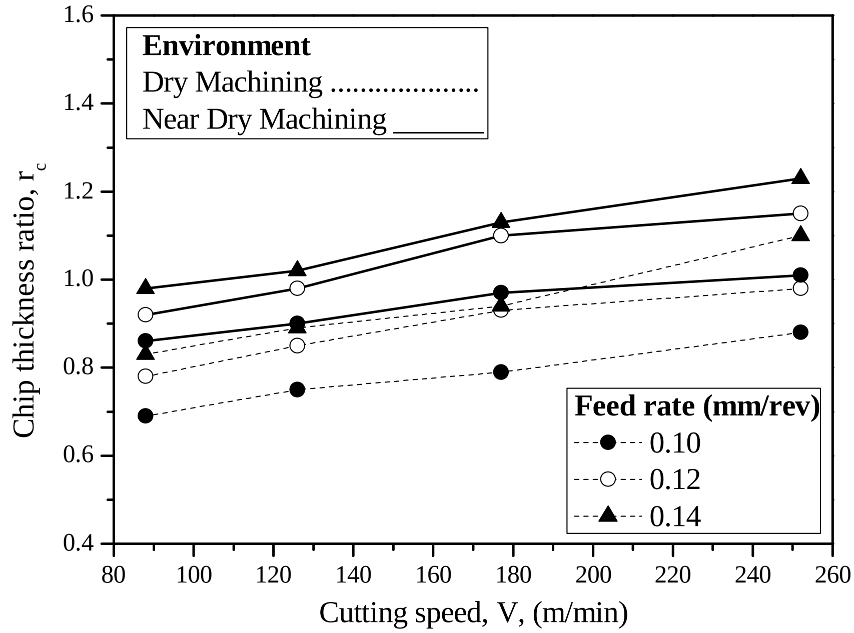


Fig. 4.12 Variation of chip thickness ratio, $r_{c,}$ with cutting speeds for different feed rates at a depth of cut 1.2mm under dry and near dry machining environments

4.4.3 Cutting Forces

Cutting forces are generally resolved into components in mutual perpendicular directions for convenience of measurement, analysis, estimation of power consumption and for design of Machine-Fixture-Tool-Work systems. In turning by single point tools like inserts, the single cutting force generated is resolved into three components namely; tangential force, P_Z, axial force or feed force, P_X and transverse force, P_y. Each of these interrelated forces has got specific significance.

In the present work, the magnitude of P_Z have been measured with a force dynamometer (Kistler) mount on carriage via a custom designed turret adapter (Kistler) for the tool holder creating a very rigid tooling fixture. The charge signal generated at the dynamometer was amplified using charge amplifiers (Kistler). The amplified signal is acquired and sampled by using data acquisition on a computer at a sampling frequency of

2000 Hz per channel. Time-series profiles of the acquired force data reveal that the forces are relatively constant over the length of cut and factors such as vibration and spindle run-out were negligible.

The effect of near dry machining on P_Z that have been observed while turning the hardened medium carbon steel specimen by coated carbide (SNMG) insert under different cutting speed, feed and depth of cut combinations is graphically shown in Fig. 4.13, 4.14 and 4.15.

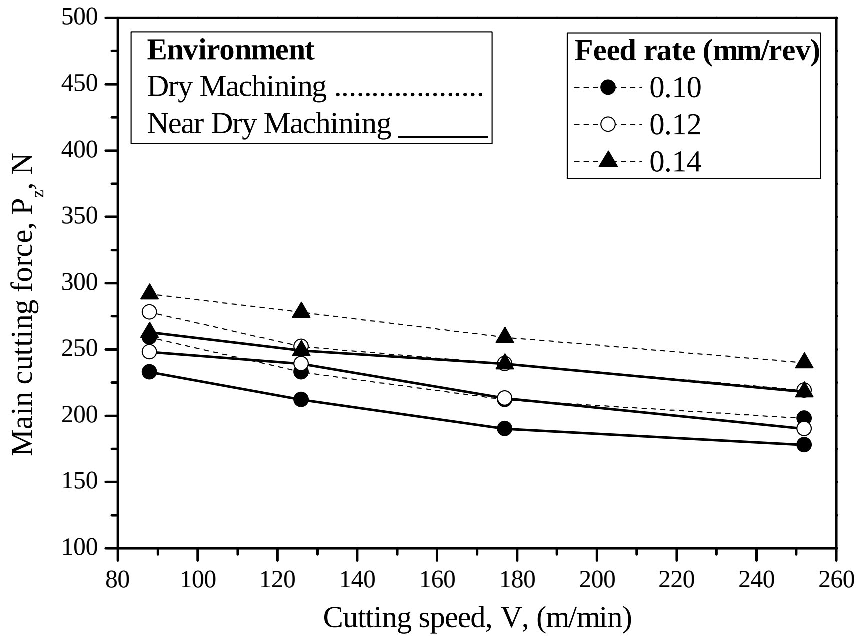


Fig. 4.13 Variation of main cutting force, P_z, with cutting speeds for different feed rates at a depth of cut 0.4mm under dry and near dry machining environments

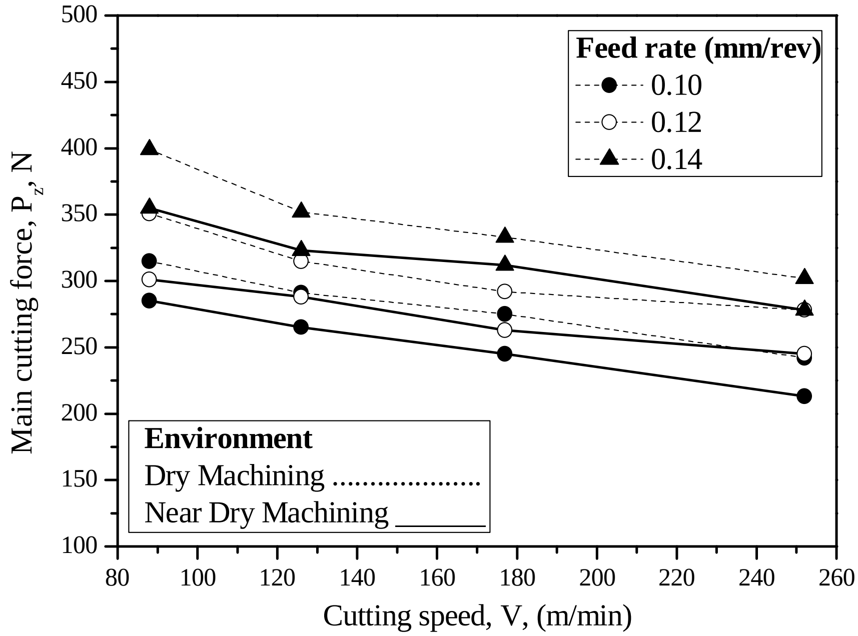


Fig. 4.14 Variation of main cutting force, P_z, with cutting speeds for different feed rates at a depth of cut 0.8mm under dry and near dry machining environments

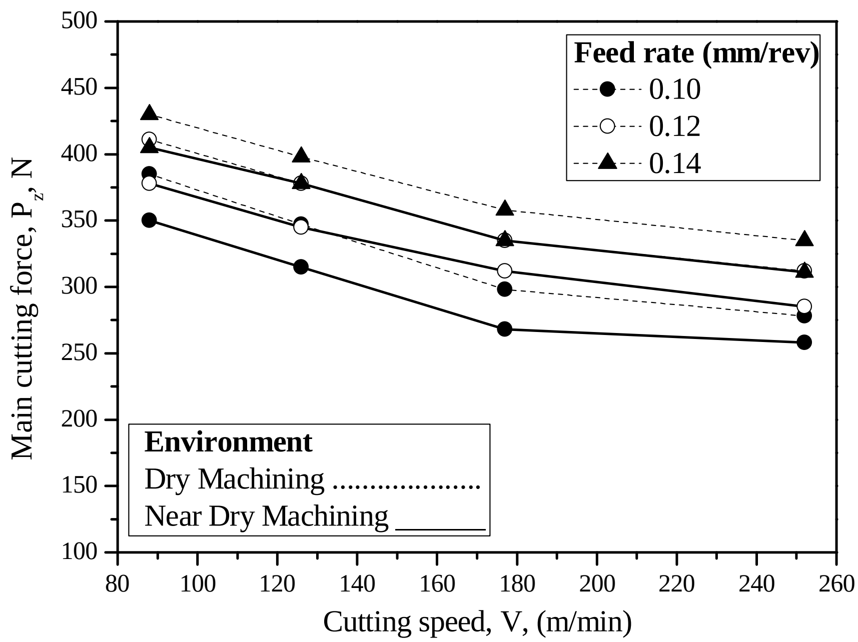


Fig. 4.15 Variation of main cutting force, P_z, with cutting speeds for different feed rates at a depth of cut 1.2mm under dry and near dry machining environments

4.4.4 Tool Wear

Productivity and economy of manufacturing by machining are significantly affected by life of the cutting tools. Cutting tools may fail by brittle fracture, plastic deformation or gradual wear. In conventional machining, particularly in continuous chip formation processes like turning, generally the cutting tools fail by gradual wear by abrasion, adhesion, diffusion, chemical erosion, galvanic action etc. depending upon the tool-work materials and machining condition. Tool wear initially starts with a relatively faster rate due to what is called break-in wear caused by attrition and micro-chipping at the sharp cutting edges. Turning by coated carbide inserts having enough strength; toughness and hot hardness generally fail by gradual wears.

With the progress of machining the tools attain crater wear at the rake surface and flank wear at the clearance surfaces due to continuous interaction and rubbing with the chips and the work surfaces respectively. The principal flank wear is the most important because it raises the cutting forces and related problems. Again the life of the tools, which ultimately fail by the systematic gradual wear, is generally assessed at least for R&D work, by the average value of the principal flank wear (VB), which aggravates cutting forces and temperature and may induce vibration with progress of machining. Wear may grow at a relatively faster rate at certain locations within the zones of flank wear apart from notching. The width of such excessive wear are expressed by VM (maximum flank wear), VS (average auxiliary flank wear) and VSM (maximum auxiliary flank wear). The reason of these preferential wears are the presence of some initial defect or variation in geometry, temperature and chip-tool interaction along the cutting edges depending upon the tool geometry, tool-work materials and the conditions of machining. The pattern and extent of the auxiliary flank wear (VS) affects surface finish and dimensional deviation of the machined parts. Growth of tool wear is sizeable influenced by the temperature and nature of interactions of the tool-work interfaces, which again depend upon the machining conditions for given tool-work pairs. In the present investigations the given insert attained significant values of VM, VS and VSM in different degree under different conditions. Fig. 4.16 shows the schematic view of general pattern of wear.

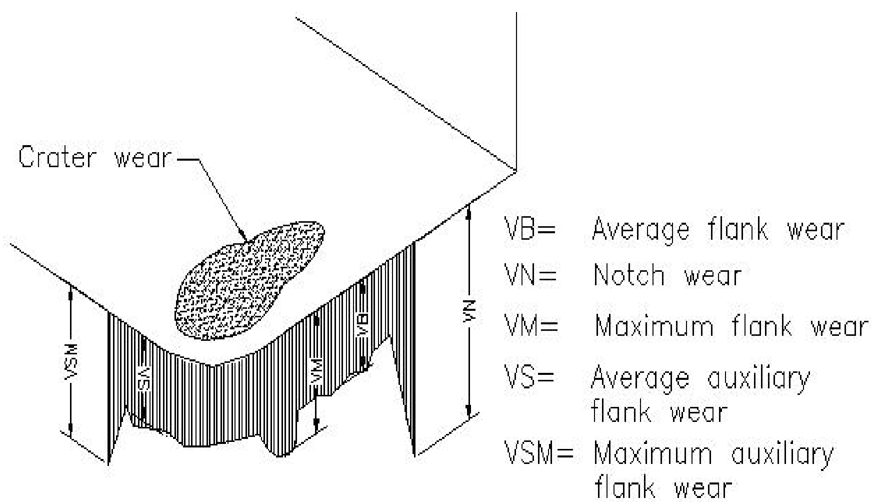


Fig. 4.16 Schematic view of general pattern of wear

During machining under each condition, the rapid growth of wears on main and auxiliary flanks was studied at regular intervals for all trials. The machining was interrupted for this purpose. An inverted metallurgical microscope (Olympus: model MG) fitted with a micrometer of least count 1 μm was used to measure the flank wears.

To reduce the rate of growth of VB, attempts should be made in all possible ways without much sacrifice the MRR. Fig. 4.17, 4.18 and 4.19 shows the growth of principal flank wear, VB with progress of machining time was recorded for different speed, feed and depth of cut combination under both dry and near dry machining condition while turning the hardened medium carbon steel by SNMG insert.

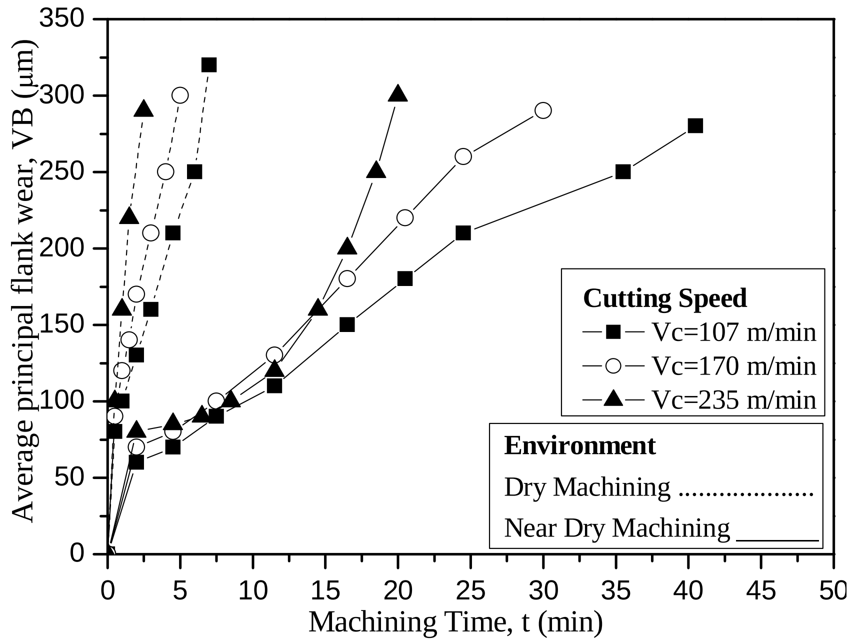


Fig 4.17 Variation of average principal flank wear (VB) with machining time for different cutting speeds. (feed rate = 0.1 mm/rev, Depth of cut= 0.8 mm)

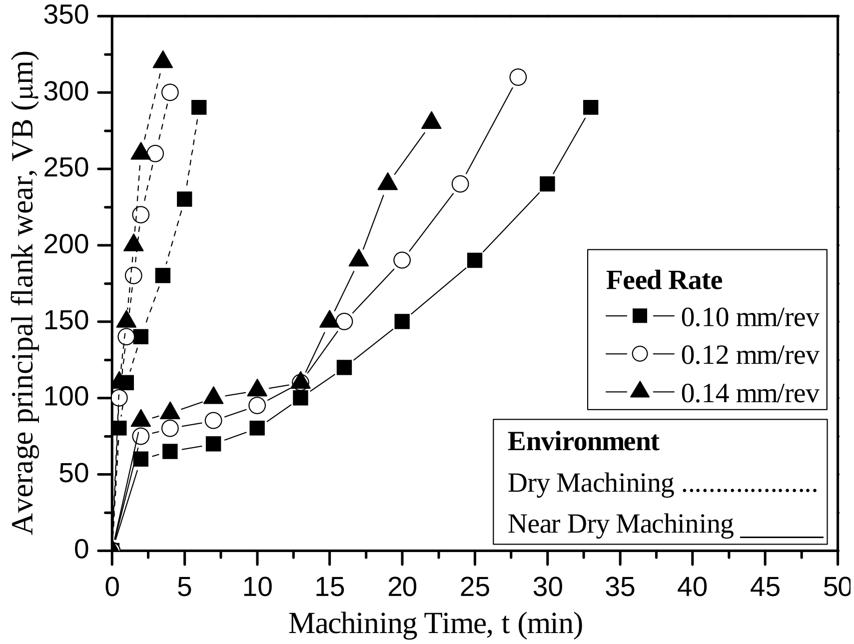


Fig 4.18 Variation of average principal flank wear (VB) with machining time for different feed rates. (Cutting speed = 150 m /min, Depth of cut= 0.4 mm)

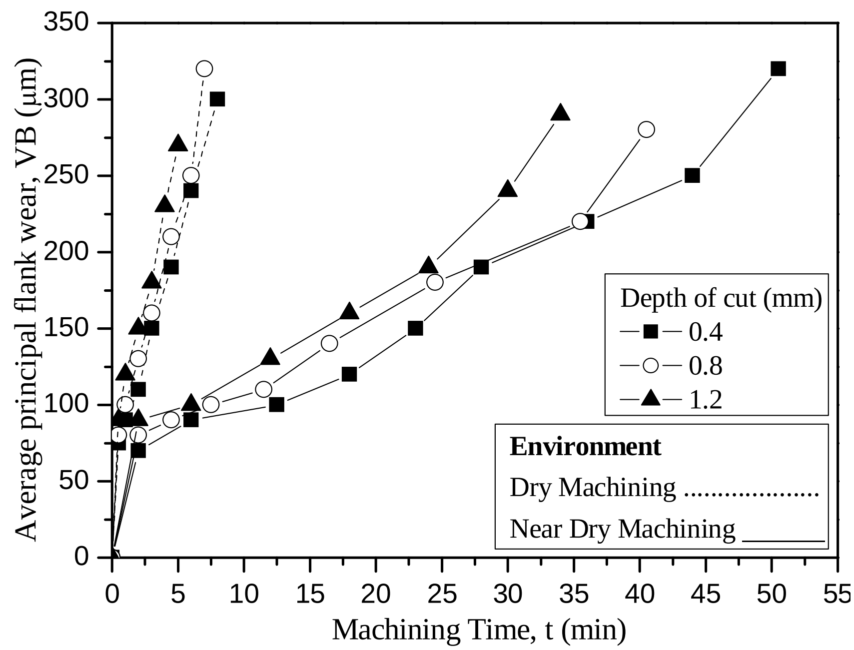


Fig. 4.19 Variation of average principal flank wear (VB) with machining time for different depth of cuts. (Cutting speed = 107 m /min, Feed rate = 0.1 mm/rev)

The auxiliary flank wear, which affects dimensional accuracy and surface finish, have also been recorded at regular intervals of machining under all the conditions undertaken. The growth of average auxiliary flank wear, VS with time of machining of the hardened medium carbon steel under different environments have been shown in Fig. 4.20, 4.21 and 4.22.

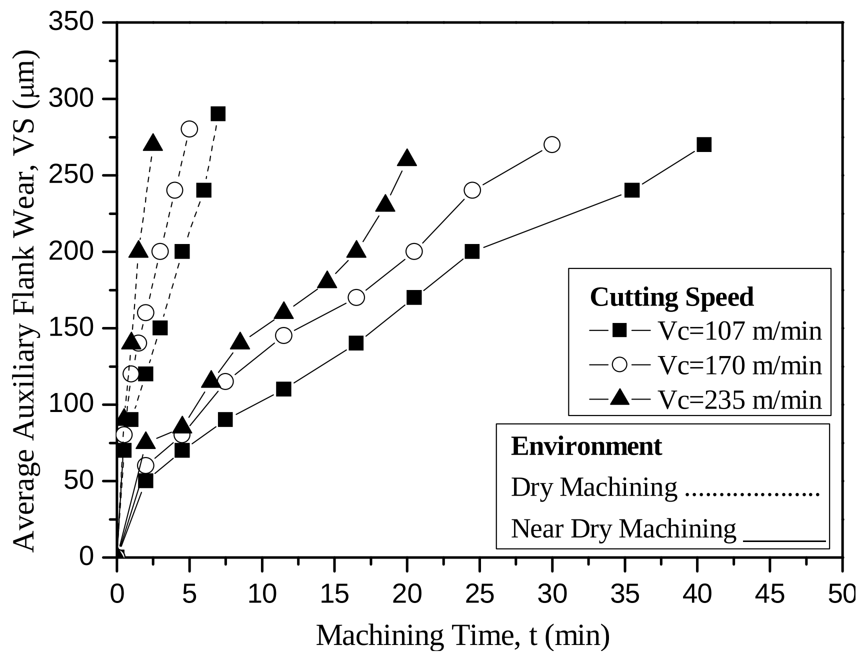


Fig. 4.20 Variation of average auxiliary flank wear (VS) with machining time for different cutting speeds. (feed rate = 0.1 mm/rev, Depth of cut= 0.8 mm)

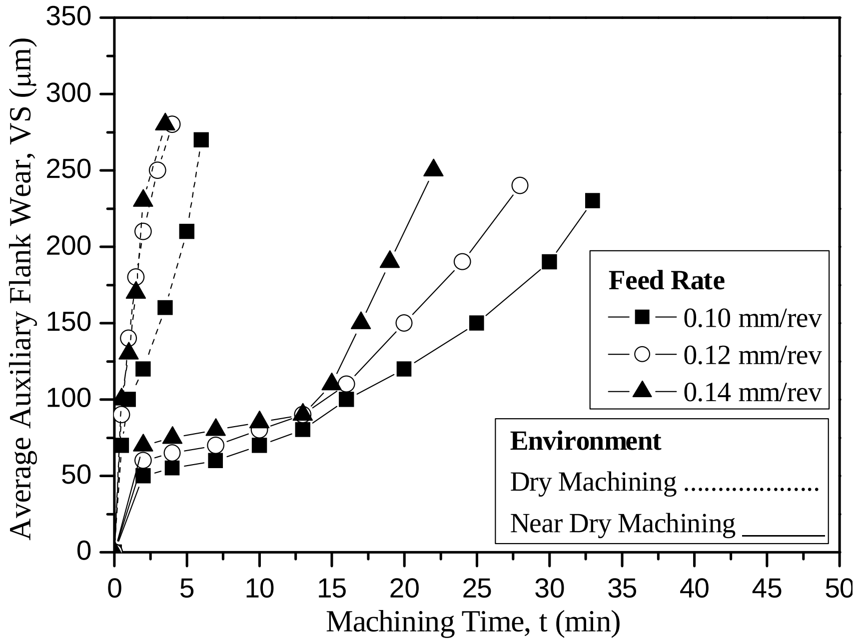


Fig 4.21 Variation of average auxiliary flank wear (VS) with machining time for different feed rates. (Cutting speed = 150 m /min, Depth of cut= 0.4 mm)

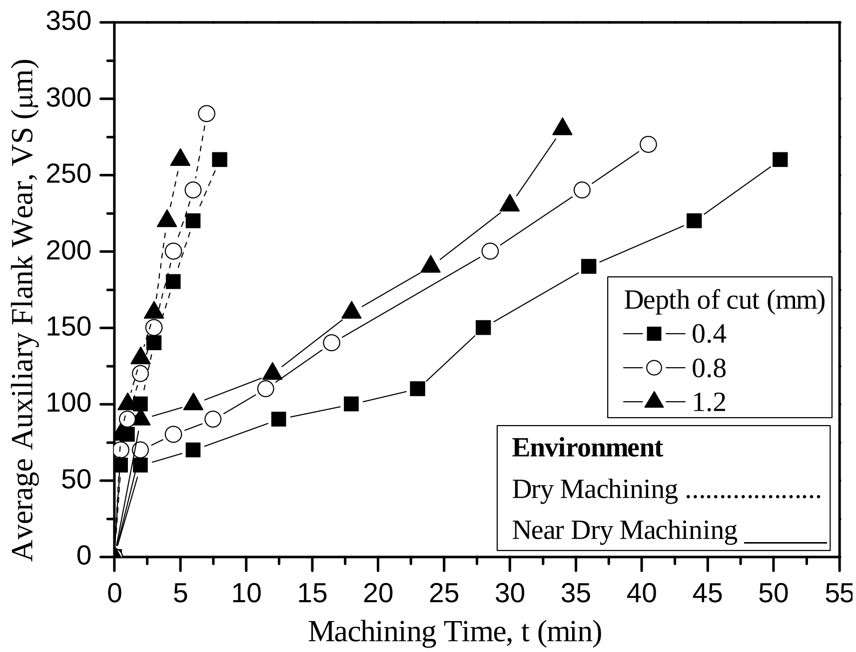


Fig. 4.22 Variation of average auxiliary flank wear (VS) with machining time for different depth of cuts. (Cutting speed = 107 m /min, Feed rate = 0.1 mm/rev)

4.4.5 Surface Roughness

Now-a-days quality of the product is very crucial thing. The performance and service life of any machined part mainly vary by the quality of that product. For a given material quality is generally assessed by dimensional and form accuracy and surface integrity of the product in respect of surface roughness, oxidation, corrosion, residual stresses and surface and subsurface micro-cracks.

Surface roughness has been measured at two stages. At first stage, the roughness of the surface was measured after a few seconds of machining with the sharp tool while recording the cutting temperature. Here the surface roughness at different V-f-d combination under dry and near dry machining condition has been measured by a Talysurf (Surtronic 3+, Rank Taylor Hobson Limited) using a sampling length of 0.10mm. This has been shown in Fig. 4.23, 4.24 and 4.25.

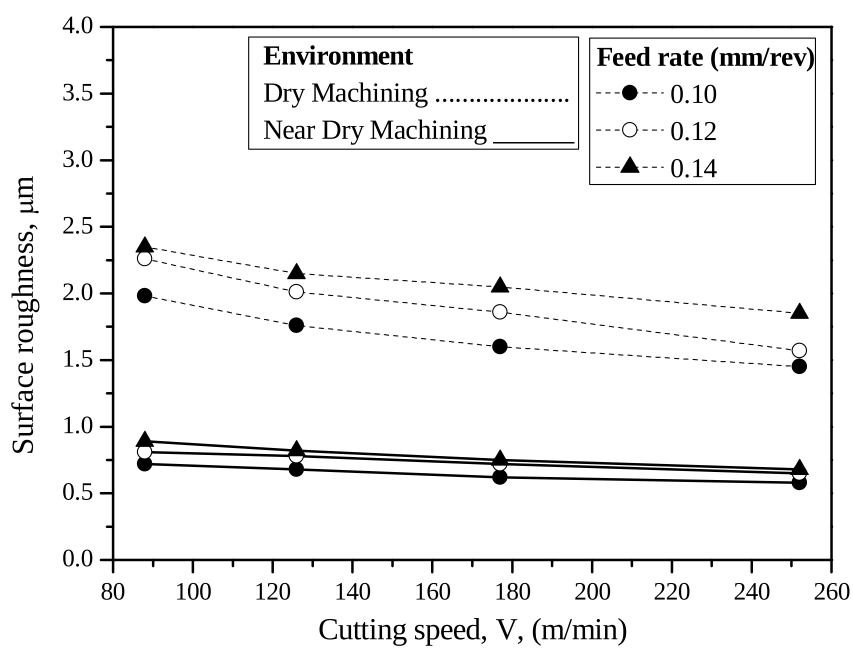


Fig. 4.23 Variation of surface roughness, R_a, with cutting speeds for different feed rates at a depth of cut 0.4 mm under dry and near dry machining environments

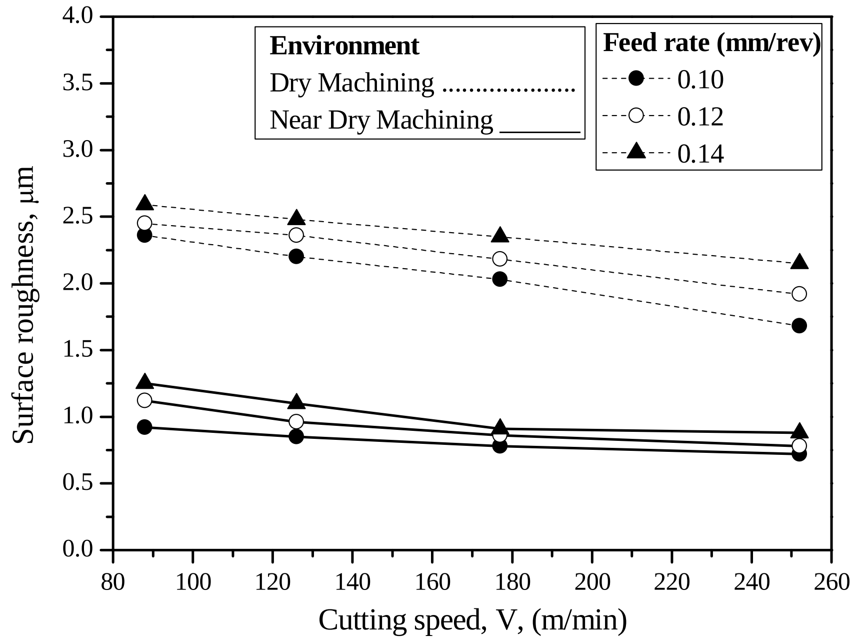


Fig. 4.24 Variation of surface roughness, R_a, with cutting speeds for different feed rates at a depth of cut 1.2mm under dry and near dry machining environments

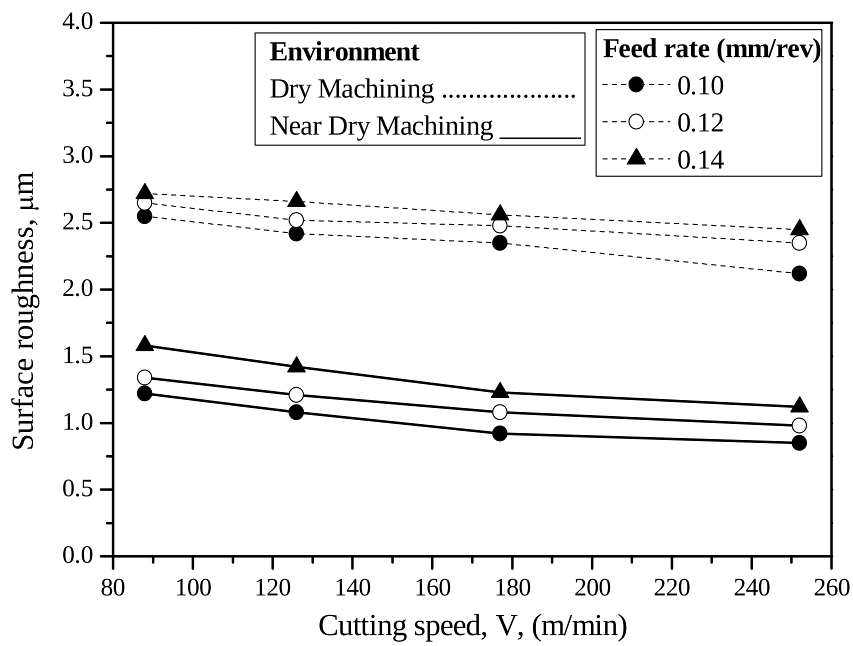


Fig. 4.25 Variation of surface roughness, R_a, with cutting speeds for different feed rates at a depth of cut 1.2mm under dry and near dry machining environments

At second stage, the surface roughness has been measured with the progress of machining while monitoring growth of tool wear with machining time at different V-f-d combinations under both the environments which have been graphically shown in Fig. 4.26, 4.27 and 4.28.

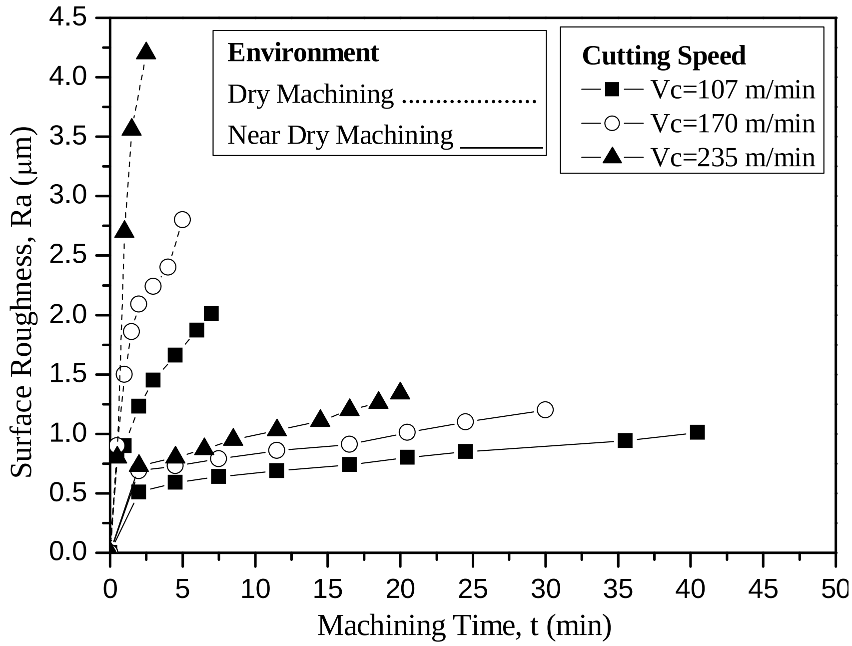


Fig. 4.26 Variation of surface roughness (Ra) with machining time for different cutting speeds. (Feed rate = 0.1 mm/rev, Depth of cut= 0.8 mm)

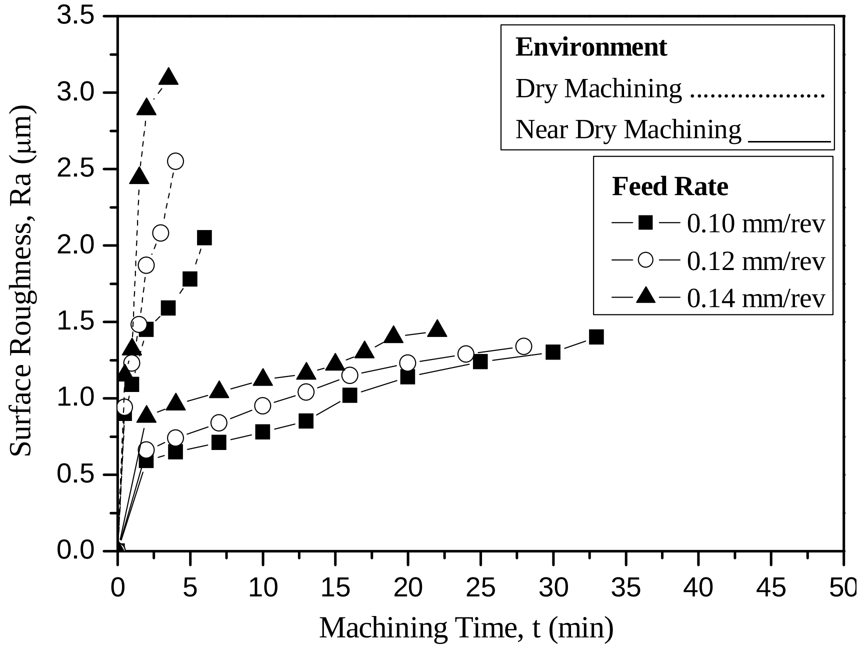


Fig. 4.27 Variation surface roughness (Ra) with machining time for different feed rates. (Cutting speed = 150 m /min, Depth of cut= 0.4 mm)

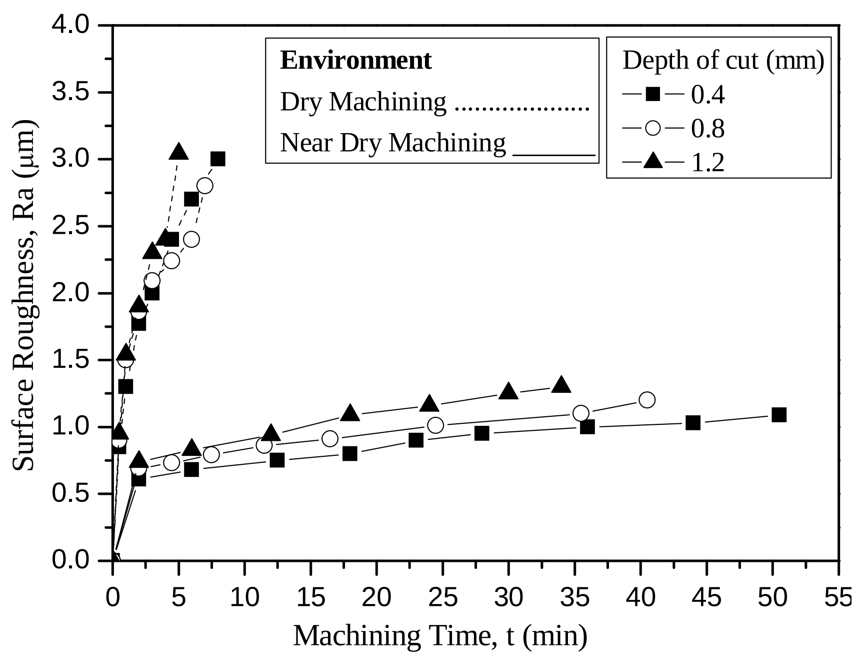


Fig. 4.28 Variation of surface roughness (Ra) with machining time for different depth of cuts. (Cutting speed = 107 m /min, Feed rate = 0.1 mm/rev)

Chapter-5

Optimization of Cutting Parameters

5.1 Introduction

Many optimization problems are very complex and hard to solve by conventional optimization techniques. Since the 1960s, there has been increasing interest in imitating living beings to solve hard optimization problems. Simulating the natural evolutionary process results in stochastic optimization techniques called evolutionary algorithms, which can often outperform conventional optimization methods when applied to difficult real-world problems. There are currently three main avenues of this research, namely GAs, evolutionary programming, and evolution strategies. Of these, the GA is perhaps the most widely known type of evolutionary algorithm today.

The concept of genetic algorithm comes from Charles Darwin's theory of natural evolution in the origin of species. In 1975 Holland, first developed how to apply principles of natural evolution to optimization problems [**1975**] and built the first genetic algorithm. Holland's theory has been furthered developed and now genetic algorithm stand up as a powerful tool for solving search and optimization problems. Genetic algorithms are directly based on the natural evolution or genetics.

The GA is motivated by the hypothesized natural process of evolution in biological populations, where genetic information stored in strings of chromosomes evolve over generations to adapt favorably to a static or changing environment. The algorithm is based on the elitist reproduction strategy, where members of a population deemed the fittest are selected for reproduction and are given the opportunity to strengthen the chromosome structure of progeny generation. This approach is facilitated by defining for a fitness function or a measure indicating the goodness of a member of the population in the given generation during the evolution process.

5.2 Working Principle of Genetic Algorithm

The genetic algorithm (GA) is a population-based search optimization technique. In general, the fittest individuals of any population tend to reproduce and survive to the next generation, thus improving successive generations. However, inferior individuals can, by chance, survive and also reproduce. Genetic algorithms have been shown to solve linear and nonlinear problems by exploring all regions of the state space and exponentially exploiting promising areas through mutation, crossover and selection operations applied to individuals in the population. The use of a genetic algorithm requires the determination of six fundamental issues, chromosome representation, selection function, the genetic operators making up the reproduction function, the creation of the initial population, termination criteria and the evaluation function [**Yanming and Chaojun, 1999**].

In a genetic algorithm, a population of strings (called chromosomes or the genotype of the genome), which encode candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem, evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

Genetic algorithms find application in bioinformatics, phylogenetics, computational science, engineering, economics, chemistry, manufacturing, mathematics, physics and other fields.

A typical genetic algorithm requires:

1. A genetic representation of the solution domain,
2. A fitness function to evaluate the solution domain.

5.3 Fitness Function

GA mimics the “survival of the fittest” principle. So, naturally they are suitable to solve maximization problems. Maximization problems are usually transformed to minimization problems by some suitable transformation. A fitness function, F(x), is derived from the objective function, f(x) and is used in successive genetic operations. For maximization problems, fitness function can be considered the same as the objective function. The minimization problem is an equivalent maximization problem such that the optimum point remains unchanged. A number of such transformations are possible.

5.4 Genetic Operators

A genetic operator is an operator used in genetic algorithms to maintain genetic diversity. Genetic variation is a necessity for the process of evolution. One of the most important decisions to make in implementing a genetic algorithm is what genetic operators to use. This decision depends greatly on the encoding strategy. There are three basic operators found in every genetic algorithm: reproduction, crossover and mutation.

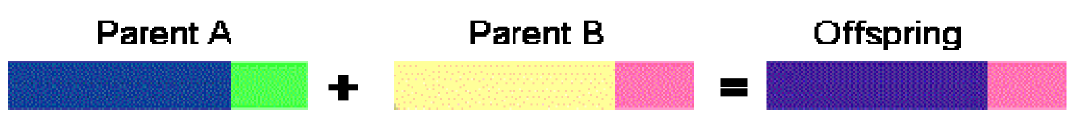
5.4.1 Reproduction

Reproduction is the first operator applied on a population. The reproduction operator allows individual strings to be copied for possible inclusion in the next generation. The chance that a string will be copied is based on the string's fitness value, calculated from a fitness function. For each generation, the reproduction operator chooses strings that are placed into a mating pool, which is used as the basis for creating the next generation.

There are many different types of reproduction operators. Among them roulette wheel selection is easiest way which have been used for the selection of individuals in the present work. Here each current string in the population has a roulette-wheel-slot-size in proportion to its fitness. In this way more highly fit strings have higher numbers of offspring in the succeeding generation. Once the string has been selected for reproduction, an extra replica of the string is made. The string is then entered into the mating pool, a tentative new population for further genetic operator action.

5.4.2 Crossover

It could be said that the main distinguishing feature of a GA is the use of crossover. After reproduction, the population is enriched with good strings from the previous generation but does not have any new string. A crossover operator is applied to the population to hopefully create better strings. The total number of participative strings in crossover is controlled by crossover probability, which is the ratio of total strings selected for mating and the population size. The crossover operator is mainly responsible for the search aspects of GA. Single−point crossover is the simplest form: a single crossover position is chosen at random and the parts of two parents after the crossover position are exchanged to form two offspring. An example of crossover operation is given below where a random number is generated between 1 and 7. If the random number is 6, the bits after the 5th position are exchanged.



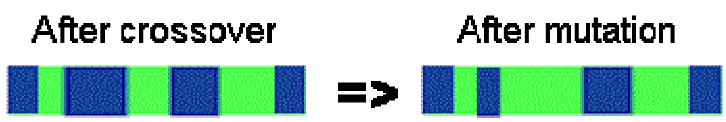
11001011+11011**111** = **11001111**

Fig. 5.1 Example of the crossover operation

Crossover is performed until the new population is created. Then the cycle starts again with selection. This iterative process continues until any user specified criteria are met. Selection and crossover alone can obviously generate a staggering amount of differing strings. However, depending on the initial population chosen, there may not be enough variety of strings to ensure the GA sees the entire problem space. Or the GA may find itself converging on strings that are not quite close to the optimum it seeks due to a bad initial population.

5.4.3 Mutation

Mutation, as in the case of simple GA, is the occasional random alteration of the value of a string position. The GA has a mutation probability, Pm, which dictates the frequency at which mutation occurs. Mutation can be performed either during selection or crossover (though crossover is more usual). For each string element in each string in the mating pool, the GA checks to see if it should perform a mutation. If it should, it randomly changes the element value to a new one. In our binary strings, 1s are changed to 0s and 0s to 1s (Fig. 3). For example, the GA decides to mutate bit position 2 in the string 11001001.



1**1**001001 => 10001001

Fig. 5.2 Example of the mutation operation

The resulting string is 10010 as the fourth bit in the string is flipped. The mutation probability should be kept very low (usually about 0.01%) as a high mutation rate will destroy fit strings and degenerate the GA algorithm into a random walk, with all the associated problems.

But mutation will help prevent the population from stagnating, adding "fresh blood", as it were, to a population. Mutation helps to maintain that diversity throughout the GA's iterations.

5.5 Termination

This generational process is repeated until a termination condition has been reached. Common terminating conditions are:

- A solution is found that satisfies minimum criteria
- Fixed number of generations reached
- The highest ranking solution's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results
- Manual inspection
- Combinations of the above

The program termination criterion is given as a particular number of generation runs or as a particular value of fitness or some other desired parameter. The termination criterion for this case was the completion of a run consisting of specific generations. The individual with the best fitness within that generation is taken as the solution.

The following is the outline of genetic algorithm.

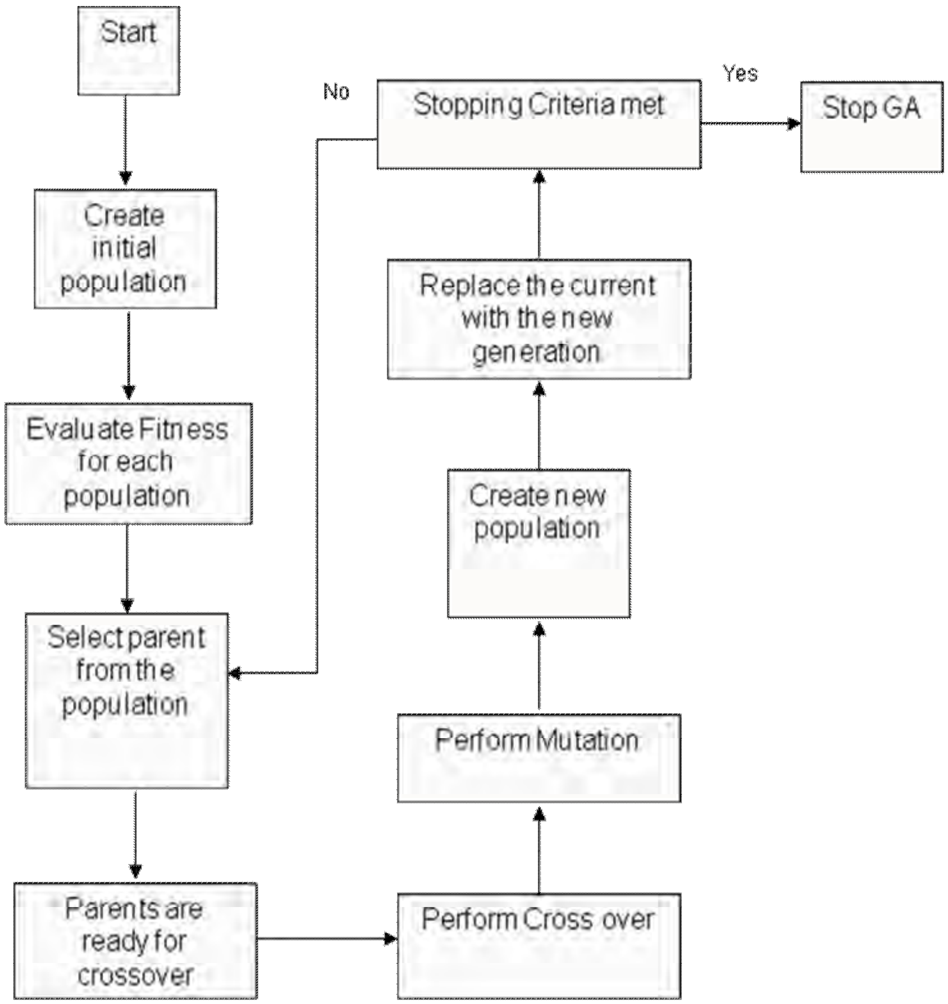


Fig. 5.3 Outline of the GA process

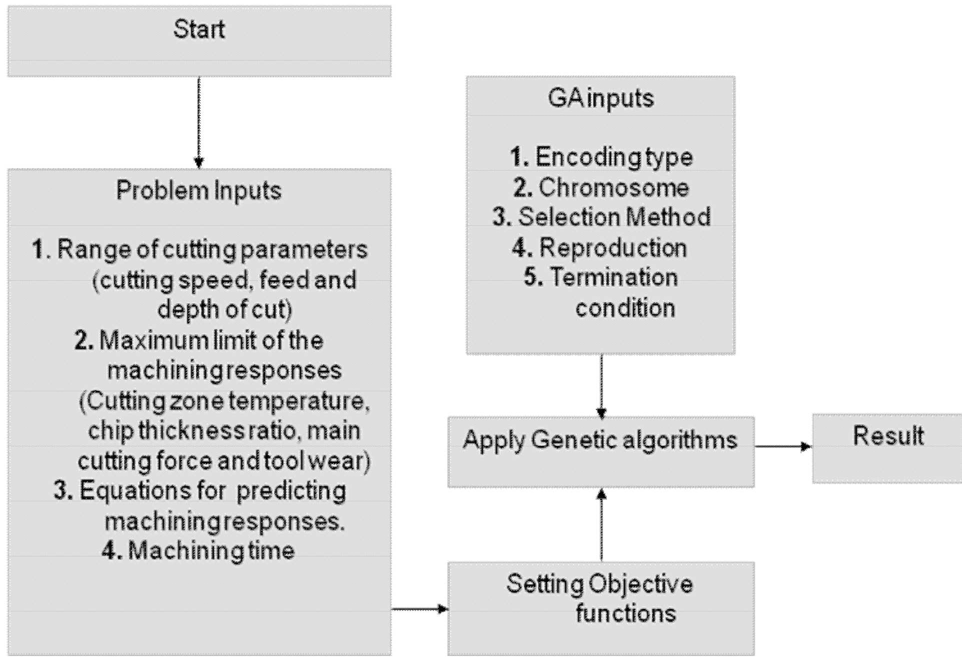


Fig. 5.4 Block diagram of the proposed GA process

5.6 Objective Function

The main objective of the present work is to determine the minimum surface roughness value of the machined product while turning hardened medium carbon steel by coated SNMG insert under both dry and near dry machining environment. Using multiple regression method under RSM, surface roughness can be estimated from the equation given below:

$$Minimize\ \ R_a = \ln \frac{(1.494)(50.3762)^{f}(1.00001)^{V^2}(1.1302)^{d^2}(324.164)^{fd}}{(1.00149)^{V}(1.06382)^{d}(2.8339)^{f^2}(1.01688)^{Vf}(1.0017)^{Vd}} \quad \text{.........} \quad (5.1)$$

Where, Ra = Surface Roughness

V = Cutting Speed

f = Feed Rate

d = Depth of Cut

The total analysis was carried out using un-coded units. The co-efficient of correlation is 98.68% indicating that the equation is able to predict the surface roughness values with 98.68% accuracy.

Table 5.1 Regression coefficients for surface roughness

Term	Co-efficient	SE Co-efficient	T	P
Constant	0.40146	0.3731	1.076	0.292
V	-0.00149	0.0008	-1.870	0.673
f	3.91952	5.9618	0.657	0.517
d	-0.06187	0.1480	-0.418	0.079
V^2	0.00001	0.0000	5.751	0.000
f^2	-1.04167	24.4521	-0.043	0.966
d^2	0.12240	0.0611	2.002	0.056
V×f	-0.01674	0.0046	-3.641	0.213
V×d	-0.00170	0.0002	-7.376	0.001
f×d	5.78125	0.8645	6.687	0.015

Here the P-values (P) is used to determine which of the effects in the model are statistically significant. The α value is assumed as 0.05. From table 5.2, it can be clearly stated that linear effects and interaction effects of the cutting process variables are statistically significant since their P-value is less than 0.05. Now from regression table, finally it can be stated that among the set elements of linear effects depth of cut is significant and within interaction effects set, interaction between cutting speed and depth of cut and interaction between feed rate and depth of cut are statistically significant. Since the P-value for squared elements become larger than 0.05, the square effect is not dominant here.

Table 5.2 Analysis of Variance for surface roughness

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	2.01429	2.014291	0.223810	292.44	0.000
Linear	3	1.89991	0.003300	0.001100	1.44	0.025
Square	3	0.02838	0.028380	0.009460	12.36	0.405
Interaction	3	0.08600	0.086003	0.028668	37.46	0.001
Residual Error	26	0.01990	0.019898	0.000765		
Total	35	2.03419				

5.7 Constraints

This section shows optimizing the machining parameters for minimizing surface roughness of the machined part while turning hardened medium carbon steel with coated SNMG insert by using genetic algorithm. In this problem, the objective function is minimizing surface roughness in turning operation.

There are several factors limiting the cutting parameters. Those factors originate usually from technical specifications and organizational considerations. The following limitations are taken into account. For the selected tool, workpiece and the machine the permissible range of cutting constraints are:

$$\left.\begin{array}{l} V_{\min} \le V \le V_{\max} \\ f_{\min} \le f \le f_{\max} \\ d_{\min} \le d \le d_{\max} \end{array}\right\} \quad \text{..........} \quad (5.2)$$

Also there are some constraints related to the machine features. These constraints that should be considered in machining economics include: tool-wear constraint, cutting force constraint, chip-tool interface temperature constraint and chip thickness ratio constraint. These machinability indices should not be greater than a certain maximum value.

$$\left.\begin{array}{l} \theta(V, f, d) \le \theta_{\max} \\ P_Z(V, f, d) \le P_{Z\max} \\ r_c(V, f, d) \le r_{c\max} \\ VB(V, f, d, t) \le VB_{\max} \end{array}\right\} \quad \text{..........} \quad (5.3)$$

5.7.1 Cutting Temperature

The cutting temperature is a key factor which directly affects cutting tool wear, workpiece surface integrity and machining precision according to the relative motion between the tool and work piece [**Ming et al., 2003**]. The amount of heat generated varies with the type of material being machined and cutting parameters especially cutting speed which had the most influence on the temperature [**Liu et al., 2002**]. During the machining process, a considerable amount of the machine energy is transferred into heat through plastic deformation of the workpiece surface, the friction of the chip on the tool face and the friction between the tool and the workpiece. Trent and Wright [**2000**] suggest that 99 per cent of the work done is converted into heat. This results in an increase in the tool and workpiece temperatures. Thus temperature works as a major constraint in the optimization of the cutting parameters. Using multiple regression method under RSM, cutting zone temperature (θ) can be estimated from the equation given below:

$$\begin{aligned}\theta &= 129.21 + 2.06V + 3783.91f + 435.81d + 1666.67f^2 \\ &\quad - 79.43d^2 - 6.73V - 0.29Vd - 398.44fd\end{aligned} \qquad \text{.........................} \qquad (5.4)$$

The total analysis was carried out using un-coded units. The co-efficient of correlation is 98.96% indicating that the equation is able to predict the cutting zone temperature values with 98.96% accuracy.

Table 5.3 Estimated Regression coefficients for cutting zone temperature

Term	Co-efficient	SE Co-efficient	T	P
Constant	129.21	151.16	0.855	0.400
V	2.06	0.32	6.387	0.000
f	3783.91	2415.48	1.567	0.129
d	435.81	59.95	7.270	0.000
V^2	0.00	0.00	0.388	0.701
f^2	1666.67	9906.95	0.168	0.868
d^2	-79.43	24.77	-3.207	0.004
V×f	-6.73	1.86	-3.613	0.001
V×d	-0.29	0.09	-3.158	0.004
f×d	-398.44	350.26	-1.138	0.266

From table 5.4, it can be clearly stated that square effects and interaction effects of the cutting process variables are statistically significant since their P-value is less than 0.05. Now from regression table, finally it can be stated that among the set elements of square effects depth of cut is significant and within interaction effects set, interaction between cutting speed and feed rate and interaction between cutting speed and depth of cut are statistically significant. Since the P-value for linear effect become larger than 0.05, the linear effect is not dominant here.

Table 5.4 Analysis of Variance for cutting zone temperature

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	420033	420033.3	46670.36	371.49	0.000
Linear	3	415663	11159.4	3719.80	29.61	0.600
Square	3	1315	1314.5	438.17	3.49	0.030
Interaction	3	3056	3055.6	1018.54	8.11	0.001
Residual Error	26	3266	3266.4	125.63		
Total	35	423300				

5.7.2 Cutting Force

The cutting force information is important to part accuracy, tool wear and heat generations that may cause part thermal damages. Cutting forces being a substantial dependent variable of the machining system has been investigated by many researchers in various cutting processes through formulation of appropriate models for their estimation.

Using multiple regression method under RSM, cutting force (P_Z) can be estimated from the equation given below:

$$P_Z = 219.67 - 0.73V - 805.44f + 160.55d + 6666.67f^2 - 34.90d^2 + 0.34Vf - 0.31Vd + 640.63fd \quad \text{............................} \quad (5.5)$$

The total analysis was carried out using un-coded units. The co-efficient of correlation is 98.17% indicating that the equation is able to predict the cutting force values with 98.17% accuracy.

Table 5.5 Estimated Regression coefficients for main cutting force

Term	Co-efficient	SE Co-efficient	T	P
Constant	219.67	104.35	2.105	0.045
V	-0.73	0.22	-3.294	0.503
f	-805.44	1667.44	-0.483	0.633
d	160.55	41.38	3.880	0.571
V^2	0.00	0.00	3.359	0.002
f^2	6666.67	6838.90	0.975	0.339
d^2	-34.90	17.10	-2.041	0.052
V×f	0.34	1.29	0.268	0.791
V×d	-0.31	0.06	-4.791	0.000
f×d	640.63	241.79	2.649	0.114

From table 5.6, it can be clearly stated that all three effects (linear, square and interaction) of the cutting process variables are statistically significant since their P-value is less than 0.05. Now from regression table, finally it can be stated that among the set elements of square effects cutting speed is statistically significant. Among interaction effects interaction between cutting speed and depth of cut is more significant. Since the P value of linear effect becomes greater than 0.05, the linear effect is not dominant here.

Table 5.6 Analysis of Variance for main cutting force

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	112930	112929.78	12547.754	209.60	0.000
Linear	3	110150	1660.14	553.381	9.24	0.100
Square	3	982	981.66	327.220	5.47	0.005
Interaction	3	1799	1798.60	599.532	10.01	0.000
Residual Error	26	1557	1556.52	59.866		
Total	35	114486				

5.7.3 Tool Wear

Although there are many economic advantages of replacing grinding with hard turning, tool wear remains a major obstacle. The effects of tool wear are not only reduced tool life, but also changes in surface finish, increased cutting forces, tensile residual stress, and white layer surface damage. Tool wear highly depends on the cutting speed, feed and depth of cut. Wear rate increases with the increase of these cutting parameters. Hence tool wear is considered as one of the most crucial constraints in the optimization of cutting parameters. Using multiple regression method under RSM, principal flank wear (VB) can be estimated from the equation given below:

$$\begin{aligned} VB = {} & 227.88 - 0.30V + 1098.73f + 15.06d + 1.05t \\ & - 4936.62f^2 - 11.49d^2 \end{aligned} \quad \text{..........................} \quad (5.6)$$

The total analysis was carried out using un-coded units. The co-efficient of correlation is 98.68% indicating that the equation is able to predict the principal flank wear values with 98.68% accuracy.

5.7.4 Chip Thickness Ratio

Chip thickness ratio, r_c (ratio of chip thickness before and after cut) is another important machinability index. For given tool geometry and cutting conditions, the value of r_c depends upon the nature of chip-tool interaction, chip contact length, curl radius and chip form, all of which are expected to be influenced by the levels of V, f and d. Using multiple regression method under RSM, chip thickness ratio (r_c) can be estimated from the equation given below:

$$r_c = \frac{(1.0023)^V (114.496\times10^3)^f (1.1649)^d (1.0089)^{Vf} (1.86)^{fd}}{(1.442)(4.34\times10^{17})^{f^2} (1.03169)^{d^2} (1.0001)^{Vd}} \quad \text{......................} \quad (5.7)$$

The total analysis was carried out using un-coded units. The co-efficient of correlation is 97.57%.

Table 5.7 Estimated Regression coefficients for chip thickness ratio

Term	Co-efficient	SE Co-efficient	T	P
Constant	-0.3661	0.2600	-1.408	0.171
V	0.0023	0.0006	4.114	0.000
f	11.6483	4.1546	2.804	0.009
d	0.1527	0.1031	1.481	0.151
V^2	0.0000	0.0000	-4.847	0.000
f^2	-40.6125	17.0399	-2.383	0.125
d^2	-0.0312	0.0426	-0.733	0.470
V×f	0.0089	0.0032	2.785	0.010
V×d	-0.0001	0.0002	-0.826	0.416
f×d	0.6231	0.6025	0.311	0.311

From table 5.8, it can be clearly stated that linear effects, squared effects and interaction effects of the cutting process variables are statistically significant. Now from regression table, finally it can be stated that among the set elements of linear effects feed rate and cutting speed are significant. Among squared elements cutting speed is more significant and within interaction effects set, interaction between cutting speed and feed rate is statistically significant.

Table 5.8 Analysis of Variance for chip thickness ratio

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.525264	0.525264	0.058363	157.03	0.000
Linear	3	0.510689	0.008957	0.002986	8.03	0.001
Square	3	0.011042	0.011042	0.003681	9.90	0.000
Interaction	3	0.003534	0.003534	0.001178	3.17	0.041
Residual Error	26	0.009663	0.009663	0.000372		
Total	35	0.534927				

5.8 Model Validation

Fig. 5.5 to 5.9 shows the predicted values and observed values for five response variables namely average chip-tool interface temperature (θ), main cutting force (P_Z), surface roughness (R_a), average principal flank wear (VB) and chip thickness ratio (r_c) respectively. From the graphs it is clear that the proposed models used as the objective function and constraints for the optimization of cutting parameters by genetic algorithm can predict values which are nearly very close to experimental observations for each of the output parameters. The results show that response surface methodology (RSM) can be used easily for prediction of various responses and hence help in optimum selection of cutting parameters (V, f, d) for the purpose of manufacturing process planning. The test cutting conditions along with the experimental and predicted values of the average chip-tool interface temperature (θ), main cutting force (P_Z), surface roughness (R_a), average principal flank wear (VB) and chip thickness ratio (r_c) are given in Appendix.

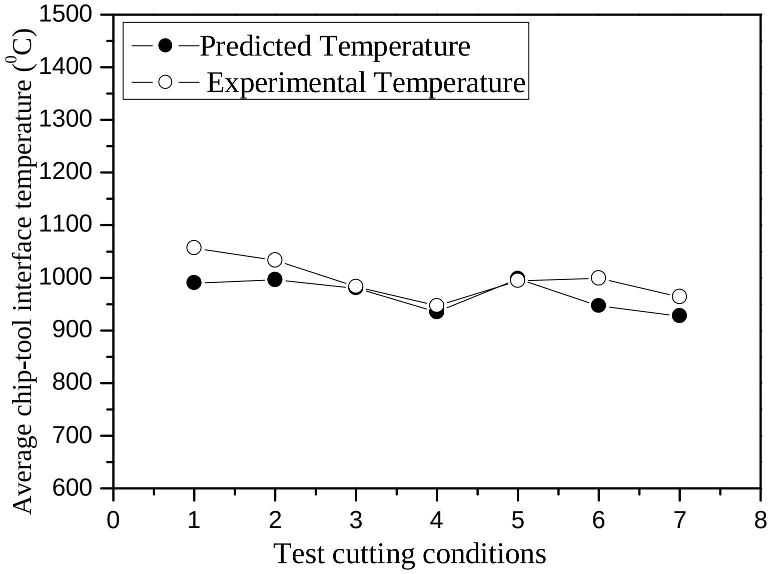


Fig. 5.5 Experimental Vs. predicted results of average chip-tool interface temperature for 7 test cutting conditions (maximum deviation 6.71%)

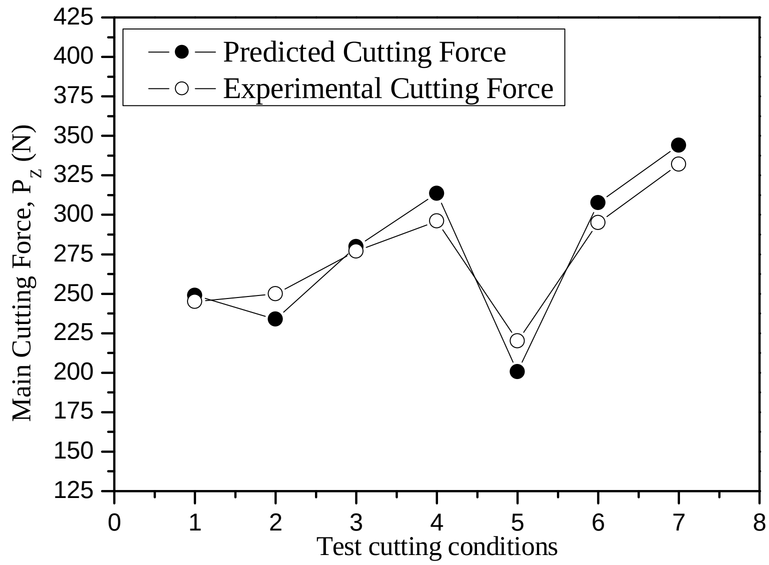


Fig. 5.6 Experimental Vs. predicted results of main cutting force for 7 test cutting conditions (maximum deviation 8.79%)

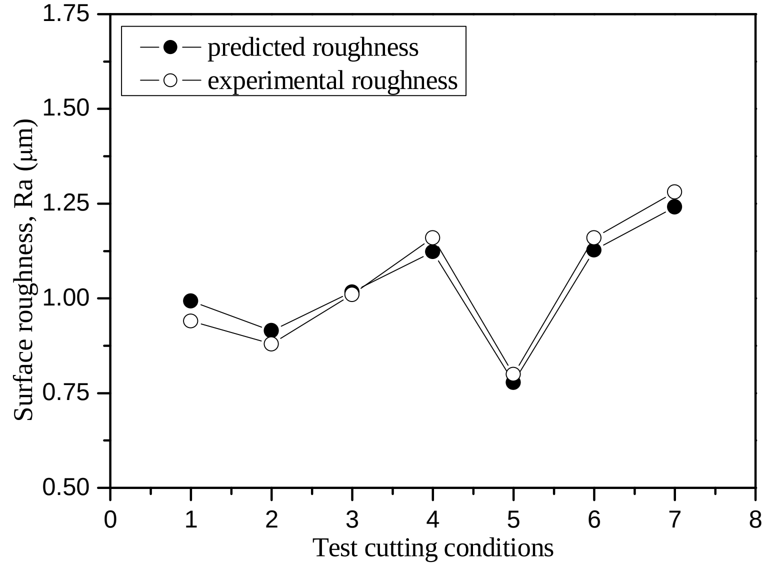


Fig. 5.7 Experimental Vs. predicted results of surface roughness for 7 test cutting conditions (maximum deviation 5.27%)

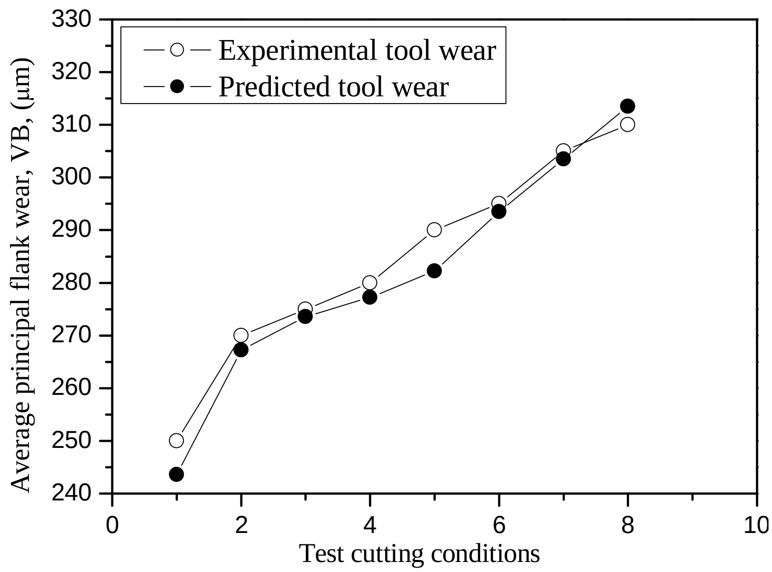


Fig. 5.8 Experimental Vs. predicted results of average principal flank wear for 8 test cutting conditions (maximum deviation 2.68%)

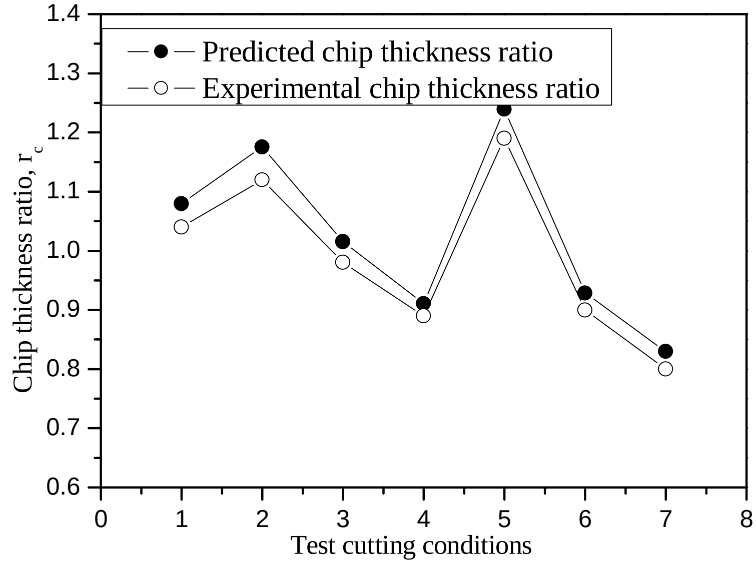


Fig. 5.9 Experimental Vs. predicted results of chip thickness ratio for 7 test cutting conditions (maximum deviation 4.12%)

5.9 Genetic algorithm: Steps involved

The following briefly describes the algorithm used in this research work.

N no. of chromosomes has been created (cutting parameters)

S_1 = [91] [0.10] [0.6]

S_2 = [180] [0.13] [0.6]

S_3 = [117] [0.10] [0.8]

S_4 = [192] [0.10] [1.1]

S_5 = [99] [0.10] [0.5]

S_6 = [97] [0.11] [0.9]

S_7 = [145] [0.12] [0.7]

S_8 = [181] [0.13] [0.5]

S_9 = [118] [0.10] [0.4]

S_{10} = [123] [0.10] [0.8]

The fitness function was evaluated which has been given below:

S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
0.839	0.832	0.882	0.901	0.772	1.052	0.889	0.779	0.695	0.869

The probability p_i and cumulative probability q_i was calculated for i chromosomes.

p_1	0.09849	q_1	0.09849	r_1	0.617698
p_2	0.09766	q_2	0.19615	r_2	0.886838
p_3	0.10355	q_3	0.29970	r_3	0.789759
p_4	0.10580	q_4	0.40550	r_4	0.784641
p_5	0.09068	q_5	0.49618	r_5	0.154303
p_6	0.12426	q_6	0.62044	r_6	0.644160
p_7	0.10443	q_7	0.72487	r_7	0.414201
p_8	0.09147	q_8	0.81634	r_8	0.354635
p_9	0.08157	q_9	0.89791	r_9	0.542974
p_{10}	0.10205	q_{10}	1.00000	r_{10}	0.477755

$$\left[p_i = probability \quad q_i = cumulative\_probability \quad r_i = random\_number \right]$$

The chromosomes were then selected with some selection mechanism. Roulette wheel mechanism is used. A new population has been selected to breed.

$$S_1' = [97]\cdots[0.11]\cdots[0.9] = S_6$$
$$S_2' = [118]\cdots[0.10]\cdots[0.4] = S_9$$
$$S_3' = [181]\cdots[0.13]\cdots[0.5] = S_8$$
$$S_4' = [181]\cdots[0.13]\cdots[0.5] = S_8$$
$$S_5' = [180]\cdots[0.13]\cdots[0.6] = S_2$$
$$S_6' = [145]\cdots[0.12]\cdots[0.7] = S_7$$
$$S_7' = [99]\cdots[0.10]\cdots[0.5] = S_5$$
$$S_8' = [192]\cdots[0.10]\cdots[1.1] = S_4$$
$$S_9' = [97]\cdots[0.11]\cdots[0.9] = S_6$$
$$S_{10}' = [99]\cdots[0.10]\cdots[0.5] = S_5$$

The chromosomes were selected as Parents which will undergo breeding for to create next generation. A crossover rate (P_c) and mutation rate (P_m) was given as computer program input. P_c = 0.8 and P_m = 0.07 has been set. This means 80 percent of chromosomes will undergo crossover. Roughly 5 (80% of 7 chromosomes) chromosomes should undergo crossover. 7 percent of the total bits (7×10) should undergo mutation.

Crossover, P_c = 0.8**.** Generate 10 random numbers between 0 to 1.

r_{c1}	0.89	r_{c6}	0.86
r_{c2}	0.91	r_{c7}	**0.24**
r_{c3}	0.90	r_{c8}	**0.08**
r_{c4}	0.79	r_{c9}	**0.09**
r_{c5}	**0.24**	r_{c10}	0.89

S'_5, S'_7, S'_8 and S'_9 are selected for crossover operation.

A pair of chromosomes was created. If the number is even then create pair. If the number is odd then take a closest value just higher that P_c.

$$pair\_1 = \; S'_5 = [180]\cdots[0.13]\cdots[0.6] \qquad pair\_2 = \; S'_8 = [192]\cdots[0.10]\cdots[1.1]$$
$$= \; S'_7 = [99]\cdots[0.10]\cdots[0.5] \qquad = \; S'_9 = [97]\cdots[0.11]\cdots[0.9]$$

Next the crossover points have to identify. A random number between 1 to N_{cp} (N_{cp} = M-1) was selected.

$$\begin{bmatrix} r_{cp1} & 2 \\ r_{cp1} & 1 \end{bmatrix}$$

$$pair\_1 = \; S'_5 = [180]\cdots[0.13]\cdot\Big|\cdot[0.6] \qquad pair\_2 = \; S'_8 = [192]\cdot\Big|\cdot[0.10]\cdots[1.1]$$
$$= \; S'_7 = [99]\cdots[0.10]\cdot\cdot\Big|[0.5] \qquad = \; S'_9 = [097]\cdot\Big|\cdot[0.11]\cdots[0.9]$$

$pair\_1 = \; S_5'' = [180]\cdots[0.13]\cdots[0.5]$ $\quad$ $pair\_2 = \; S_8'' = [192]\cdots[0.11]\cdots[0.9]$

$= \; S_7'' = [99]\cdots[0.10]\cdots[0.6]$ $\quad$ $= \; S_9'' = [97]\cdots[0.10]\cdots[1.1]$

New population after crossover

$S_1' = [97]\cdots[0.11]\cdots[0.9]$

$S_2' = [118]\cdots[0.10]\cdots[0.4]$

$S_3' = [181]\cdots[0.13]\cdots[0.5]$

$S_4' = [181]\cdots[0.13]\cdots[0.5]$

$S_5'' = [180]\cdots[0.13]\cdots[0.5]$

$S_6' = [145]\cdots[0.12]\cdots[0.7]$

$S_7'' = [99]\cdots[0.10]\cdots[0.6]$

$S_8'' = [192]\cdots[0.11]\cdots[0.9]$

$S_9'' = [97]\cdots[0.10]\cdots[1.1]$

$S_{10}' = [99]\cdots[0.10]\cdots[0.5]$

Mutation rate, P_m = 0.07 which means 70 random numbers between 0 to 1 was generated. The bits which are less than or equal to 0.07 has been selected. There are total 3 bits. They are marked as bold in the next population.

$S_1' =$ [097] $\cdots$[0.11] $\cdots$[0.9]

$S_2' =$ [118] $\cdots$[0.10] $\cdots$[0.4]

$S_3' =$ [181] $\cdots$[0.13] $\cdots$[0.5]

$S_4' =$ [181] $\cdots$[0.13] $\cdots$[0.5]

$S_5'' =$ [18**0**] $\cdots$[0.13] $\cdots$[0.5]

$S_6' =$ [145] $\cdots$[0.1**2**] $\cdots$[0.7]

$S_7'' =$ [099] $\cdots$[0.10] $\cdots$[0.6]

$S_8'' =$ [19**2**] $\cdots$[0.11] $\cdots$[0.9]

$S_9'' =$ [097] $\cdots$[0.10] $\cdots$[1.1]

$S_{10}' =$ [099] $\cdots$[0.10] $\cdots$[0.5]

After Cross over and Mutation operation new population:

$$
\begin{array}{lll}
S_1' = & [097] \cdots [0.11] \cdots [0.9] & = 1.058 \\
S_2' = & [118] \cdots [0.10] \cdots [0.4] & = 0.695 \\
S_3' = & [181] \cdots [0.13] \cdots [0.5] & = 0.779 \\
S_4' = & [181] \cdots [0.13] \cdots [0.5] & = 0.779 \\
S_5'' = & [1\mathbf{0}8] \cdots [0.13] \cdots [0.5] & = 0.898 \\
S_6' = & [145] \cdots [0.\mathbf{2}1] \cdots [0.7] & = 1.357 \\
S_7'' = & [099] \cdots [0.10] \cdots [0.6] & = 0.821 \\
S_8'' = & [1\mathbf{2}9] \cdots [0.11] \cdots [0.9] & = 0.908 \\
S_9'' = & [097] \cdots [0.10] \cdots [1.1] & = 1.189 \\
S_{10}' = & [099] \cdots [0.10] \cdots [0.5] & = 0.772
\end{array}
$$

It seems that the new generation minimum value is worse than the initial population value. To avoid this problem, one elitism strategy can be used. In each generation best two chromosomes from previous generation will be added. Hence the new population after one generation (replacing S_5'' and S_6' by S_5 and S_9).

Final population after one generation:

$$
\begin{array}{lll}
S_1' = & [097] \cdots [0.11] \cdots [0.9] & = 1.058 \\
S_2' = & [118] \cdots [0.10] \cdots [0.4] & = 0.695 \\
S_3' = & [181] \cdots [0.13] \cdots [0.5] & = 0.779 \\
S_4' = & [181] \cdots [0.13] \cdots [0.5] & = 0.779 \\
S_5'' = & [1\mathbf{0}8] \cdots [0.13] \cdots [0.5] & = 0.898 \\
S_5 = & [99] \cdots [0.10] \cdots [0.5] & = 0.772 \\
S_7'' = & [099] \cdots [0.10] \cdots [0.6] & = 0.821 \\
S_8'' = & [1\mathbf{2}9] \cdots [0.10] \cdots [0.9] & = 0.908 \\
S_9 = & [118] \cdots [0.10] \cdots [0.4] & = 0.695 \\
S_{10}' = & [099] \cdots [0.10] \cdots [0.5] & = 0.772
\end{array}
$$

A generation is complete and a new set of population (offspring) has been created. The fitness function value for the new population has been evaluated and save the best value. This process of iteration continues until certain stopping conditions are met. Here predefined number of generations was used as the stopping rule. After certain iteration best result can be found. Best chromosome is:

$$S_{best} = [136]\cdots[0.1]\cdots[0.4] = 0.669094$$

In this study a maximum of 1000 generations of the GA are used. For cross-over probability (P_c), trial value of 0.5 and 0.8 are chosen. For the implementation of the genetic algorithm four subpopulations were used with 50, 70, 100 and 200 individuals respectively. The maximum number of generations obtained was 400 for a population size (N) 50. With these values of N and P_c and a high value of mutation probability (P_m=0.1), GA is run and evolution of the population best fitness value is observed and this has been depicted in fig 5.8. The convergences occur at 400 generations. At this point the value of the cutting parameters (V, f and d) are 136m/min, 0.1mm/rev and 0.4mm.

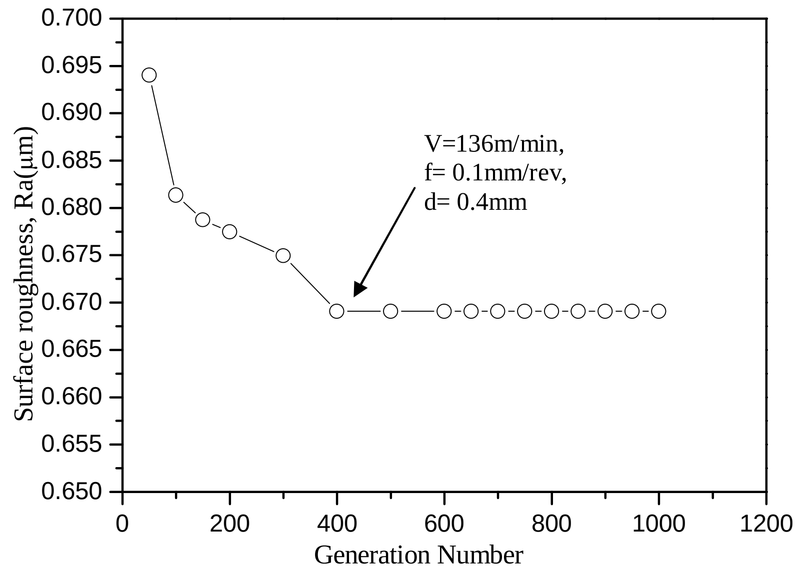


Fig. 5.10 Evaluation of surface roughness of the best individual for consecutive generations

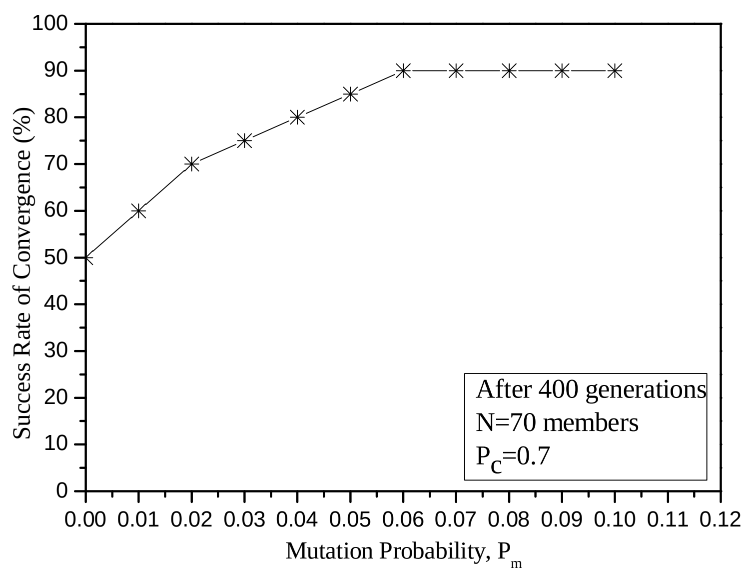


Fig. 5.11 Mutation probability from success rate of convergence

To determine the value of P_m, variation of success rate with change in P_m was observed and this has been shown in fig. 5.9. From this figure, it can be seen that for P_m = 0.06 onwards, the success rate is 90%. Hence, P_m = 0.06 has been selected for solving the problem.

Chapter-6

Discussion on Results

6.1 Cutting Temperature

It is known to all that the higher the cutting speed and feed rate the higher the metal removal rate. But it is also true that such higher cutting speed and feed rate increases cutting zone temperature which undoubtedly affects, directly and indirectly, various machining indices such as chip formation, cutting forces, tool life, dimensional accuracy and surface integrity of the machined parts. That is why cutting zone temperature is an important index of machinability and needs to be reduced as far as possible. Generally cutting fluids are used for this purpose. If the coolant stream can be directed more precisely, noticeably more heat can be removed from the cutting zone. Additionally minimum quantity lubricant jet helps break up chips and remove them from the cutting area more efficiently. Therefore application of near dry lubricant jet is expected to improve the aforesaid machinability characteristics which play vital role on productivity, product quality and overall economy in addition to environment friendliness in machining particularly when the cutting zone temperature is very high.

During machining temperature becomes maximum at the chip-tool interface which was measured in the present work. The average chip tool interface temperature

(θ_{avg}) has been determined using the tool work thermocouple technique and plotted against cutting velocity for different feeds and depth of cuts. From figure 4.7 to 4.9, the effect of near dry lubricant jet in comparison to dry machining condition under different cutting velocities, feed rates and depth of cuts is showing as compared to each other. However it is clear from the aforementioned figures that though the average chip-tool interface temperature (θ_{avg}) increases with the increase in V and f under both dry and near dry machining condition due to increased energy input at higher V-f combinations, near dry machining shows better result for all three cutting depths compared to dry because of successful penetration to the plastic contact length of chip over tool surface. It can also be observed that near dry machining is able to reduce the temperature from 5.15~16.33% irrespective of the difference in depth of cut. The most effective performance has been found at the velocity range of 126~177 m/min and at lower feed 0.1 mm/rev for all depth of cuts. At higher depth of cut reduction of temperature is not as much significant as it is at lower depth of cut.

It is evident from Fig. 4.7 to 4.9 that as the cutting velocity and feed rate increase, the percentage reduction in average cutting temperature decreases. It may be for the reasons that, the bulk contact of the chips with the tool with the increase in V and f do not allow significant entry of coolant jet. Only possible reduction in the chip-tool contact length by the near dry coolant jet particularly that which comes along the auxiliary cutting edge can reduce the temperature to some extent particularly when the chip velocity is high due to higher cutting velocity. So, at industrial speed-feed conditions, this amount of reduction in average cutting temperature is quite significant in pertaining tool life and surface finish.

The percentage saving in average chip-tool interface temperature θ attained by near dry machining for different V-f combinations have been extracted from the previous figures and shown in Table 6.1 for hardened medium carbon steel.

Table 6.1. Percentage reduction in chip-tool interface temperature (θ) due to minimum quantity lubricant

Feed Rate, f mm/rev	Cutting velocity, V m/min	Percentage reduction in θ_{avg} under near dry machining condition		
		Depth of cut 0.4mm	Depth of cut 0.8mm	Depth of cut 1.2mm
0.1	88	15.30	13.57	11.39
	126	16.33	14.46	10.23
	177	15.87	13.74	10.62
	252	10.49	8.91	8.04
0.12	88	13.18	11.71	11.16
	126	11.88	11.09	9.11
	177	11.68	13.35	9.72
	252	8.73	9.49	6.84
0.14	88	11.11	12.32	9.13
	126	11.95	11.00	8.84
	177	12.23	13.20	5.59
	252	8.40	8.26	5.15

6.2 Chip Morphology

The form (shape and colour) and thickness of the chips directly and indirectly indicate the nature of chip-tool interaction influence by the machining environment. The pattern of chips in machining ductile metals are found to depend upon the mechanical properties of the work material, tool geometry particularly rake angle, levels of V and f, nature of chip-tool interaction and cutting environment. In absence of chip breaker, length and uniformity of chips increase with the increase in ductility and softness of the work material, tool rake angle and cutting velocity unless the chip-tool interaction is adverse causing intensive friction and built-up edge formation.

From the Table 4.2 it is stated that under dry and near dry machining condition the shape of the most of the chips are snarled ribbon. But when V=88 m/min, f=0.14 mm/rev and depth of cut 0.8 mm, the shape of the chips are long tubular under the near dry machining environment. Again from Table 4.2 it is clear that when V and f increase, the chip-tool interaction temperature increases. Thus chip become much deeper, i.e. from metallic to golden. Again the colour of the chips have also become much lighter depending upon V and f due to reduction in cutting temperature by near dry machining condition. At dry condition the colour of the chips are very deeper, i.e. from blue to burnt blue due to high temperature.

It is important to note in Table 4.2 that the role of near dry machining has been more effective in respect of form (shape) and colour of the chips when the same steel was machined by the groove type SNMG insert. Such improvement can be attributed to effectively larger positive rake of the tool and better cooling by the jets coming along the groove parallel to the cutting edges. However, the colour of the chips of the hardened steels significantly changed with the application of minimum quantity lubricant comparing to dry condition. The colour of the chips is lighter in near dry machining condition than dry machining. This seemingly happened due to reduction in chip-tool and work-tool interface temperature.

The chip-thickness ratio (r_c) is an important index of chip formation and specific energy consumption for a given tool-work combination. It is evaluated from the ratio,

$$r_c = \frac{a_1}{a_2} = \frac{f \sin \varphi}{a_2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (6.1)$$

Where, r_c = Chip thickness ratio

a_1 = Chip thickness before cut = f sinφ

a_2 = Chip thickness

φ = Principal cutting edge angle

During the machining of the metals and alloys, continuous chips are produced and the value of r_c is generally less than 1.0 because chip thickness after cut (a_2) becomes greater than chip thickness before cut (a_1) due to almost all sided compression and friction at the chip-tool interface. Smaller value of r_c means larger cutting forces and friction and hence is undesirable.

The thickness of the chips directly and indirectly indicates the nature of chip-tool interaction influenced by the machining environment. The chip samples were collected during short run and long run machining for the V-f combinations under dry and near dry machining conditions. The thickness of the chips was repeatedly measured by a slide caliper to determine the value of chip thickness ratio, r_c (ratio of chip thickness before and after cut).

The degree of chip thickness which is assessed by chip ratio, plays an important role on cutting force and hence on cutting energy requirements and cutting temperature. Fig. 4.10 to 4.12 shows the variation of chip thickness ratio with change in cutting velocity, feed rate and depth of cut as well as machining environment evaluated during hard turning. It revealed that Minimum quantity lubrication system has increased the value of chip ratio with the increase of cutting speed as well as feed due to plasticization and shrinkage of the shear zone for reduction in friction and built-up edge formation at the chip-tool interface due to increase in temperature and sliding velocity. In machining steels by tools like carbide, usually the possibility of built-up edge formation and size and strength of the built-up edge, if formed gradually increase with the increase in temperature due to increase in V and also f and then decrease with the further increase in V due to too much softening of the chip material and its removal by high sliding speed.

Variation of chip thickness is quite significant in case of chip thickness ratio where it shows an decreasing trend with the increase of depth of cut under both dry and near dry machining environment. On the other hand, the effectiveness of near dry machining is more dominant and consistent for d = 0.8 mm if compared to dry. Up to 26.88% upsurge in chip thickness ratio has been observed under near dry machining condition. It is evident that the average value of percentage increment in chip-thickness ratio for near dry machining by cutting oil are 19.27% for depth of cut 0.4mm, 21.10% for 0.8mm and 17.98% for 1.2mm. The best performance however has been observed at the cutting speed range of 126~177 m/min and at lower feed values (0.1 mm/rev) for 0.8mm depth of cut. The percentage increment in chip-thickness ratio, r_c attained by near dry machining for different cutting velocity, feed and depth of cut have been calculated from the previous figures and shown in Table 6.2 for hardened medium carbon steel.

Table 6.2. Percentage increment in chip thickness ratio (r_c) due to minimum quantity lubricant

Feed Rate, f mm/rev	Cutting velocity, V m/min	Percentage increment in r_c under near dry machining condition		
		Depth of cut 0.4mm	Depth of cut 0.8mm	Depth of cut 1.2mm
0.1	88	17.24	18.75	24.65
	126	25.77	20.29	20.00
	177	25.35	25.16	22.78
	252	16.46	18.07	14.77
0.12	88	15.86	14.57	17.95
	126	18.71	20.35	15.29
	177	23.08	25.93	18.28
	252	18.82	23.60	17.35
0.14	88	15.78	17.95	18.07
	126	15.19	18.07	14.61
	177	18.07	23.60	20.21
	252	20.88	26.88	11.82

6.3 Cutting Forces

The cutting force information is important to part accuracy, tool wear and heat generations that may cause part thermal damages. The cutting forces increase almost proportionally with the increase in chip load and shear strength of the work material. Apart from chip load and strength of the work material there are some other factors which also govern magnitude of the cutting forces. However, attempt should always be made to minimize the magnitude of the cutting forces without sacrificing MRR and product quality.

Factors that dominate the magnitude of cutting force in turning are generally expressed by the following expression,

$$P_Z = df\tau_s(\xi - \tan\gamma + 1) \qquad (6.2)$$

Where, P_Z = Tangential component of the cutting force

d and f = Depth of cut and feed rate

τ_s = Dynamic yield shear strength of the work material

γ = Effective rake angle

ξ = Chip reduction co-efficient

The heat influence on the cutting forces is mainly because of the following reasons-the friction coefficient is tightly dependent upon temperature and the properties of cut material also depend on temperature. Besides, force is a function of chip thickness ratio as well as chip tool interaction. Cutting force usually decreases with increase in cutting speed and increase with increase in feed, as chip thickness ratio increase under those situations. Formation of built up edge causes fluctuation of cutting force as well as energy consumption. Equations 1 indicate that for the same chip load the magnitude of the cutting forces are governed mainly by the value of chip reduction coefficient (ξ) which is inverse function of chip thickness ratio (r_c).

Fig. 4.13, 4.14 and 4.15 clearly shows the variation of the main cutting force, P_z for various speed-feed and depth of cut combinations under both dry and near dry machining condition. It is distinct from the graph that cutting forces gradually decreases with the increase of cutting speed and increases with increase in feed like usual manner and employment of near dry machining decreased the cutting force under all the treatments. Less chance of built up edge formation under near dry machining environment is evident as a very small fluctuation of force is observed. Again, specific energy consumption is greater at higher depth of cut. It has also been observed that at the lower depth of cut (0.4 mm), approximately 7.72~13.24% reduction in the main cutting force has been carried out almost for all cutting speeds and feeds by the application of near dry machining as compared to dry where as upto 14.25% reduction has been observed for all speed feed combination at 0.8 mm depth of cut. Maximum effectiveness is found in the range of 177~252 m/min along with 0.1~0.14 mm/rev and at 0.8 mm depth of cut. The percentage reduction in cutting force attained by near dry machining for different cutting velocity, feed and depth of cut have been calculated from the previous figures and shown in Table 6.3 for hardened medium carbon steel.

Table 6.3. Percentage reduction in cutting force (P_z) due to minimum quantity lubricant

Feed Rate, f mm/rev	Cutting velocity, V m/min	Percentage reduction in P_z under near dry machining condition		
		Depth of cut 0.4mm	Depth of cut 0.8mm	Depth of cut 1.2mm
0.1	88	10.04	9.52	9.09
	126	9.01	8.93	9.22
	177	10.38	10.91	10.07
	252	10.10	11.98	7.19
0.12	88	10.79	14.25	8.03
	126	5.16	8.57	8.73
	177	10.88	9.93	6.87
	252	13.24	11.87	8.65
0.14	88	9.93	11.03	5.81
	126	10.43	8.24	5.03
	177	7.72	6.31	6.42
	252	9.17	7.95	7.16

6.4 Tool Wear

It's quite possible that tool wear which is the key element that drives overall tooling expenditures is the most disruptive event and cause of missed production time on manufacturing floor. The cutting tools in conventional machining, particularly in continuous chip formation processes like turning, generally fail by gradual wear by abrasion, adhesion, diffusion, chemical erosion, galvanic action etc. depending upon the tool-work materials and machining condition. Tool wear initially starts with a relatively faster rate due to what is called break-in wear caused by attrition and microchipping at the sharp cutting edges [**Paul et al., 2000**].

Cutting tools may also often fail prematurely, randomly and catastrophically by mechanical breakage and plastic deformation under adverse machining conditions caused by intensive pressure and temperature and/or dynamic loading at the tool tips particularly if the tool material lacks strength, hot-hardness and fracture toughness. However, in the present investigations with the tool and work material and the machining conditions undertaken, the tool failure mode has been mostly gradual wear. In general wear of cutting tools are quantitatively assessed by the magnitudes of VB, VS, VM, VSM etc. Among the aforesaid wears, the principal flank wear (VB) is the most important because it raises the cutting forces and the related problems. The life of carbide tool, which mostly fail by wearing, is assessed by the actual machining time after which the average value (VB) of its principal flank wear reaches a limiting value, like 0.3 mm [**Dhar and Islam, 2005**]. Therefore, attempts should be made to reduce the rate of growth of flank wear (VB) in all possible ways without making a concession in MRR.

The rapid growth of wears on main and auxiliary flanks was studied at regular intervals for all trials. The machining was interrupted for this purpose. An inverted metallurgical microscope (Olympus: model MG) fitted with a micrometer of least count 1 μm was used to measure the flank wears.

Fig. 4.17, 4.18 and 4.19 show the variation of average principal flank wear (VB) with machining time for different cutting speeds, feed rates and depth of cuts respectively. From these graph it is evident that VB increases with the machining time as the cutting speed, feed rate and depth of cut increases. It is clearly observed from these graphs that the principal flank wear (VB) decreases significantly under near dry machining condition. Such improvement by near dry machining jet can be attributed mainly to retention of hardness and sharpness of the cutting edge for their steady and intensive cooling, protection from oxidation and corrosion and absence of built-up edge formation, which accelerates both crater and flank wear by flaking and chipping.

In the process of systematic growth of cutting tool wear, the cutting tools usually first undergo rapid wear called break-in wear at the beginning of machining due to attrition and micro-chipping and then uniformly and relatively slow mechanical wear followed by faster wear at the end. The mechanism and rate of growth of cutting tool wear depend much on the mechanical and chemical properties of tool and the work materials and their behavior under the cutting condition. Diffusion wear is often accompanied by the decomposition of a component of one of the sliding surface. In cutting hardened steel material with a tungsten carbide tool, as the speed, feed and depth of cut increases, cutting zone temperature increases. As a result α-iron from the surface of the work material transforms to γ-iron on the surface of the chip [**Opitz, 1963**]. The γ-iron has a strong affinity towards carbon. The tungsten carbide (WC) crystals in the surface decompose and the carbon released diffuses into the surface of the chip. According to Opitz [**1963**], the increased carbon concentration strengthens the surface of the chip which in turn increases wear rate.

Similar phenomenon can be observed in case of auxiliary flank wear (VS) which governs the surface finish on the job as well as dimensional accuracy. This is another important tool wear criteria and its variation with machining time for different cutting speeds, feed rates and depth of cuts are shown in Fig.4.20, 4.21 and 4.22 respectively. It also increases with the increase of time and tool wear rate is proportional to increased values of cutting speed, feed rate and depth of cut. The result of the experimental study clearly depicts that near dry machining permits quick reduction in VS with the progress of machining. Pressurized jet of near dry lubricant has easily been dragged into the plastic contact by its high energy jet, cools the interface and lubricate properly. It not only cools the interface but also reduces frictional heat generation by lubricating the friction zones.

The auxiliary flank wear, which occurs due to rubbing of the tool tip against the finished surface, causes dimensional inaccuracy and worsens the surface finish. Gradual decrease in depth of cut which is proportional to the width VS of that wear increases the diameter of the job in straight turning with the progress of machining. And the irregularity developed in the auxiliary cutting edge due to wear impairs the surface finish of the product.

6.5 Surface Roughness

Surface roughness is an important measuring criterion of machinability because performance and service life of the machined component are often affected by its surface finish, nature and extent of residual stresses and presence of surface or subsurface micro-cracks, if any, particularly when that component is to be used under dynamic loading or in conjugation with some other mating part. Generally, good surface finish, if essential, is achieved by finishing processes like grinding but sometimes it is left to machining. The major causes behind development of surface roughness in continuous machining processes are:

- regular feed marks left by the tool tip on the finished surface
- irregular deformation of the auxiliary cutting edge at the tool-tip due to chipping, fracturing and wear
- vibration in the machining system
- built-up edge formation, if any

Even in absence of all other sources, the turned surface inherently attains some amount of roughness of systematic and uniform configurations due to feed marks. The peak value of such roughness depends upon the value of feed, f and the geometry of the turning inserts. Nose radius essentially imparts edge strength and better heat dissipation at the tool tip but its main contribution is drastic reduction in the aforesaid surface roughness as indicated by the simple relationship,

$$h_m = \frac{f^2}{8r} \qquad (6.3)$$

Where, h_m = Peak value of roughness caused due to feed marks

r = Nose radius of the turning inserts

f = Feed rate

In actual machining, particularly at high feed and cutting velocity, the peak value, h_m may decrease, due to rubbing over the feed mark ridges by the inner sharp edge of the flowing chips. Further deterioration of the cutting edge profile takes place due to chipping, wear etc. Formation of built-up edge may also worsen the surface by further chipping and flaking of the tool materials and by overflowing to the auxiliary flank at the tool-tip.

Feed force as well as chip thickness ratio is responsible for surface roughness along the longitudinal direction of the turned job. Usually surface roughness decreases with the increase in cutting velocity as cutting force decreases and chip thickness ratio increases with the increase in cutting speed. Fig 4.23, 4.24 and 4.25 show the variation of the values of surface roughness, Ra attained of machining of hardened medium carbon steel by the sharp SNMG inserts at various V-f-d combinations under dry and near dry machining conditions. The surface roughness increases with the increase in feed, f and decreases with the increase in V. Reduction in Ra with the increase in V may be attributed to smoother chip-tool interface with lesser chance of built-up edge formation in addition to possible truncation of the feed marks and slight flattening of the tool-tip. Increase in V may also cause slight smoothing of the abraded auxiliary cutting edge by adhesion and diffusion type wear and thus reduces surface roughness. Again increase in Ra with feed rate may be due to irregular deformation of the auxiliary cutting edge at the tool-tip by chipping, fracturing and wear. It can be stated from the experimental results that surface roughness decreases at a faster rate with the increase in cutting speed under near dry machining condition if compared to dry environment. This improvement in surface roughness may be attributed to reduction in break-in wear and also possibly reduction or prevention of built-up edge formation depending upon the work material and cutting condition.

Fig. 4.23 to 4.25 clearly shows that surface quality tremendously increases with the application of near dry lubrication. It has been observed that roughness values are lower at 0.4 mm depth of cut. near dry machining environment shows 41~63% reduction in surface roughness as compared to dry machining irrespective of different V-f-d combinations. This indicates that hard turning under near dry machining environment has provided a better lubricating effect which in turn reduces the friction at the tool-workpiece interface and increases the surface finish. The percentage reduction in surface roughness attained by near dry machining for different cutting velocity, feed and depth of cut have been calculated from the previous figures and shown in Table 6.4 for hardened medium carbon steel.

Table 6.4. Percentage reduction in surface roughness (Ra) due to minimum quantity lubricant

Feed Rate, f mm/rev	Cutting velocity, V m/min	Percentage reduction in θ_{avg} under near dry machining condition		
		Depth of cut 0.4mm	Depth of cut 0.8mm	Depth of cut 1.2mm
0.1	88	63.64	61.02	55.37
	126	61.36	61.36	60.85
	177	61.25	61.58	59.91
	252	60.00	57.14	49.43
0.12	88	64.16	54.29	51.98
	126	61.19	59.32	56.45
	177	61.29	60.55	58.30
	252	58.60	59.38	41.91
0.14	88	62.13	51.74	46.62
	126	61.86	55.65	51.95
	177	63.41	61.28	54.29
	252	63.24	59.07	55.37

Surface roughness for each treatment was also measured at regular intervals while carrying out machining for tool wear study. It was found that surface roughness grew substantially, though in different degree under different machining conditions, with the progress of machining time. Comparison of the figures from 4.26 to 4.28 with those from 4.23 to 4.25 reveals that the pattern of growth of surface roughness bears close similarity with that of growth of auxiliary flank wear, VS in particular. This has been more or less true for all the V-f-d combinations undertaken. Such observations indicate distinct correlation between auxiliary flank wear and surface roughness.

6.6 Discussion on the Outcome of the Optimization Process

Genetic algorithms use a number of parameters to control their evolutionary search for the solution to their given problems. Some of these include rate of crossover, rate of mutation, maximum number of generations, number of individuals in the population, and so forth. There are no hard and fast rules for choosing appropriate values for these parameters. An optimal or near-optimal set of control parameters for one genetic algorithm or genetic algorithm application does not generalize to all cases. Choosing values for the control parameters is often handled as a problem of trial and error. It is common practice to hand optimize the control parameters by tuning each one at a time. However this can be a very time consuming and tedious task.

In this study a trial value of 0.8 for cross-over probability (P_c) is chosen. For the implementation of the genetic algorithm five subpopulations were used with 50, 70, 90, 100 and 200 individuals respectively. The maximum number of generations obtained was 400 for a population size (N) 50. With these values of N and P_c and a high value of mutation probability (P_m=0.1), GA is run and evolution of the population best fitness value is observed which has been demonstrated in fig. 5.10. The code implanting the algorithm in this study takes about 6-7 minutes to run on C++ on a Pentium dual-core laptop with the full 1000 generations of the GA. The convergences occur at 400 generations. At this point the value of the cutting parameters (V, f and d) are 136m/min, 0.1mm/rev and 0.4mm. The obtained values of the cutting parameters as the outcome of the optimization process with respect to surface roughness, cutting temperature, cutting force and the amount of tool wear for 30 minute machining time is given in table 6.5. A conservative value of 400 is hence chosen for the number of generations needed for convergence.

Table 6.5. Values of cutting parameters obtained as outcome of the optimization process

No. of Generation, (G)	Cutting speed, V (m/min)	Feed rate, f (mm/rev)	Depth of cut, d (mm)	Surface Roughness, R_a (μm)	Cutting Temperature, θ (deg)	Chip Thickness Ratio, r_c	Cutting Force, P_Z(N)	Principal Flank Wear, VB (μm)
50	118	0.1	0.4	0.693995	886.209	0.95703	183.426	280.144
100	126	0.1	0.4	0.681334	830.091	0.870517	186.734	286.272
150	128	0.1	0.4	0.678726	832.633	0.876817	185.094	285.672
200	129	0.1	0.4	0.677452	833.904	0.879967	184.274	285.372
300	131	0.1	0.4	0.674964	836.446	0.886267	182.634	284.772
400	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
500	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
600	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
650	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
700	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
750	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
800	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
850	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
900	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
950	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272
1000	136	0.1	0.4	0.669094	842.801	0.902017	178.534	283.272

To determine the value of P_m, variation of success rate with change in P_m was observed. The success rate here is defined as the percentage of runs for which the GA converged to the global optimum after 400 generations. At each value of P_m, 20 GA runs were performed with different initial populations to determine the success rate. From Fig. 5.11 it can be seen that for P_m=0.06 onwards, the success rate is 90%. Hence, P_m=0.06 has been selected for solving the problem.

After running the program for several times it is clear that minimum surface roughness is obtained at a cutting speed 136 m/min, feed rate 0.1 mm/rev and depth of cut 0.4 mm. This is the optimum cutting parameter that satisfies all the constraints mentioned above as well as the objective function. The cutting conditions obtained from the output of the program using genetic algorithm are shown in Table 6.6.

Table 6.6 Predicted machining conditions and corresponding surface roughness

Generation (G)	Population (N)	Crossover Probability (P_c)	Cutting speed, V (m/min)	Feed rate, f (mm/rev)	Depth of cut, d (mm)	Surface Roughness, R_a (μm)
50	50	0.5	104	0.12	0.6	0.918
		0.8	118	0.1	0.4	0.694
	70	0.5	127	0.1	0.4	0.681
		0.8	122	0.1	0.4	0.689
	100	0.5	129	0.1	0.4	0.677
		0.8	125	0.1	0.4	0.685
	200	0.5	131	0.1	0.4	0.675
		0.8	134	0.1	0.4	0.672
100	50	0.5	115	0.11	0.5	0.789
		0.8	126	0.1	0.4	0.682
	70	0.5	118	0.1	0.4	0.694
		0.8	123	0.1	0.4	0.688
	100	0.5	121	0.1	0.4	0.690
		0.8	108	0.1	0.4	0.711
	200	0.5	125	0.1	0.4	0.685
		0.8	135	0.1	0.4	0.671
200	50	0.5	124	0.1	0.4	0.686
		0.8	129	0.1	0.4	0.677
	70	0.5	127	0.1	0.4	0.681
		0.8	115	0.1	0.4	0.699
	100	0.5	132	0.1	0.4	0.674
		0.8	130	0.1	0.4	0.678
	200	0.5	133	0.1	0.4	0.675
		0.8	136	0.1	0.4	0.669
300	50	0.5	122	0.1	0.4	0.689
		0.8	131	0.1	0.4	0.675
	70	0.5	133	0.1	0.4	0.675
		0.8	132	0.1	0.4	0.674
	100	0.5	130	0.1	0.4	0.678
		0.8	133	0.1	0.4	0.675
	200	0.5	131	0.1	0.4	0.675
		0.8	136	0.1	0.4	0.669
400	50	0.5	131	0.1	0.4	0.675
		0.8	136	0.1	0.4	0.669
	70	0.5	128	0.1	0.4	0.681
		0.8	134	0.1	0.4	0.672
	100	0.5	130	0.1	0.4	0.678
		0.8	135	0.1	0.4	0.671
	200	0.5	130	0.1	0.4	0.678
		0.8	136	0.1	0.4	0.669

Chapter-7

Conclusions and Recommendations

7.1 Conclusions

The present research work is concentrated to the optimization of cutting parameters (cutting speed, feed rate and depth of cut) while turning hardened medium carbon steel by coated carbide insert (SNMG 120408 TN 4000) under near dry machining condition. Optimization was done using genetic algorithm. The objective function of the optimization process was to determine the cutting parameters that minimize surface roughness. Here for the selected tool, the tool maker specifies the limitations of the cutting conditions. Also cutting zone temperature, chip thickness ratio, cutting force and principal flank wear should not be greater than some certain maximum value. Statistical models have been developed to establish the objective function and also the constraints for solving the problem. Based on the research work which contains mainly experimental investigation, the following issues can be concluded.

i. This research work outlines the development of genetic algorithm approach for optimization of cutting parameters in turning. This approach is quite advantageous in order to have the minimum surface roughness values, and their corresponding optimum cutting parameters, for certain constraints.

ii. By defining minimize surface roughness as the objective function, surface roughness of 0.669094μm was obtained with the optimized parameters. The values of corresponding cutting zone temperature, cutting force, chip thickness ratio and the average principal flank wear for 30 minute of machining time are 842.801^0C, 178.534 N, 0.902017 and 283.272 μm respectively.

iii. The method seems to converge quickly in about 400 generations. At this point the values of cutting parameters (v, f and d) are 136m/min, 0.1mm/rev and 0.4mm.

iv. Genetic algorithm uses a number of parameters such as number of individuals in the population, maximum number of generations, crossover probability, mutation probability etc to control their evolutionary search for the solution of the given problem. Here the values of these parameters are chosen as 50, 400, 0.8 and 0.06 respectively.

v. With the GA based optimization system developed in this work, it would be possible to increase machining accuracy (surface roughness and geometrical tolerances) by using optimal cutting parameters.

vi. This work shows that in constrained optimization problem like turning process, GA approach is necessary to get the optimum solutions faster. This would be helpful for a manufacturing engineer to choose machining conditions for desired machining performance of a product.

vii. During turning steels with cutting tool, huge amount of heat is generated at the cutting zone due to inelastic deformation of materials. This high temperature is found to be proportional with cutting speed, feed rate and depth of cut. Application of near dry machining reduces this high cutting temperature when compared to dry cutting.

viii. Near dry machining enabled 5.15~16.33% reduction in average chip-tool interface temperature at a speed range of 126~177 m/min and 0.1 mm/rev feed rate.

ix. Due to the application of near dry machining in turning hardened medium carbon steel, the shape and colour of the chips became favourable for more effective and efficient cooling and improved chip-tool interaction. Chip thickness ratio increases more predominantly under near dry machining environment than dry condition because near dry machining reduces the friction and compression of the chip ahead of the advancing tool. Up to 26.88% enhancement in chip thickness ratio as compared to dry condition can be achieved under near dry machining condition. near dry machining is most effective at medium speed range (126~177 m/min) and lower feed rate.

x. The trends of cutting forces can be increasing or decreasing with the increase of cutting process parameters. This behavior solely depends on the range of cutting process variables that are considered as experimental condition of a particular research. In the present work, main cutting force is found to decrease with the increase of cutting speed and increases with the increase of feed rate and depth of cut. 5.16~14.25% reduction in the main cutting force is found under near dry machining with comparison to dry machining. However maximum effectiveness is found in the range of 177~252 m/min along with 0.1~0.14 mm/rev and at 0.8 mm depth of cut.

xi. Both auxiliary and principal flank wears increase gradually as the machining time increases. The higher the value of speed, feed and depth of cut, the higher the wear rate of cutting tool. This gradual increase of tool wear is not linear with cutting time.

xii. It has been observed that the rate of growth of VB increases from 6.91 ~ 15μm/min irrespective of feed and depth of cut with the increase of speed under near dry machining condition. But if we compare this with dry environment it has been found that rate of growth of VB increases from 45 ~115μm/min with the increase of speed, which is much higher than that of near dry machining environment. Such reduction in tool wear might have been possible for retardation of abrasion and notching, decrease or prevention of adhesion and diffusion type thermally sensitive wear at the flanks and reduction of built-up edge formation which accelerates wear at the cutting edges by chipping and flaking. Cutting tool wear, flank wear in particular have decreased substantially due to the retardation of the temperature sensitive wear, like diffusion and adhesion when turning hardened steel under near dry machining by VG 68 cutting oil in comparison to other environment.

xiii. Tool wear increases from 8.78~12.72 μm/min and 6.33 ~8.52 μm/min with the increase of feed and depth of cut respectively under near dry machining environment while the rate of growth of VB increases from 48~ 91μm/min and 37~ 54 μm/min under dry cut.

xiv. Chip segmentation enhances surface finish which becomes distinct in this research. Around 41~63% reduction in surface roughness at higher range of speed-feed- depth of cut clearly indicates the effective performance of near dry machining environment.

7.2 Recommendations

i. In this research optimization of cutting parameters have been performed for a particular tool work combination. The optimum value would be more accurate if experimental data can be taken for several tool work combinations.

ii. In the present optimization process, oil and air flow rate was kept constant. Oil and air flow rate have considerable impact upon the machining responses. Thus further study can be conducted to find optimum air and oil flow rate along with the machining parameters.

iii. Selection of fluid for near dry machining is a crucial decision to take because it is proved from the previous research works that cutting fluid used by the near dry machining applicator has a great influence upon machining performance. Thus it is recommended that further study can be conducted for determining optimum machining condition by taking experimental data for different cutting fluids.

iv. All testing presented in this work used SNMG tool geometry, although it is not expected that this geometry is optimal for any or all cases. Previous work has shown that tool geometry affects nearly everything about the process: chip formation mode, cutting temperature, tool wear and failure, surface finish, residual stresses, and white layer generation. So experimental work should be used to identify the best tool geometry for different materials, cutting conditions, and applications.

v. This research work only focused on the determination of optimum cutting parameters that minimizes surface roughness of the machined part. It can be extended for multi-objective optimization i.e., maximization of tool life, minimization of cutting zone temperature and minimization of cutting force can also be included in the objective function in the future works.

vi. In this work, the optimum value of cutting parameters that have been obtained is valid for 30 minute of machining time. Further research can be carried out that can estimate the machining time along with the other machining responses.

vii. Integration of the proposed approach with an intelligent manufacturing system will lead to reduction in production cost, reduction in production time, flexibility in machining parameter selection and overall improvement of the product quality.

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Appendix

Appendix A:

Table A. Experimental and Predicted values of Principal Flank Wear (VB):

Test Cutting Condition	Cutting Speed, v (m/min)	Feed Rate , f (mm/rev)	Depth of cut, d (mm)	Machining Time, t (min)	Experimental value of Principal Flank Wear	Predicted value of Principal Flank Wear
1	235	0.1	0.8	20	250	243.5812
2	150	0.14	0.4	22	270	267.23
3	170	0.1	0.8	30	275	273.5812
4	150	0.12	0.4	28	280	277.2259
5	150	0.1	0.4	33	290	282.2224
6	107	0.1	1.2	34	295	293.5132
7	107	0.1	0.8	40.5	305	303.5062
8	107	0.1	0.4	50.5	310	313.4974

Table B: Experimental and predicted values of machining responses:

Test Condition	Cutting Speed, v m/min	Feed Rate , f mm/rev	Depth of cut, d mm	Experimental value of				Predicted value of			
				Temperature	Cutting Force	Surface Roughness	Chip Thickness Ratio	Temperature	Cutting Force	Surface Roughness	Chip Thickness Ratio
1	165	0.1	1.2	990	245	0.94	1.04	1056.48	248.85	0.992	1.112
2	163	0.12	0.8	996	250	0.88	1.12	1033.16	233.85	0.914	1.144
3	114	0.12	0.8	980	277	1.01	0.98	983.167	279.78	1.017	0.9837
4	78	0.12	0.8	935	296	1.16	0.89	946.43	313.52	1.122	0.865
5	163	0.14	0.4	998	220	0.8	1.19	994.221	200.64	0.778	1.1311
6	110	0.1	1.2	947	295	1.16	0.9	999.337	307.59	1.127	0.9433
7	76	0.1	1.2	927	332	1.28	0.8	964.017	343.94	1.241	0.839

Appendix B:

Program code for running the GA:

```
#include<iostream>
#include<cstring>
#include<fstream>
//#include<cmath>
#include <stdio.h>
#include <math.h>
#include <stdlib.h>
#include <time.h>
#include<ctime>
#define LEN 1000
#define GN 10500
#define X 1000 //population
using namespace std;
char *addr=new char[10];
int LX=70;
double QC[X*3+2];//20;  qumulitive cross
double RC[X*3+2];//20 rand cross
double PRO[X*3+2];//20 X
int KC[X*3+2] ={0};
double T=0,Rc=0,F=0,Ra=0;
double Thmin=786; //theta min
double Thmax=1235; //theta max
double Fmin=178; //F min
double Fmax=405 ; //F max
double Rcmin=.68 ; //Rc min
double Rcmax=1.23; // Rc max

double VBL=300;

double chrom3[GN][3]={0};
double array[3]={0};
double RAND_MUTE[LEN]={0};
int Selected[X*3+2]={0};
int CS[X+2]={0};
double MinVal=5;
double G=0;
int Count=0;
double Tvalue=30;
double Best_Array2[3]={0};
double Best_Array[3]={0};
int ITERATION=0;
//float B_A[3]={0};
int B_A=0;

class chromosome{
    public:
        double v;
        double f;
        double d;
        double vb;
        double t;
        double th;//theta
        double F;
```

```
double rc;
double Ra;
chromosome()
{

}
void init(double a,double b,double c)
{
 v=a;
 f=b;
 d=c;
 }

 double calc_th() //theta
 {

 th=129.21+2.06*v+3783.91*f+435.81*d+1666.67*f*f-79.43*d*d-6.73*v*f-.29*v*d-398.44*f*d;
 return  th;
 }
 double calc_t()
 {
  // t = 66.15-0.03*v+1176.56*f+28.57*d-183.81*Ra+29.07*Ra*Ra    ;
  t=Tvalue;
   //t=62.1854-.02222*v-20.3125*f-42.8511*d-.2404*Ra;
    return t;
 }
 double calc_vb()
 {
     float e= calc_t();
                                      return vb=227.88-0.30*v+1098.73*f+15.06*d+1.05*t-4936.62*f*f-
11.49*d*d;
     // return vb= 308.05-1.809*v+562.5*f-119.846*d+1.25*e+0.006*v*v+125.913*d*d;
    //return vb= 1.11*pow(10,-20 )* pow(v,8.389)* pow(f,3.338)*pow(d,12.37)*pow(t,4.734);
 }
 double calc_rc()
 {

  rc=-.3661+.0023*v+11.6483*f+.1527*d-40.6125*f*f-.0312*d*d+.0089*v*f-.0001*v*d+.6231*f*d;
 return  rc;
 }
 double calc_f()
 {
  F=219.67-.73*v-805.44*f+160.55*d+6666.67*f*f-34.90*d*d+.34*v*f-.31*v*d+640.63*f*d;
  return  F;
 }
 int check_vb()
 {
    double vv=calc_vb();
    if (vv<=VBL)
    return 1;
    else return 0 ;
 }
 int check_th()
   {
       double tt=calc_th();
       if(tt>=Thmin&&tt<=Thmax)
       return 1 ;
       else
```

```
            return 0;
        }
        int check_f()
        {
            double ff=calc_f();
            if(ff>=Fmin&&ff<=Fmax)
            return 1 ;
            else
            return 0;
        }
        int check_rc()
        {
            double rr=calc_rc();
            if(rr>=Rcmin&&rr<=Rcmax)
            return 1 ;
            else
            return 0;
        }
       double calc_Ra()
        {
           // float x;
            if(v<88)
            return -1;
            else if (v>252)
            return -1;
            else if(check_th()!=0&&check_rc()!=0&&check_f()!=0)
             {
                Ra=.40146-.00149*v+3.919152*f-.067187*d+.00001*v*v-1.04167*f*f+.12240*d*d-
.01674*v*f-.00170*v*d+5.78125*f*d;
                if(check_vb()!=0)
                return Ra;
                else
                return Ra=-1;
             }

            else
             Ra=-1;


            return  Ra;
        }

   };
  chromosome Chrom[X];
  chromosome Chrom2[X];
void Create_rand(int n)
{
   // float k;
   srand (time(NULL) );
    for(int i=0;i<n;i++)
   {
      double v= (rand() %253);
      double f= (rand() %15);
      double d= (rand() %13);



      if(v<88) v=88 +(rand() %15);
```

```
        if(f<10) f=10+(rand() %4) ;
        if(d<4) d=4+(rand() %6);

        f=f/100;
        d=d/10;
       // Chrom[i].v=v;
       // Chrom[i].f=f;
        Chrom[i].init(v,f,d);
     //  cout<<RC[i]<<endl;
    }

}
void Create_Probability()
{
              int i;
    double P[X+1];//={0,.421,.395,.283,.293,.288,.356,.397,.307,.336,.404};
//    float P2[21];
        double sum=0;
        double sum2=0;
        for(i=0;i<LX;i++)
        {
            P[i]=Chrom[i].calc_Ra();
            sum=sum+P[i];
        }

      for(i=0;i<LX;i++)
      {
          PRO[i]=P[i]/sum;
          sum2=sum2+PRO[i];
          QC[i]=sum2;
          //cout<<"****"<<sum2<<endl;
      }
}

int find_cum1(double r)
{

    int i=LX-1;//
    while(i>1)
    {
        if(QC[i]>r)
        i--;
        else
        {
          //  cout<<"here returns  "<<i<<endl;
            return i;
        }
    }
   // cout<<"here returns  "<<i<<endl;
    return i;
}

void find_cumulative()
{
              int i;
     double Ra[X+2];
        srand (time(NULL) );
```

```
   //    cout<<endl<<"Ra"<<endl;
   for(i=0;i<X;i++)
     {
        Ra[i]=0;
     }
    for(int p=0;p<LX;p++)
   {
      double j= (rand() %9)*10000+(rand() % 9)*1000+(rand() %9)*100+(rand() %9)*10+(rand() %9);
      //float j= rand() % 8110+rand() % 1001+rand() %613+rand() % 98;
      Ra[p]=j/100000;
//       cout<<Ra[p]<<endl;
   }

   for( i=0;i<LX;i++)
     {
        CS[i]=find_cum1(Ra[i]);
     }
}
 void New_GEN()
{
   int i,j;


   Create_Probability();
  // Create_rand_cross();
   find_cumulative()  ;
   // cout<<"after new gen"<<endl;
      for(i=0;i<LX;i++)
        {
                 //  cout<<CS[i]<<" "<<" #"<<i<<"  ";

            Chrom2[i].v=Chrom[CS[i]].v;
            Chrom2[i].f=Chrom[CS[i]].f;
            Chrom2[i].d=Chrom[CS[i]].d;
            Chrom2[i].th=Chrom[CS[i]].th;
            Chrom2[i].F=Chrom[CS[i]].F;
            Chrom2[i].Ra=Chrom[CS[i]].Ra;
            Chrom2[i].rc=Chrom[CS[i]].rc;
            Chrom2[i].vb=Chrom[CS[i]].vb;
            Chrom2[i].t=Chrom[CS[i]].t;
          //   cout<<Chrom2[i].v<<" "<<Chrom2[i].f<<" "<<Chrom2[i].d<<endl;

      }
     for(i=0;i<LX;i++)
        {
            Chrom[i].v=Chrom2[i].v;
            Chrom[i].f=Chrom2[i].f;
            Chrom[i].d=Chrom2[i].d;
            Chrom[i].th=Chrom2[i].th;
            Chrom[i].F=Chrom2[i].F;
            Chrom[i].Ra=Chrom2[i].Ra;
            Chrom[i].rc=Chrom2[i].rc;
            Chrom[i].vb=Chrom2[i].vb;
            Chrom[i].t=Chrom2[i].t;
            cout<<Chrom[i].v<<" "<<Chrom[i].f<<" "<<Chrom[i].d<<"    "<<Chrom[i].calc_Ra()<<endl;
        }

}
```

```
void Create_rand_cross()
{
   srand (time(NULL) );
    for(int i=0;i<LX;i++)
   {
      double j= (rand() %9)*10000+(rand() % 9)*1000+(rand() %9)*100+(rand() %9)*10+(rand() %9);
      RC[i]=j/100000;

    //  cout<<RC[i]<<endl;
   }

}
int Choose_Cross_Set(double PC)
{
   int j=0;

   for(int i=0;i<LX;i++)
   {
      if(RC[i]<=PC)
      KC[j++]=i;
     // cout<<j;
   }
   if(j%2!=0)
   {
      KC[j]=rand() %(LX-1);//
      return (j);
   }
   return j;
}
void Make_Cross_Over(int i,int ran)
{
   int b=0;
   double t,t2;
   int j=0;
            if(ran>0&&i<LX&&KC[i+1]<LX&&ran!=3)
            {

                        b=ran;
                                          if(b==1)
                                          {


                 t=Chrom[KC[i]].f  ;
                 t2=Chrom[KC[i]].d;
                 Chrom[KC[i]].f=Chrom[KC[i+1]].f;
                 Chrom[KC[i]].d=Chrom[KC[i+1]].d;
                 Chrom[KC[i+1]].f=t;
                 Chrom[KC[i+1]].d=t2;
                                                     //t=CL[KC[i]].array[j];
               //  chrom3[KC[i]][j]=chrom3[KC[i+1]][j];
                                          //         CL[KC[i]].array[j]=CL[KC[i+1]].array[j];
                                          //         chrom3[KC[i+1]][j]=t;
                                                     //CL[KC[i+1]].array[j]=t;
                                          }
                                          else if(b==2)
                                          {
                  t2=Chrom[KC[i]].d;
                 Chrom[KC[i]].d=Chrom[KC[i+1]].d;
```

```
                                        Chrom[KC[i+1]].d=t2;
          }
                                      cout<<"yaa ran= "<<ran<<" i= "<<i<<" KC "<<KC[i]<<" KC[i+1] "<<
KC[i+1]<<"\n";
                //                    cout<<endl;


                                                   cout<<endl<<"yes crossovered "<<KC[i]<<endl;
         }

}
 int Start_cross_over(double PC)
{
   int i;
   New_GEN();
   int j=Choose_Cross_Set(PC);
   int ran=0;
   if(j==0)
   {
     //  cout<<"sorry random is too random";
      return -1;
   }
   else
   {
       //cout<<"*--->j   "<<j;
      for(int i=0;i<=j;i=i+2)//1
      {
         ran= rand() % (3)+1;//MS-2  ?????????
         // cout<<"ran"<<ran<<endl;;
         Make_Cross_Over(i,ran)  ;
      }
   }

  cout<<"after crossover \n";
     for(i=0;i<LX;i++)
     {
                cout<<"# "<<i<<"  ";
          cout<<Chrom[i].v<<" "<<Chrom[i].f<<" "<<Chrom[i].d<<"   "<<Chrom[i].calc_Ra()<<endl;
     }

              return 1;
}

double swap0(float u)
{
     int i,j,k;
     i=j=k=0;
     i=u/10;
if(u>100)
     j=i/10; //1
     k=u-i*10;//3
     i=(u-j*100-k)/10; //2
   int ran= rand() % (3);
     if(u<100)
   {
      if(u>10)
         u=k*10+i;
      else
```

```
      u=k;
      return u;
    }

   if(ran==0)
     u=k*100+j*10+i;
   else if(ran==1)
     u=j*100+k*10+i;
   else if (ran==2)
     u=i*100+k*10+j;
      return u;
 }

void Swap(int ran)
{
  //  int array[LX+1];
    int i,p,q,k,s,j;
    float u;

cout<<endl<<"RAN   "<<ran<<"   swap ";
    for( i=0;i<=ran;i++)
    {

                s=Selected[i];
                if(s>0)
                {
                    p=s/3;
                    q=s-3*(p);
                    cout<<"s= "<<s<<" p= "<<p<<" q=  "<<q<<endl;
                    if(q==0)
                    {
                    u=Chrom[p].v;
                    Chrom[p].v=swap0(u);
                    }
                    else if(q==1)
                    {
                    ;
                    }
                    else if(q==2)
                    {
                    ;
                    }
                }
    }
    int l;
    cout<<"\n after swapping \n";
            for(l=0;l<LX;l++)
               {
                    cout<<l<<"     ";
                  cout<<Chrom[l].v<<" "<<Chrom[l].f<<" "<<Chrom[l].d<<"     "<<Chrom[l].calc_Ra()<<endl;;
               }


}
void Create_RAND_MUTE()
{
   srand (time(NULL) );
     for(int i=0;i<LX*3;i++)
```

```
    {

       double j= (rand() %9)*10000+(rand() % 9)*1000+(rand() %9)*100+(rand() %9)*10+(rand() %9);
       RAND_MUTE[i]=j/100000;
    }
}
int Mark_S(double PM)
{

           int i;
    for(i=0;i<3*LX+1;i++)
      {
           Selected[i]=0;
      }
         int k=0;
    //cout<<"**marking**"<<endl;
    for(i=0;i<LX*3;i++)
      {
         if(RAND_MUTE[i]<=PM)
         {
            Selected[k++]=i;
         }
      }
    return k;
}

void find_best_S()
{
     int i=0;
     int j=0;
     double min=-1;
        int k=-1 ;
   // float min=MAX;
     for(j=0;j<LX;j++)
    {
       if(Chrom[j].calc_Ra()!=-1)
        {  min=Chrom[j].calc_Ra();
          k=j;
          break;
        }

    }
         Best_Array[0]=Chrom[k].v;
         Best_Array[1]=Chrom[k].f;
         Best_Array[2]=Chrom[k].d;
        // cout<<Best_Array[i]<<" ";

  //     vals[G]=MAX;


    for(i=0;i<LX;i++)
    {
       double m=Chrom[i].calc_Ra();
       if(m!=-1)
        {
         if(min>m)
          {
             k=i;
```

```
              min=m;
            }
          }
    }
    if (min==-1)
                        min=MinVal;
    if(k>-1&&min!=-1)
    {
           B_A=k;
          Best_Array[0]=Chrom[k].v;
          Best_Array[1]=Chrom[k].f;
          Best_Array[2]=Chrom[k].d;
//        vals[G]=MAX;
       //cout<<"\n";
    }
    if(MinVal>min&&min!=MinVal)
      {
              MinVal=min;
           for(i=0;i<3;i++)  //L
        {
          Best_Array2[i]=Best_Array[i];
        //  chrom3[Count][i]=Best_Array[i];;
        }
        ITERATION=0;

      }
    else
    {
         ITERATION++;
       //   G++;
    }
    cout<<"here minimum (best) "<<min;
      for(i=0;i<3;i++)  //L
        {

          chrom3[Count][i]=Best_Array[i];


        }

}


void Place_largest_S()
{
    int i,j;
            double max=-5;//=Chrom[0].calc_Ra();
               int k;
            for(j=0;j<LX;j++)
    {
       if(Chrom[j].calc_Ra()==-1)
        {  max=Chrom[j].calc_Ra();
            k=j;
          break;
        }

    }
```

```
/*          for(i=0;i<LX;i++)//L
          {
             Best_Array[i]=chrom3[0][i];

      //        cout<<chrom2[k][i]<<" ";//$$$close
          }
       //    vals[G]=max;
    */

    //cout<<"\n ^^now:^^^"<<endl;
   if(max!=-1)
    {
    for(i=0;i<LX;i++)
     {
       double m=Chrom[i].calc_Ra();
      //  if(m!=-1)
       {
          if(m>max)
          {
              max=m;
              k=i;
          }
       }
     }
    }
  /*    if(max<total_cost(B_A))//? FIX IT
       {
      // G++;
       }
       else
     */

       cout<<"\n max ** "<<max<<endl<<endl;
       //cout<<endl;
     //  if(max>MinVal)
       {   cout<<"#"<<k<<" ";

             Chrom[k].v=Best_Array[0];
             Chrom[k].f=Best_Array[1];
             Chrom[k].d=Best_Array[2];

          cout<<Chrom[k].v<<" "<<Chrom[k].f<<" "<<Chrom[k].d<<endl;

         //  cout<<" min-> "<<min<<endl<<endl;

              //ITERATION=0;
              }
             /* else
              {
          ITERATION++;
       }
              */
}


void Mutation(float PM)
{
```

```
    Create_RAND_MUTE();
    int j=Mark_S(PM);
    Swap(j);
    find_best_S();
    Place_largest_S();
}
void print_file()
{
    cout<<"\n\n Output file name \n";
    cin>>addr;

            int k=0;
            int i=0;
            while(addr[k]!='\0')
    {
        k++;
    }
    addr[k]='.';
    addr[k+1]='t';
    addr[k+2]='x';
    addr[k+3]='t';
    addr[k+4]='\0';

    ofstream fout3(addr);
            if(!fout3)
            {
                    cout<<"Fatal error:  File"<<addr<<" can't be opened.";
                            exit(1);

            }
fout3<<"     v   f   d       Ra       Theta       Rc         F       VB       t"<<endl<<endl;
            for(int j=0,i=0;j<G;j++,i++)
      {


                    Chrom[0].init(chrom3[j][0],chrom3[j][1],chrom3[j][2]);
                if(Chrom[0].calc_Ra()!=-1)
                fout3<<"#"<<i<<"  "<<Chrom[0].v<<" "<<Chrom[0].f<<" "<<Chrom[0].d<<"
"<<Chrom[0].calc_Ra()<<"   "<<Chrom[0].calc_th()<<"    "<<Chrom[0].calc_rc()<<"
"<<Chrom[0].calc_f()<<"   "<<Chrom[0].calc_vb()<<"    "<<Chrom[0].calc_t()<<endl;


      }         fout3<<endl<<endl<<"BEST "<<endl;
              for(i=0;i<1;i++)
                {
                    //fout3<<i<<" ";
                    Chrom[0].init(Best_Array2[0],Best_Array2[1],Best_Array2[2]);

                fout3<<"#"<<"  "<<Chrom[i].v<<" "<<Chrom[i].f<<" "<<Chrom[i].d<<"
"<<Chrom[i].calc_Ra()<<"   "<<Chrom[0].calc_th()<<"    "<<Chrom[0].calc_rc()<<"
"<<Chrom[0].calc_f()<<"   "<<Chrom[0].calc_vb()<<"    "<<Chrom[0].calc_t()<<endl;
                }
}
int main ()
{
    int n,GEN=100;
    int iteration=100;
    int Set=10;
```

```
  float PC=.25,Pm=.07;
  G=0;
  //X=Set;

 cout<<"\n        GENETIC ALGORITHM PARAMETERS   ";
            cout<<"\n\nNUMBER OF INITIAL POPULATION (<=70)          ";
    cin>>Set;
            cout<<"NUMBER OF GANERATIONS (<=100)                    ";
    cin>>GEN;

    cout<<"CROSSOVER RATE Pc ( 0.5 )                      ";
   cin>>PC;
    cout<<"MUTATION RATE Pm ( 0.07 )                      ";
    cin>>Pm;

    cout<<"LAST N TIMES BEST VALUE DIDNT CHANGED (50)       ";
    cin>>iteration;
    cout<<" value of Time"  ;
    cin>>Tvalue;
    cout<<"VB limit       ";
    cin>>VBL;

// cin>>n;
LX=Set;
 n=LX+10;
  int i,j,k=0;
 j=0;

 Best_Array2[0]=0;
 Best_Array2[1]=0;
 Best_Array2[2]=0;
 Create_rand(n);

/* for(i=0;i<30;i++)
 {

      cout<<Chrom[i].v<<" "<<Chrom[i].f<<" "<<Chrom[i].d<<endl;
        }
      //  Start_cross_over(.25);
      //  Mutation(Pm);
  */
          for( k=0;k<GEN;k++)

        {    //  if(ITERATION<iteration)
              {
               G++;
              //  clear();
               Create_rand(n);
               Start_cross_over(PC);
               Mutation(Pm);
               Count++;
              //show_gen();
              }
            //  else ITERATION=0;

        }

          cout<<endl;
```

```
        for(i=0;i<LX;i++)

         cout<<"#"<<i<<"  "<<Chrom[i].v<<" "<<Chrom[i].f<<" "<<Chrom[i].d<<"
"<<Chrom[i].calc_Ra()<<endl;

       cout<<endl;
     for(i=0;i<3;i++)  //L
   {
     cout<<Best_Array2[i]<<"  ";

   }

       cout<<" ->"<<MinVal;

       print_file();


  cin>>n;
  return 0 ;
}
```