

**EXPERIMENTAL STUDY, NEURAL NETWORK
MODELLING AND OPTIMIZATION OF ENVIRONMENT-
FRIENDLY AIR-COOLED AND DRY TURNING
PROCESSES**

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of

DOCTOR OF PHILOSOPHY

by

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CERTIFICATE

It is certified that the work contained in the Thesis entitled “**Experimental Study, Neural Network Modelling and Optimization of Environment-friendly Air-cooled and Dry Turning Processes**” submitted by **Mr. Deba Kumar Sarma** to the Indian Institute of Technology Guwahati for the award of the degree of Doctor of Philosophy has been carried out under my supervision in the Department of Mechanical Engineering, Indian Institute of Technology Guwahati. This work has not been submitted elsewhere for the award of any other degree or diploma.

22-10-2009

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Dedicated to.....

Mr. D.B. Sarma

Mrs. A. Devi

My parents for their blessing and guidance

Mrs. Nabanita Chakraborty

My wife for her great understanding and encouragement

Master Jubin Kashyap

Miss Gargee Sarma

My son and daughter for their love and affection

Ms. Gitanjali Sarma

My sister who always inspires me

Acknowledgement

I wish to express my deep gratitude to all those who have helped me in various ways during the tenure of my PhD work at IITGuwahati. I have been supported and accompanied by many people and each one has played an indispensable role during my work. I am grateful to all of them. I may have missed out a few names in the following list; my sincere apologies are due for any such inadvertent oversight.

I am greatly indebted to my supervisor Professor U.S. Dixit who inspired me to pursue research in the field of manufacturing. I am highly grateful to Professor Dixit for his guidance and encouragement during the research work. Without his support, advice and motivation, it would have just been an impossible task for me to carry over this research work. I would like to thank my doctoral committee members, Prof P.S. Robi, Prof. P.K. Bora and Prof. S.K. Kakoty for their valuable suggestions and encouragement during the period of my research work. I am also grateful to the past and present heads of the mechanical engineering department, Prof. U.S. Dixit and Prof. D. Chakraborty for extending various facilities during the tenure of my doctoral programme.

I am very much thankful to Mr. Naga Raju Abburi, M.Tech student and Mr. Kaustubh Acharyya, Scientific Officer, IITG for their help during conducting experimental work. I wish to express my sincere thanks to Mr. Rituraj Saikia, Mr. Pranjol Paul, Mr. Dhruvajyoti Bordoloi, Mr. Nandan Kanan Das, Mr. Amal Kalita, Mr. Jiten Basumatary, Mr. Sanjib Sarma and Mr. Nip Borah for their assistance whenever needed during experimentation. I also like to extend my sincere thanks to Late Ramananda Das who helped me a lot in Material Science laboratory prior to his demise.

I am very much thankful to the workshop staff Mr. Bijoy Kumar Choudhury, Mr. Dhaneswar Khaklary, Mr. Upen Gohain, Mr. Minesh Chandra Medhi, Mr. Dipak Kumar Deka, Mr. Nidul Saikia, Mr. Mrinal Sarma, Mr. Parag Saikia, Mr. Dilip Chetri, Mr. Manoj Kumar Baishya, Mr. Lakhinath Gogoi, Mr. Joykrishna Saikia, Mr. Tapan Barua and Mr. Kulen Chandra Deka for their efficiency and cheerful readiness to help me in conducting experimental work precisely & accurately.

I acknowledge the office staff of Mechanical Engineering Department Mr. Lalit Saikia, Mr. Dhruva Saikia and Mr. Ranjan Patowary for their sincere help during any official work related to my Ph.D.

My sincere thanks go to Dr. Anil Borah and Dr. Prashant P. Guddur for their help, support and advice in different occasion of my PhD work.

I sincerely acknowledge Prof. Amarendra Kumar Das for his kind assistance in taking some colour printouts for the thesis.

I shall always be grateful to my parents (Mr. D.B. Sarma and Mrs. A. Devi) for their great encouragement, love and warm wishes. The mental support I got from my sister (Gitanjali) is very effective and highly appreciable. Most deeply, I thank my wife Nabanita for her constant encouragement, support, patience and motivation for the completion of this thesis work. Love and affection of my son Jubin and daughter Gargee are source of inspiration during my entire PhD programme.

Lastly, I will be always grateful to the God, in whichever form it exists.

22nd October 2009

Deba Kumar Sarma
IIT Guwahati



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Nomenclature

a	Constant used in Equation 4.15
b	Constant used in Equation 4.15
b, b_j	Bias
C	Cost of turning of a job
C_a	Cost of air per minute
C_0	Operating cost per minute
C_t	Tool edge cost
c	Constant used in Equation 4.2
c	A factor used in Equation 5.32
c_k	RBF centre associated with k^{th} neuron
D	Diameter of a job
d	Depth of cut in mm
d_{max}	Maximum Euclidean distance between the centres
E	Total predicted error of experimental data
e_i	Distribution of total error E at the i^{th} node (Equation 4.18)
f	Activation function used in neural network
f	Feed in mm/rev
$f(T_i)$	Weibull probability density function
$F(T_i)$	Cumulative density function
k	Size of testing data set (used in Equation 4.9)
k	Constant used in Equation 4.20
K	Total number of RBF centres

L	Machining length
N	Number of neurons in the hidden layer
N	Sample size used in Equation 5.2
N_i	Shape functions at i^{th} node
o_j	Neural network predicted output for j^{th} data
P_0	Probability
p_f	Prescribe value of error in a data set
R_a	Center line average (CLA) surface roughness value
Ra_i	Experimentally observed value of surface roughness
$\hat{R}a_i$	Neural network predicted value of surface roughness
RMS_{err}^f	Root mean squared (RMS) fractional error
T	Tool life/Tool failure time in minute
T_p	Time for producing a work piece
\bar{T}	Mean tool life
T_i	Times-to-failure in ascending order where i is the failure order number used in Equation 5.3
t_c	Tool change time
v	Cutting speed in m/min
w	Tool flank wear
w_{\max}	Maximum flank wear
w_{ji}	Weights associated with the j^{th} neuron of the layer and the i^{th} neuron of the previous layer
w_k	Weight associated with the k^{th} node in the hidden layer
\mathbf{x}	Input vector of RBF network
x	Euclidian distance between the centre and the input vector
x_i	Input signals emitted from the i^{th} neuron of a layer
$\phi(x)$	Gaussian function
$\phi_x(\cdot)$	A processing function of the k^{th} neuron in the hidden layer

β	Shape parameter of the Weibull distribution
η	Scale parameter of the Weibull distribution
ξ, η, ζ	Natural coordinate used in Equation 4.17
σ	Spread parameter
Γ	Gamma function



Synopsis

Manufacturing processes are studied scientifically for improving the quality and productivity. Lately, there has been an increasing concern about the consideration of environment in manufacturing [Sheng and Srinivasan, 1995; Gungor and Gupta, 1999; Yan *et al.*, 2007], which is not only related with the protection of human and the surrounding environment, but is also related with the reduction of the resource consumption in manufacturing processes. Green manufacturing and green engineering in general have become popular in industrial processes and products. According to the US Environmental Protection Agency, green engineering is the design, commercialization and use of processes and products, which are feasible and economical while minimizing (a) generation of pollution at the source and (b) risk to human health and the environment.

Machining is one of the important and widely investigated manufacturing processes. Nevertheless, the practical implementation of research findings is very difficult due to a variety of factors and the statistical nature of the machining process. For example, the maximum performance in turning can be achieved by selecting the proper process parameters and coolant. However, the cutting behavior is different for each tool-workpiece material combination, besides being dependent on several other factors such as the rigidity of the machine tool. This necessitates conducting of a number of experiments for each tool-work material combination. The rigorous experimental work under various cutting conditions and at different cutting environment can help to take a conclusive decision in achieving the desired performance of the machining. The focus of the present thesis is on exploring the environmental-friendly options for the turning process. Hence, dry turning and air-cooled turning processes have been studied. The dry and air-cooled turning processes do not use a cutting fluid, thus avoiding the pollution at the shop floor and

during disposal of the cutting fluid. The cutting fluids have been reported to cause skin rupture and allergy to the operator; these problems are avoided in dry and air-cooled turning processes. Air-cooled turning does not incur a high cost, as the air is a natural resource and the only additional process is to compress and discharge the air with a set pressure.

In this thesis, an experimental study was carried out to compare the cutting performances of various cutting tools in terms of surface finish of the machined work-piece, tool wear, cutting forces, vibrations and tool life. A series of experiments was conducted under dry and air-cooled cutting conditions using high speed steel, coated and non-coated carbide, ceramic and cubic boron nitride tools. A full factorial design was employed for selecting the operating conditions. It has been noticed that air-cooling has a great influence in reducing tool wear and increasing the tool life. However, air-cooling does not help in improving the surface finish. This was ascertained by conducting a number of replicates for different cutting conditions. The air-cooling is particularly highly useful in hard turning (workpiece hardness more than 45 HRC). The investigation carried out with cubic boron nitride (CBN) tool in turning of H13 steel reveals that although the air-cooling does not reduce the surface roughness and cutting forces, it reduces tool wear and the formation of the built-up edge considerably.

To derive the maximum advantage from a manufacturing process, its mathematical modelling is very important. With this motivation, machining processes are being modeled in a number of different ways since the pioneering work of Taylor [1907]. In recent years, there has been an emergence of soft computing methods that have been found effective in the modelling of machining processes. Neural networks, fuzzy logic and genetic algorithms are the major soft computing techniques used by the most of the researchers for modelling and optimization of machining processes. These techniques are especially suitable for online prediction and control of the machining processes. Among these, neural networks have been employed to obtain the functional relationship between the process parameter and the performance parameter in machining. A neural network is composed of a large number of highly interconnected processing elements called the

neurons that receive inputs and produce an output according to a specified rule. There are different types of architecture of neural networks such as the multi-layer perceptron (MLP) and the radial basis function (RBF) neural networks [Ham and Kostanic, 2001]. An RBF neural network can be trained at a faster rate, but it requires more training data. On the other hand in an MLP neural network, less training data are needed; but it takes more time in training.

In the present work, different models have been developed using the MLP and the RBF network for prediction of surface finish, cutting force and tool life. To train the network, a number of training and testing data are generated experimentally following the methodology suggested by Kohli and Dixit [2005]. A novel modelling procedure has been developed considering limited and noisy experimental data, in which the MLP and the RBF network are used in combination. The RBF neural network can be used alone when sufficient number of training data is available. This was done in the modelling of cutting forces as a function of process parameters and time. It is notable that the neural network could not be used for the estimation of tool wear based on the cutting force measurements. Due to this, a simplified method was proposed for the indirect estimation of tool wear based on the observation of Smithey *et al.* [2000] that for a given tool and workpiece material, the incremental increases in the cutting forces due to the flank wear are solely functions of the amount and nature of the wear and is independent of cutting conditions. Thus, knowing the initial wear, the wear at any time can be estimated by the machining force measurement if the rate of change of the wear with respect to the main cutting and/or the feed force is known. However, the present thesis concludes that estimation of the wear can be done only in a probabilistic manner.

The results found from the neural networks were assessed with the hypothesis test using Student's *t*-test at 95% confidence level. This assessment is essential due to the statistical variation of experimental data in machining. Generally, the Student's *t*-test is used when the size of sample is less than 30. The main application of *t*-distribution is to test if the sample mean (\bar{x}) differs significantly from the hypothetical value of population mean (μ) and to test the significance of the difference between two sample means. In the present work, replicate experiments

were carried out for both dry and air-cooled turning at different cutting conditions. The results of replicate experiments were used in Student's *t*-test calculation.

The ultimate objective of a machining research is the optimization of the machining process. A number of techniques have been used for the optimization of process parameters as discussed in the review paper by Mukherjee and Ray [2006]. In these techniques, the knowledge of dependency of tool life on cutting parameters is essential. However, in practical application, the dependency of tool life on cutting conditions may not be known. It is also not economical to conduct the tool life test at each cutting tool-workpiece combination. In view of this, the work of Basak *et al.* [2007] has been extended to develop a heuristic method for the optimization of cutting conditions in finish turning. The proposed method does not require *a priori* information of tool life.

In order to study the statistical nature of tool life, a series of experiment was conducted for finish turning operation considering maximum allowable tool wear and surface roughness as a tool life criterion. The design variable was cutting speed. Sensitivity of tool life on cutting speed was observed for both dry and air-cooled turning. The Weibull distribution [Murthy *et al.*, 2004] has been fitted on the tool life data. The Weibull distribution has been chosen due to its capability to model a great variety of life characteristics.

Simple strategies have been proposed for enhancing the tool life in a finish turning operation. It has been observed that tool life based on surface roughness is generally more for dry turning than for air-cooled turning. A strategy has been developed to utilize the tool in dry turning that has been consumed in air-cooled turning. This procedure increases the effective tool life. The failed tool can be further utilized by reducing the feed.

The important conclusions of the present thesis are summarized below:

1. It is observed that, during dry turning of grey cast iron with a ceramic tool at a cutting speed more than 480 m/min, rapid flank wear occurred and the surface roughness of the machined workpiece increased. At a combination of high speed and high feed, the crater wear was observed along with the flank wear. The

crater wear was not seen when the cutting speed was less than 400 m/min.

2. It has been observed that air-cooling has a great influence in reducing the tool wear and increasing the tool life compared to dry turning for the tool-workpiece combination studied in this thesis. However, air-cooling does not help in improving the surface finish. It has been observed that air cooling is highly useful in hard turning, where it reduces the tool wear and the built-up edge.
3. Neural network modelling helps in prediction of surface finish, tool life and cutting forces. The MLP network used for prediction of surface finish and tool life in the machining of mild steel with coated carbide tool gives a good result. For the prediction of the cutting force in turning of grey cast iron with ceramic tool, an RBF network was used. The prediction accuracy of the model was found satisfactory. However, in the case of prediction of surface roughness and tool life in turning of grey cast iron with ceramic tool, the prediction error was more due to limited and noisy data. Therefore, a novel neural network modelling was developed to suppress the noisy data generated during machining. This improved the accuracy of modelling.
4. The neural network could not be used for the indirect estimation of tool wear based on the measurement of cutting forces. However, a simplified procedure is proposed that can estimate the tool wear in a probabilistic manner.
5. The simple strategies have been proposed for efficient utilization of a cutting tool in a green manufacturing environment. A heuristic method for the optimization of cutting conditions in finish turning operation has been developed.

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Introduction

Machining is one of the oldest basic manufacturing processes. Before the industrial revolution of 18th century, hand tools were used for machining. Since the advent of steam power, power driven machine tools became common in industries. Some of the popular machining processes are turning, milling, drilling and grinding. Among these, turning is the most widely used machining process. In view of its importance and simplicity compared to other machining processes, the present thesis investigates the turning process from a view point of obtaining higher productivity in a green manufacturing environment. Experimental study, neural network (a soft computing method) modelling and optimization of dry and air-cooled turning process are reported in this thesis. The keywords of this thesis are turning process, environmental aspects, soft computing techniques and optimization. These are briefly introduced from Section 1.1–1.3. Organization of the thesis is presented in the last section of this chapter.

1.1 Turning Process

Turning is a traditional machining process for obtaining cylindrical, conical or tapered parts. In this process a single point turning tool of relatively harder material compared to workpiece and having a sharp cutting edge is fed against the rotating work piece. The cutting action takes place due to fracture of the work-piece material at shear zone so as to remove the unwanted part for producing the desired geometry. However, it is observed that under normal machining conditions at moderate and high speeds the thickness of the shear zone is very small and it can be idealized as a

plane. The plane where the shear occurs is known as the shear plane and its inclination with the machined surface is called the shear angle. Figure 1.1 shows the schematic of a cylindrical turning operation.

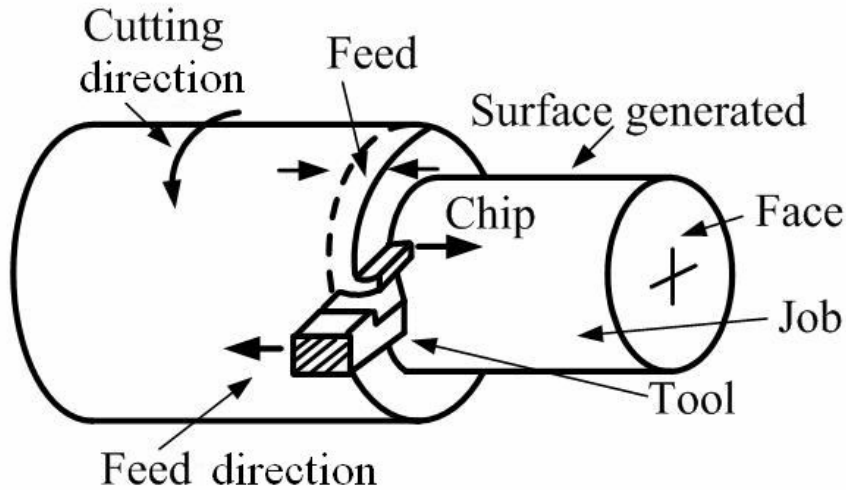


Figure 1.1. A three dimensional view of turning process

Modelling of turning process is more than a century old with the pioneering work of Taylor [1907]. Taylor's empirical model relates cutting speed and tool life in an empirical manner requiring a huge amount of data for each tool-workpiece combination. The predictions by this model are in an average sense. In general, there is a large amount of statistical variation in the tool life in machining. Ernst and Merchant (1941) were perhaps the first to present a physics-based mathematical model of an orthogonal machining process. They considered the idealised case of a single shear plane. The simple theory based on the idealized single shear plane model is good enough to predict the approximate values of power consumption. However, as discussed by Astakhov (2005), the model of Ernst and Merchant is inadequate for a realistic modelling of the machining processes. A number of other physics based models have been proposed, but all of them invariably contain several simplifying assumptions. Moreover, to use these models for the machining performance prediction, often a large amount of data from experiments is needed.

In the turning operation, the main process parameters are speed, feed and depth of cut, whose optimum value depends upon the workpiece and tool material. The major performance parameters are surface finish, dimensional accuracy, tool wear, tool life, cutting forces, vibrations *etc.* Some of the other important parameters are tool geometry, tool material, work material, work dimensions, cutting fluid, stability of machine tool, motor power, temperature at the cutting zone *etc.* that have a direct influence on the turning process. Tool geometry includes various cutting angles and nose radius which affect chip formation, tool strength, tool wear rate, cutting forces, surface finish and tool chatter. The cutting force and vibration have a direct influence towards the surface finish and the dimensional deviation of the turned job. These in turn are dependent on speed, feed and depth of cut along with tool-work material combination and cutting fluid used. It is always important to work with optimum turning process parameters to obtain better surface finish, maximum tool life, minimum production cost, maximum production rate or a weighted combination of these.

1.2 Environmental Aspects in Turning Processes

Environmental concerns call for the reduction of cutting fluid in metal cutting practice and nowadays it has become an important objective in industry. Efficient utilization of cutting tool in machining is an important focus of the researchers working in metal cutting area. The performance of a cutting tool depends on the process parameters and the cutting environment. Many a times, a cutting fluid is used to enhance the tool life and/or to improve the surface integrity. The fluids that are used to lubricate in metal forming and machining, contain environmentally harmful or potentially damaging chemical constituents. Prolonged exposure to coolants during machining may lead to respiratory irritation, asthma, pneumonia, dermatitis, cancer *etc.* [Burge, 2006]. The concept of dry machining has the advantages of non-pollution of the atmosphere and water, no residue on the swarf resulting in the reduction of the disposal and cleaning cost, and no danger to health such as skin rupture and allergy *etc.* Moreover, it offers cost reduction in machining.

As such, dry machining has become popular with regards to safety of the environment as well as low production cost. However, sometimes the performance of finished product in dry turning is not superior to the finished product in wet turning. The concept of using minimal cutting fluid in turning seems to be a better alternative compared to dry turning and conventional wet turning [Varadarajan *et al.*, 2002]. However, this system cannot be termed as highly eco-friendly. The mist formed in the process is partly evaporated and remnants are carried away by the work and chip. The mist in the industrial environment can have serious respiratory effects on the operator. In view of this, there is a good possibility of using dry compressed air as an alternative to coolant in turning. Air is a natural resource and it has no adverse effect on human body. The only processes required are to compress, dry and discharge the air with a set pressure.

1.3 Soft Computing Techniques and Optimization Methods

The mathematical modeling in turning process is mostly empirical or physics based. In the empirical models, large amounts of data from the experiments are needed. The data contains a lot of statistical variation too. In recent years, researchers have incorporated new modeling techniques in turning process known as soft computing techniques. Unlike conventional methodologies (hard computing techniques), soft computing techniques are tolerant of imprecision, uncertainty and partial truth. Soft computing techniques do not suffer from the brittleness and inflexibility of conventional algorithmic approaches. Neural networks (NN), fuzzy set theory, genetic algorithms (GA) *etc* form part of soft computing techniques. Soft computing techniques rely more on the data than the physics of the process, although knowledge of the physics of the process may enhance the effectiveness of the soft computing techniques. These techniques are more suitable for online prediction due to lesser complexity and faster execution.

Neural network modeling is one of the widely used soft computing techniques in machining process since late 1980s [Rangwala and Dornfeld, 1989]. A neural network having artificial intelligence behaves like a biological neural system. The

networks can 'learn' the complex relationships among the data. This feature makes a neural network technique very useful in modeling the complex processes for which mathematical modeling is difficult or impossible. The most commonly used neural networks are multilayer perceptron (MLP) neural network and radial basis function (RBF) neural network.

In the modelling of the turning processes, quicker estimations of parameters are important for online control and optimization. Optimization of turning process parameter is a widely used research topic for most of the researchers. Many researchers opt for traditional optimization techniques in turning process considering practical constraints. However, since recent years, a trend of using non-traditional techniques has become popular in the optimization process. Optimization during metal cutting is the determination of the optimal set of operating conditions to satisfy an objective within the operating constraints. A number of objective functions to measure the optimality of machining conditions are: (1) minimum unit production cost, (2) maximum production rate, (3) maximum profit rate and (4) weighted combination of several objective functions. The cutting constraints to be considered in machining are surface finish constraint, tool-life constraint, cutting force constraint, power constraint, chip-tool interface temperature constraint *etc.* There are a plethora of papers on the optimization of machining processes (Mukherjee and Ray, 2006). The present work focuses on the optimization of finish turning process using a novel heuristic method with smart utilization of cutting tools.

1.4 Objectives and Organization of the Thesis

The primary objectives of the present thesis are to study the cutting performance, modelling of the performance parameters and optimization of cutting conditions in an environment-friendly air-cooled and dry turning processes. Experimental work is carried out to study the effect of air-cooled turning on cutting performance for different tool-workpiece combinations. Neural networks are used for modelling of surface finish, tool life, cutting forces and tool wear. Some strategies such as enhancing the tool life with air-cooling, enhancing the time to failure of cutting tool

by changing cutting conditions *etc.* are developed for the efficient utilization of cutting tools in finish turning. A strategy has been developed for the optimization of the finish turning process without *a priori* knowledge of tool life.

The thesis consists of six chapters, which are organized as follows:

- The first chapter provides the introduction along with the objectives and organization of the thesis.
- Chapter 2 elaborates a brief review of literature of the turning process, environment-friendly machining, mathematical models, soft computing techniques and optimization techniques. Finally, different challenging issues, scope and detailed objectives of the present thesis have been described.
- Chapter 3 deals with a comparative study of dry and air-cooled turning for different cutting tools *viz.* high speed steel (HSS), coated and non-coated carbide tool, ceramic tool and cubic boron nitride (CBN) tool.
- In Chapter 4, the neural network modelling of surface finish, tool life and cutting force is described. A simple method has been described for the indirect estimation of tool wear in a probabilistic manner. Statistical analysis considering experimental data has been carried out to assess the results of neural network models.
- Chapter 5 deals with some strategies for efficient utilization of cutting tools in finish turning. A heuristic method for optimizing the finish turning process is explained in this chapter.
- Chapter 6 presents the conclusions and scope for future work followed by references and appendices.

Review of Literature

2.1 Introduction

The process parameters in the turning operations are feed, speed and depth of cut, which depending upon the work-piece, tool material and other factors affect the surface finish and dimensional accuracy. The other important factors that have a direct influence on the turning process are tool geometry, work dimensions, cutting fluid, stability of machine tool *etc.* Tool geometry includes various cutting angles and nose radius, which affect chip formation, tool strength, wear-rate of tool, cutting forces, surface finish, dimensional deviation and chatter. Cutting forces and vibrations significantly affect the dimensional deviation of the job and surface finish. These in turn are dependent on speed, feed and depth of cut along with tool-work material combination and cutting fluid.

Of late there has been an increasing concern about environmental consideration in manufacturing. Green manufacturing, in particular, and green engineering, in general, has become popular in industrial processes and products. Many a times, coolant is used to enhance the tool life and/or improve the surface integrity. However, the coolant poses environmental and health hazards. Therefore, an environmentally-conscious strategy of tool utilization should avoid or at least minimize the requirement of the coolants. Machining with minimal cutting fluids minimizes the environmental hazards but does not completely eliminate it. Moreover, one has to bear the additional cost of technology associated with such application. Use of air during turning may enhance the tool life without adversely affecting the surface finish of the job. The air is a freely available natural resource and it has no adverse effect on the health of the operator.

In these days, there are a large number of tools and work materials available. There is always more than one choice to obtain the desired product. The optimum selection of cutting tools and conditions should not be simply based upon the familiarity, experience and the memory of individuals. It is always better to have a guiding system for selecting the cutting tool, work piece and the cutting conditions. Several researchers have presented different strategies for optimizing the process parameters in machining. However, many of these strategies are difficult to employ at shop floor conditions and are of academic interest only.

In this chapter, a review of available literature in the area of turning process as well as environment-friendly machining is presented in different sections. Section 2.2 discusses the experimental studies on machining performance of turning. Section 2.3 discusses the various approaches for mathematical modelling of turning process. Application of soft computing techniques for various modelling techniques in turning is discussed in Section 2.4. Section 2.5 presents the literatures on green manufacturing and its spread to turning process. Different optimization techniques used in turning are discussed in Section 2.6. In Section 2.7, challenging issues in turning are discussed. Detailed objectives of the present work have been presented in Section 2.8. Finally, summary is presented in Section 2.9.

2.2 Experimental Studies on Machining Performance

In general, a large number of variables are involved in machining that influence its performance. The main performance parameters in machining are surface finish, tool wear, tool life, cutting force, vibration, dimensional deviation *etc.* Most of the manufacturers focus on producing a desired surface finish which needs to be controlled within an acceptable limits for the specific application. The tool wear can be measured with various equipment, however a precise definition for tool life is still lacking. The performance of a turning process is dependent on the speed, feed and depth of cut along with tool-work material combination and cutting fluid used. This section presents a review of the literature on experimental studies on various machining performance parameters.

2.2.1 Surface Roughness and Dimensional Deviation

Surface finish in machining is defined as the degree of smoothness of a finished product. On the otherhand, dimensional deviation is defined as the radial difference between the set depth of cut and the obtained depth of cut. Surface finish is closely related to the accuracy or tolerance of machined component. A close tolerance dimension requires a very high surface finish. Experienced human operators are able to adjust process parameters such as feed rates and cutting speeds to their maximum possible values, satisfying the constraints imposed by job quality requirement, force, vibrations, tool failure and cutting zone temperatures. A good predictive estimate will lead to the desired job quality and less economic loss for the manufacturer. Usually, a stylus profilometer is used for the measurement of surface roughness. Centerline average (CLA) and root mean square (RMS) values are the most widely used parameters of surface roughness. Since a long time, different researches have carried out experimental as well as theoretical studies on surface finish considering different cutting parameters. Albrecht [1956] investigated the effect of speed, feed, depth of cut and nose radius on the surface finish of a steel work-piece. Ansell and Taylor [1962] studied the effect of tool material on the surface finish of a cast iron work piece. The optimum cutting conditions for carbide and ceramic tool was investigated considering the tool life, which was defined as the time required for the CLA surface roughness value (R_a) to deteriorate to a value of 1.524 micron. Theoretically, for small depth of cut, the CLA surface roughness value R_a is expressed as

$$R_a = \frac{f^2}{32r}, \quad (2.1)$$

where f is the feed and r is the tool nose radius. According to Takeyama and Ono [1967], surface roughness is affected by several controllable factors such as feed rate, cutting speed, depth of cut and material properties of tool and job *etc.* and a number of uncontrollable factors such as chatter, wear and built-up-edge *etc.* In the absence of uncontrollable factors, the surface roughness may conform to the theoretical value.

Nassirpour and Wu [1977] defined the statistical parameters and geometric properties of the surface profile. They had conducted several experiments to study

the influence of feed rate, nose radius and cutting speed on the surface geometry. They observed that surface finish improves as the cutting speed increases. They had constructed response surface contours for surface roughness value (R_a), which can be used to choose a cutting condition for a given surface finish. Tsuwa *et al.* [1981] studied the effect of various operating conditions on the surface finish by using a vision system with a two-dimensional light sectioning method. A contour map of the patterns was utilised to study the different features of machining parameters. Baker [1988] developed a microscope image comparator, capable of recording the image intensity distribution for assessment of surface texture of workpiece. From the intensity distribution, a profile was generated to show the surface finish degradation. Mital and Mehta [1988] presented a review of major investigations carried out for prediction of surface finish. They generated surface finish data for different materials for a wide range of machining conditions such as speed, feed and tool nose radius. Using these data, they developed surface finish prediction models as a function of cutting speed, feed and tool nose radius for individual metal. Statistical analysis of experimental data indicated that surface finish is strongly influenced by the type of material, speed, feed and tool nose radius. Effects of feed and tool nose radius on surface finish were consistent, while the effect of cutting speed was not consistent. Shiraishi and Sato [1990] suggested an optical technique to detect dimensional deviation and surface roughness based on He-Ne laser beam. Surface profiles of the turned part were imaged by a laser light beam passing over the edge. The method is slightly difficult to employ in shop floor due to problems of cutting environment such as metal chips coming in the way of sensing beam of light, flow of coolant *etc.* Yan *et al.* [1996] presented an on-line approach for predicting the maximum peak to valley surface roughness produced during finish turning. Tool wear, vibration of tool and workpiece, change of tool nose radius *etc.* were considered as some of affecting factor in their method. From their study, the researchers concluded that surface roughness increases with increase of flank wear.

Lee and Tarng [2001] introduced a Computer Vision technique to sense the surface roughness value of a machined part and the image of the machined surface captured by digital camera. A relationship was then established between the features

of the image and actually measured surface roughness value. In this technique image processing was affected by cutting environments that restricted its applicability.

Selection of proper cutting tool for turning of a material is very important in terms of minimum surface finish, maximum tool life and high productivity rate. High-speed steel (HSS) tool is still in use in many organizations. However, cemented carbide tools, coated carbide tools, ceramic tools, cubic boron nitride (CBN) tools are preferred for better productivity and good quality. Tool manufacturers claim superior performance of ceramic tools compared to carbide tools for finish turning of grey cast iron [Sadasivan and Sarathy, 1999]. However, compared to carbide tools, ceramic tools are expensive. Similarly, CBN tools are more expensive than ceramic tools. Therefore, in order to manufacture the goods at a competitive price, the proper selection of the cutting tool as well as cutting parameters is of utmost importance. A good tool may produce poor performance, if the operating conditions are not proper. The performance of a cutting tool is judged mainly by machining speed, tool life and quality of the machined surface. Ezugwu and Tang [1995] compared the quality of machined surface in the turning of G-17 cast iron and nickel-based Inconel 718 alloy with round and rhomboid-shaped pure oxide ($\text{Al}_2\text{O}_3 + \text{ZrO}_2$) and mixed oxide ($\text{Al}_2\text{O}_3 + \text{T}_i\text{C}$) ceramic tools. The test results showed the round inserts to give better surface finish compared to rhomboid-shaped tools. Machining with the mixed oxide ceramic tools produced better surface finish than with the pure oxide ceramic tools, because of their improved hot hardness, fracture toughness and wear resistance. Ghani *et al.* [2002] investigated the tool life, surface finish and vibration in machining nodular cast iron using ceramic tool. Experimental results show that the tool life of ceramic insert is not satisfactory in high speed turning. Also, surface finish was found to be almost constant with the progress of flank wear under all cutting condition. However, increasing speed, feed or depth of cut influences the surface finish.

Risbood *et al.* [2003] conducted several experiments with HSS and carbide tools in dry and wet turning for the prediction of surface finish. They observed that, when turning steel rod with TiN coated carbide tool, the surface finish improves with increasing feed up to some particular feed and starts deteriorating with further increase in feed as shown in Fig. 2.1. It can be observed from the figures that

vibrations are not the minimum at the feed corresponding to the minimum surface roughness. Thus, cutting mechanics is the main factor for providing this type of behaviour. The authors did not notice such type of behaviour in case of turning by HSS tool.

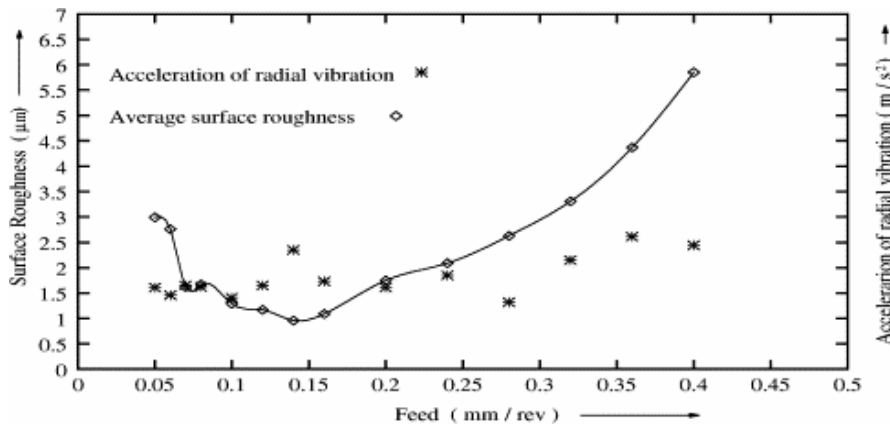


Figure 2.1. Variation of surface finish with feed using TiN coated insert. With permission from Risbood *et al.* [2003]. Copyright [2003] Elsevier.

Senthilkumar *et al.* [2003] carried out the experiments for studying the growth of wear and surface finish in the turning of 40 HRC and 45 HRC hardened EN24 steels with pure oxide and mixed oxide ceramic tool. The researchers observed that the surface roughness obtained using mixed oxide ceramic tool was better than that obtained by using pure oxide ceramic tool at different cutting speeds. Benga and Abrao [2003] conducted experiments on hard turning of 100Cr6 hardened bearing steel with hardness in the range of 60–65 HRC with mixed oxide ceramic and polycrystalline cubic boron nitride (PCBN) insert. The performance of PCBN tool was found to be better from the viewpoint of surface finish and tool life. Camuscu [2006] studied the effect of cutting speed in turning with three ceramic tools *viz.* TiN coated $\text{Al}_2\text{O}_3 + \text{TiCN}$ mixed oxide ceramic, SiC whisker reinforced Al_2O_3 and uncoated $\text{Al}_2\text{O}_3 + \text{TiCN}$ mixed oxide ceramic tool. Considering tool wear, surface finish and cutting force together, TiN coated $\text{Al}_2\text{O}_3 + \text{TiCN}$ mixed oxide ceramic tool was found to be the most suitable cutting tool for the turning of nodular cast iron.

In hard turning (turning carried on materials having hardness of more than 45 HRC), a special effect has been observed on the surface of the machining part. The surface appeared to be white under optical microscope, which is termed as white layer. The white layer is a generic term for a very hard material surface produced under a variety of situations, such as in a number of manufacturing processes *viz.* grinding, hard turning, reaming, drilling, milling, blanking, electrical discharge machining *etc* and in some service applications like sliding, rolling and impact *etc*. The white layer is often harder and more brittle than the bulk material. Due to the brittleness property of white layer, crack initiation starts and product fails. The basic mechanism for white layer formation is surface alteration, which is mainly for high temperature gradient, plastic deformation and chemical reaction.

Griffiths [1985] explained the following three mechanisms that are mainly responsible for white layer formation:

- (a) The mechanism of plastic flow, which produces a homogeneous structure or one with a very fine grain structure.
- (b) The mechanism of rapid heating and quenching which results in phase transformation.
- (c) The mechanism of surface reaction with the environment such as nitriding, carburizing and oxidizing.

Beside this, pressure, strain rate and cooling rate are some other factors for formation of white layer.

Lima *et al.* [2005] tried to evaluate the machinability of hardened steels (AISI 4340 and AISI D2 steel) at different levels of hardness (42 HRC and 50 HRC) using coated carbide and PCBN tool. The researchers have found that PCBN tools provide better surface finish than carbide tools in turning of hard materials. However, the wear rate is more in PCBN, which might be a sign of diffusive wear as commented by the researchers. The aspects related to surface quality for a case of interrupted and continuous hard turning using PCBN tools have been studied by Pavel *et al.* [2005]. The researchers found that the surface topography changes due to influence of tool flank wear in continuous and interrupted cutting. They observed a correlation between evolution of wear and surface finish. In continuous cutting, surface roughness increases significantly with tool wear while in interrupted cutting it

behaves in an opposite manner. It happens due to combined action of cutting and interruption, which leads to widening and flattening of the active nose radius. Jiang *et al.* [2005] presented a development of nanocomposite CBN-TiN coating that helps in hard turning in increasing the tool life and decreasing the surface roughness. The coated inserts (average coating thickness of 18 μm) were tested for turning hardened AISI 4340 steel (50–53 HRC) at a cutting speed of 150 m/min, feed of 0.15 mm/rev and depth of cut of 0.25 mm. The researchers obtained the surface roughness value of 0.5–0.7 μm and average tool life of 20 minute. The process was found to compete with the surface grinding process.

Chen [2000] conducted some experiment using CBN tool on hardened material to study different kinds of parameters such as force, surface roughness, edge geometry, flank wear *etc.* The researcher found that the harder the work piece material, the lower the surface roughness. This is due to reduced plastic deformation of adjacent surface in harder material. At low cutting speed, grooves developed on the flank face result in deterioration of surface finish. However, with increase in cutting speed the grooves gradually reduce and the cutting edge along with wear land becomes smoother. As a result, good surface finish is found on work piece. The researcher found less influence of depth of cut on surface roughness during hard turning by CBN tool.

Ezugwu *et al.* [2005] presented the performance of CBN tool in finish hard turning of hard alloy with various coolant supplies. A comparative study was carried out for machining of the same job with uncoated carbide tool. Three basic conditions of flow of coolant were considered: (a) conventional coolant (b) coolant at 11 MPa pressure and (c) coolant at 20.3 MPa pressure. The carbide tools provided better surface finish than the CBN tools when using coolant at 11 MPa pressure and cutting speed of 150 m/min.

The above review of the literature indicates that the surface finish is dependent on tool-work combination, cutting fluid, the method of application of cutting fluids, process parameters (cutting speed, feed and depth of cut) and a number of uncontrollable factors. It is not possible to generalize the experimental results of a study. There are also examples of contradicting results, for instance, effect of tool wear on surface finish.

2.2.2 Tool Wear and Tool Life

The tool wear is one of the most critical machining performance parameters. It is generally defined as the loss of material from the surface of cutting tool in sliding contact. There are mainly two types of wears— crater and flank wear. The crater wear takes place on the rake face of the cutting tool when the chip flows over the rake face and the flank wear takes place in the flank face when the rubbing actions occur between the work piece and the cutting tool. The flank wear is usually evaluated in terms of length of wear land, which can be measured by an optical microscope. The tool life is the maximum possible life of a cutting tool that no longer performs the desired function. The tool life (T min) is usually measured for a given cutting condition as the time to reach a given wear-land value. Some of the literatures about tool life based on experimental studies are Ezugwu and Okeke [2001], Abrao [2003], Diniz *et al.* [2005] *etc.*

Koren *et al.* [1991] established a relationship between flank wear and cutting force. Smithey *et al.* [2000] observed that the incremental increase of cutting force due to tool flank wear is solely a function of the amount of nature of wear and is independent of cutting condition. The authors observed that the region of the plastic flow on the flank of a worn tool grows linearly with increase in tool wear land. Choudhury and Kishore [2000] established a relationship between the force signals, tool wear and other cutting parameters. A mathematical model was developed that correlates the ratio of feed force to cutting force with the flank wear. Dan and Mathew [1990] reviewed tool wear monitoring techniques for turning. The direct tool wear sensing is classified into optical measurement, analysis of abraded radioactive wear particles, measuring the radioactive decay of the tool, measurement of tool-work junction resistance, measurement of change in work-piece size and measurement of the distance between tool-holder and workpiece. Indirect tool wear sensing is carried out by measuring cutting force, acoustic emission, sound, vibration, temperature, power input and roughness of machined surface. It is based on the acquisition of one or more of these signals from which tool wear can be estimated using a known relation that has to be established *a priori*.

Bhattacharyya *et al.* [1989] studied the performance of ceramic cutting tools for machining of cast iron. In their experiment they had used mixed oxide ceramic, pure

oxide ceramic and nitride ceramic tool. The dominant wear mechanisms were attrition and diffusion. The attrition was mainly dominant at slower speeds and diffusion at higher speeds. Bonifacio and Diniz [1994] studied the influence of surface roughness and tool wear on tool vibrations in finish turning of AISI4340 steel with coated carbide tool. The authors observed that although there was a poor correlation between vibration and surface roughness, the vibration signals could be used to indicate the end of tool life. This is because during the last phase of the tool life, both vibrations and surface roughness increase steeply. It was also observed that feed did not influence the vibration signal and had only a slight influence on the surface roughness. Tool vibrations correlate relatively better with tool wear.

Choudhuri and Ramesh [1995] developed an on-line control system to sense and compensate for tool nose wear. They observed that a very small tapering effect on the work-piece was caused as the tool wear occurred during turning. A relation was established between this taper and tool nose wear. A controller was designed to compensate the taper which takes feedback from the prediction model and actuates the cross-slide to increase the depth of cut. Kaye *et al.* [1995] developed a technique for on-line prediction of progressive flank wear in turning by measuring the reduction of spindle speed. The technique requires that the initial wear on the tool should be known. As tool wears out, the reduction in spindle speed with respect to its corresponding speed at initial wear stage goes on increasing for a given particular cutting condition.

Chen [2000] conducted some experiments using CBN tool on hardened material to study the different parameters such as force, surface roughness, edge geometry of cutting tool and flank wear. At low cutting speed, some small-sized grooves were developed on the flank face of tool resulting in the deterioration of surface finish of the job. However, with increase in cutting speed the grooves gradually diminished with cutting edge and wear land becoming smoother. Hence, a good surface finish was obtained. Ezugwu and Okeke [2001] conducted some experiments with TiN coated cemented carbide inserts on two grades of steel up to a cutting speed of 225 m/min and a feed of 0.44 mm/rev, respectively. The authors obtained a V-shape type of wear along the nose region of the tool face with adhering flake-like oxide debris and micro/macro chipping as the dominant failure modes. Abrasion and plastic

deformation of the sharp cutting edge were found as the main wear mechanisms that affect tool performance, particularly at higher cutting conditions. Tool life was also found to have functional correlations between the cutting force, hardness and length of wear along the nose region.

Che Haron *et al.* [2001] described the wear behaviours of coated and uncoated carbide tools based on the flank wear data. Machining tests were performed under wet and dry cutting conditions at various cutting speeds, while the feed rate and depth of cut were kept constant. The authors obtained smooth initial wear and observed that the coated carbide tools were superior to the uncoated carbide tools. As expected, the tool life was found to be more for coated carbide tools. Li *et al.* [2002] carried out a series of experiment on Inconel 718 material using carbides and ceramic tools of different tool signature and established that the cutting speed is the most important factor influencing the tool wear and tool life.

The study of different wear mechanism of the ceramic cutting tools can establish a good relationship to the surface finish in machining. Senthil Kumar *et al.* [2003] analyzed how the ceramic cutting tool materials undergo gradual progressive abrasive wear with increasing cutting speed in machining hardened steel with pure oxide and mixed oxide ceramic tool. The results show that both the cutting tools undergo abrasive wear with increase of speed. However, mixed oxide ceramic tool is affected more by adhesive wear compared to pure oxide ceramic tool. Benga and Abrao [2003] conducted a series of experiments on hard turning using mixed ceramic and polycrystalline cubic boron nitride inserts for different cutting conditions to access the tool life and surface finish. As far as tool life is concerned, the best results were obtained with the PCBN inserts followed by ceramic inserts.

Poulachon *et al.* [2004] studied the evolution of white layer during progression of tool flank wear in dry hard turning with CBN tool. The researchers did their experiment on hard working material of hardness around 54 HRC and found that tool-wear rate increases with increase of cutting speed and feed. It was observed that white layer thickness grows with increase of flank wear and reduces with decrease of flank wear. Diniz *et al.* [2005] mainly focused on the interrupted turning of hardened steel using CBN tool. They used two types of CBN cutting tool, one is low CBN tool of 60% CBN and another is high CBN containing 90% CBN. Experiments

were conducted on three different types of work piece surfaces— continuous, interrupted and semi-interrupted. Low CBN content tool gives a longer tool life for continuous and semi-interrupted cutting and high CBN content tool gives longer tool life in interrupted cutting. The end of tool life for high CBN content tool was mainly due to flank and crater wears. For low CBN content, end of tool life was due to chipping or breakage of tool. Pavel *et al.* [2005] did some experiment on interrupted and continuous hard turning using PCBN tool to monitor the change of surface topography due to tool flank wear. In continuous cutting, surface roughness increases significantly with tool wear while in interrupted cutting it behaves in an opposite manner. It happens due to combined action of cutting and interruption, which leads to widen and flatten the active nose radius.

Avila *et al.* [2006] studied the performance of TiN coated carbide tools and uncoated carbide tools for the growth of crater wear during machining. The TiN coated carbide tool outperformed the uncoated carbide tool in terms of crater wear. Galoppi *et al.* [2006] also observed that coating layer of CBN tool prevents the formation of crater wear. Once the coating layer is completely removed by wear, the cracking starts. This indicates that the tool life is improving due to the coating over the tool. Noordin *et al.* [2007] used TiAlN coated carbide tool for hard turning of stainless steel. They found the maximum tool life at low cutting speed and low feed combination. In their observation, crater wear was the prime tool wear condition for hard turning. Rahim and Sharif [2007] studied different tool failure modes and wear mechanism using TiAlN and supernitride coated carbide tool.

The review of the literature indicates that like surface finish, the tool life and tool wear is also dependent on several factors and it is difficult to develop a generalized model. The determination of tool wear based on the indirect sensing is still a challenging task. A few contradictory results have been reported in the literature [Dan and Mathew, 1990]. For example, although a number of researchers have developed the models for the estimation of tool wear based on the measurement of cutting forces, Micheletti *et al.* [1968] claimed that it was impossible to derive accurate information about tool wear based on the measurement of cutting forces in turning.

2.2.3 Cutting Force

Cutting force is an important performance parameter that has direct influence on turning process. Tool breakage, tool-wear and work-piece deflection are mainly due to cutting force developed during machining process. Generally, three force components act during turning *viz.* vertical force or cutting force (F_z) in the peripheral velocity direction, feed force (F_x) in the feed direction and radial force (F_y) in the radial direction of the workpiece. There have been a number of attempts to correlate cutting force with tool wear. Wear and breakage of the tool are usually monitored by measuring force, load current, vibration, acoustic emission and temperature. Oraby and Hayhurst [1991] developed mathematical models to describe the wear time and wear force relationships. For cylindrical turning, they have found that the ratio between the radial and vertical force components can provide a good basis for tool wear and failure monitoring. Ravindra *et al.* [1993] developed multiple-regression models to describe the wear-time and wear-force relationships for turning operation. Cutting force components have been found to correlate well with progressive wear and tool failure. Smithey *et al.* [2000] observed analytically and experimentally that for a given tool and work-piece material, the incremental increases in the cutting forces due to flank wear are solely a function of the amount and nature of the wear and are independent of cutting conditions. Choudhury and Kishore [2000] found that the cutting force increases linearly with the tool wear land width.

Chen [2000] conducted some experiment using CBN tool on hardened material to study different parameters such as force, surface roughness, edge geometry, flank wear etc. of cutting tool. According to him, the radial thrust force (passive force) is the most sensitive to tool wear. With increasing cutting speed, the radial thrust force and main cutting force decreases. Zhou *et al.* [2003] conducted some experiments using CBN cutting tool and measured different cutting forces to establish a correlation with flank wear. The experimental results show that all the force components increase with the progression of flank wear. However, the passive (radial) force significantly increases than the other two forces *viz.* cutting force and feed force. The study also shows a good correlation between flank wear and

frequency energy of the passive force. The frequency energy refers to the power in a certain frequency range. Dimla [2004] studied the effect of cutting conditions on cutting forces and vibrations due to tool wear. He experimented with sharp and worn tool inserts. Time and frequency domain was used to pinpoint the exact nature of changes on the signals due to alteration of the cutting conditions. Mativenga and Hon [2005] did experimental study on dynamic cutting forces during high speed end milling operation on H13 steel with coated carbide tool. Dynamic force signals were studied using a real-time data acquisition system for various spindle speeds. Frequency domain studies were also carried out for a large tool in different spindle speeds.

The review of the literature regarding the cutting force indicates that the cutting force components can bring out the valuable information regarding the process. However, instead of raw data of cutting force components, the processed data is more effective. The relative magnitude of cutting force components is dependent on the tool-work combination and the condition of the tool.

2.3 Mathematical Models

Modeling of machining processes is more than a century old with the pioneering work of Taylor [1907]. Taylor's empirical model relates cutting speed and tool life in an empirical manner requiring a huge amount of data for each tool-job combination. The predictions by this model are in an average sense. In general, there is a large amount of statistical variation in the tool life in machining. Ernst and Merchant [1941] were perhaps the first to present a physics based mathematical model of an orthogonal machining process. However, as discussed by Astakhov [2005], the model of Ernst and Merchant is inadequate for a realistic modeling of the machining processes. A number of other physics based models have been proposed, but all of them invariably contain several simplifying assumptions. Moreover, to use these models for the machining performance prediction, often a large amount of data from experiments is needed. Bhattacharyya [1984] has presented different mathematical models for obtaining the optimum machining parameters in turning process. However, these models do not have provision to incorporate the quality of

machined parts. Nassirpour and Wu [1977] defined the statistical parameters and geometric properties of the surface profile. Experiments were conducted to study the influence of feed rate, nose radius and cutting speed on the surface geometry. They observed that surface finish improves as the cutting speed increases. They have constructed response surface contours for centerline average (R_a) values of surface roughness, which can be used to choose a cutting condition for a given surface finish.

Sundaram and Lambert [1981] studied the effect of speed, feed, nose radius, depth of cut, time of cut and tool coating. They used multiple regression technique to develop mathematical model. Rao [1986] developed a microcomputer-based technique for monitoring flank wear on a single point cutting tool in turning operation. He used a *wear index* in real time as the ratio of the dynamic force amplitude of the tool holder to the amplitude of the vibration at the same frequency. This *wear index* was found to be independent of all cutting force variables within the range of variables investigated, but is affected by work-piece hardness. Koren *et al.* [1991] proposed three methods for flank wear estimation under varying cutting conditions in turning. These methods use recursive least-squares algorithms and can be applied when there are stepwise variations in one of the cutting conditions. Method 1 was based on a standard error-estimation algorithm. In this method, change in cutting force was analysed. Methods 2 and 3 contain real time test of the estimation of reliability and therefore start the wear estimation after some initial observation period. Oraby and Hayhurst [1991] and Ravindra *et al.* [1993] proposed mathematical models to describe the wear-time and wear-force relationships for turning operation. Cutting force components have been found to correlate well with progressive wear and tool failure. The results show that the ratio between force components is a better indicator of the wear process, compared with the estimate obtained using absolute values of the forces.

Subhash *et al.* [2000] established the empirical relations for predicting surface residual stresses, surface roughness, dimensional instability and tool life by response surface methodology as a prerequisite for their proposed optimization technique. They used regression analysis and found that feed and depth of cut are most influencing parameters on residual stresses, dimensional stability as well as surface

finish. Choudhury and Kishore [2000] developed a mathematical model for the estimation of flank wear and concluded that force increases linearly with tool wear land width. Flank wear has been calculated indirectly by measuring an easily measurable quantity such as ratio of the feed force to vertical force.

Smithy *et al.* [2000] developed a model to predict the worn tool forces. Their theoretical analysis shows that for a given tool and work-piece material combinations, the incremental increase in the cutting force due to tool flank wear is solely a function of the amount and nature of the wear and is independent of cutting condition in which tool wear was produced. However, in practical shop floor experiments, there is a lot of statistical variation and uncertainty in data and results may not conform to their theory.

Kumar *et al.* [2001] developed some empirical relations to relate the surface roughness with feed and vibration. These empirical relations are developed based on theoretical reasoning and experimental observation. It was observed that to a reasonable degree of accuracy, vibration feedback could play a role in predicting the surface roughness. Suresh *et al.* [2002] developed a surface roughness prediction model in turning using a response surface methodology to produce the factor effects of the individual process parameters. The surface roughness prediction model was optimized using genetic algorithm (GA). Noordin *et al.* [2004] studied the application of response surface methodology to describe the performance of coated carbide tools in turning of AISI 1045 steels. The response variables were surface finish and tangential force. ANOVA revealed that feed was the most significant factor influencing the response variables that were investigated. Ozel and Karpaz [2005] studied the predictive modeling of surface roughness and tool wear in hard turning using regression model and neural network model. In their study, effects of cutting edge geometry, workpiece hardness, feed rate and cutting speed on surface roughness and tool wear were experimentally investigated. They used a four factor two level factorial design.

Several physics based models have been proposed for the prediction of cutting forces in turning [Reddy *et al.*, 2001; Rao and Shin, 1999, Clancy and Shin, 2002; Parakkal *et al.* 2002]. The more detailed information about the machining can be obtained by finite element method (FEM), which is a numerical method for solving

differential equations by discretizing the domain into a number of small elements. A number of researchers have employed the FEM for the prediction of temperature in machining as described in the survey paper by Abukhshim *et al.* [2006]. Joshi *et al.* [1994] analyzed the orthogonal machining process by using an Eulerian FEM formulation. They considered the viscoplasticity in modeling of the material. Özel [2006] simulated the orthogonal machining process using an updated Lagrangian FEM formulation and investigated the effect of friction models on the results. Besides the simulation of machining process, the finite element model has been used for the predictions of tool wear and fracture of the cutting tool [Ahmad *et al.*, 1989; Xie *et al.*, 2005; Cakir and Sik, 2005; Filice *et al.* 2007]. It has also been used for predicting the integrity (residual stresses, micro-hardness and microstructure) of machined surfaces [Monaghan and Brazil, 1997; Wen *et al.*, 2006].

Difficulty in the determination of input parameters required in a physics-based model has prevented its applicability at the shop floor. For example, determination of appropriate value of flow stress and friction during machining is a challenging task [Özel, 2006]. The empirical models do not require the determination of any basic parameter like flow stress; however, they require a huge amount of experimental data for proper fitting of the model. Often it is difficult to find a suitable function that can fit the experimental data. This prompted the researchers to explore the application of soft computing based methods to machining, which is discussed in the following section.

2.4 Application of Soft Computing Technique

Soft computing refers to a collection of computational techniques in computer science, machine learning and some engineering disciplines, which study, model and analyze very complex phenomena for which conventional methods have not yielded low cost, analytical and complete solutions. Soft computing became a formal computer science area of study in the early 1990's [Zadeh 1994]. Earlier computational approaches could model and precisely analyze only relatively simple systems. More complex systems arising in biology, medicine, humanities, management science and similar fields often remained intractable to conventional mathematical and analytical methods. Soft computing techniques such as neural

networks (NN), fuzzy systems (FS), evolutionary computation (EC), swarm intelligence (SI), genetic algorithm (GI), ant colony optimization (ACO), simulated annealing (SA) *etc* have received a lot of attention of the researchers due to their potentials to deal with highly non-linear, multi dimensional and ill-behaved complex engineering problems. The application of soft computing techniques is increasing with successful applications in different areas like engineering design, optimisation, manufacturing system, process control, simulation and communication systems etc. In the recent years, many researchers have incorporated soft computing techniques for the analysis of turning process. The modelling using soft computing techniques may be called data-based modelling as against the physics-based modelling.

In the following subsections, a brief review of the application of soft computing techniques in machining is provided with more focus towards the neural network applications in the turning process. Neural networks have been found suitable for modelling of the turning processes, albeit there are still challenging issues. Use of fuzzy set in conjunction with neural networks is also common in turning.

2.4.1 Surface Finish and Dimensional Deviation

In machining, surface finish and dimensional deviation are two major attributes of quality of turned job. Rangwala and Dornfeld (1989) proposed an artificial neural network method for the prediction of machining performance parameters. An artificial neural network is an information-processing model that is inspired by the way biological nervous systems, such as the brain, process information. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data can be used to extract patterns and detect trends that are too complex to be noticed by either human or other techniques. A trained neural network can be thought of as an “expert” in the category of information it has to analyze. This expert can then be used to provide predictions given unseen situations.

With the pioneering work of Rangwala and Dornfeld (1989), there have been a number of applications of neural networks in machining. In the neural networks, various nodes called neurons are interconnected in the network. These can be used for finding out the relationship between input variables and output. In the recent past, different types of networks have been used for finding out the relation between

the output and the input vector. Two most common types of neural networks are multi-layer perceptron (MLP) neural network and radial basis function (RBF) neural network (Ham and Kostanic, 2001). Most of the researchers used multilayer perceptron (MLP) network trained by a back propagation algorithm for the prediction of machining parameters. Azouzi and Guillot [1997] proposed neural network model to predict surface finish and dimensional deviation of the job taking feed back from various sensors. Feed, depth of cut, radial force and feed force provides the best combination to make a model for on-line prediction of surface roughness and dimensional deviation. Several researchers have compared the effectiveness of neural network model with multiple regression models [Chryssolouris and Guillot, 1990; Lin *et al.*, 2001; Feng and Wang, 2003]. Performance of neural network model was found superior to multiple regression models of Chryssolouris and Guillot [1990] and Lin *et al.* [2001], whereas Feng and Wang [2003] found that both are equally effective.

Risbood *et al.* [2003] used neural network to predict surface finish and dimensional deviation for dry and wet turning of steel with HSS and carbide tool. They observed that, when turning steel rod with TiN coated carbide tool, the surface finish improved with increasing feed up to some particular feed range and then started deteriorating with further increase in feed. However, the authors did not notice such type of behaviour in case of turning by HSS tool. Pal and Chakraborty [2005] predicted the surface roughness considering cutting force, feed force, cutting speed, feed and depth of cut as input parameters in the network. Ozel and Karpat [2005] predicted surface roughness using two different models, one is online model and the other is offline model. Kohli and Dixit [2005] predicted surface roughness in turning process using multi layer perceptron (MLP) neural network with small size of data set as training and testing data. Their methodology of using small size of training and testing dataset is interesting, as generally, the neural network requires a large number of experimental data. Sun *et al.* [2006] proposed a method for the selection of training data for a neural network. In this work, a systematic procedure is provided to perform the data selection. The generalization error surface is divided into three regions and proper sampling factors are chosen for each region to prune the data points from the original training set.

Besides MLP network, another network called radial basis function (RBF) network is being used as a substitute of MLP network. RBF network can be trained faster compared to MLP network. However, RBF network require more training data than the MLP network. Sonar *et al.* [2006] studied the performance of RBF network for predicting lower, most likely and upper estimates of surface roughness in turning. Basak *et al.* [2007] also used RBF network for prediction of surface roughness in finish hard turning. The authors observed that the spread parameter, which is essentially governs the zone of influence of a neuron, plays a significant role in RBF training.

A number of other soft computing techniques have been used for the prediction of surface finish. Fang and Jawahir [1994] presented a methodology for assessing the aspects of total machining performance encompassing surface finish, tool wear rate, dimensional accuracy, cutting power and chip breakability. They quantified the effects of influencing process parameters on total machining performance by fuzzy-set method and developed a series of fuzzy-set models to give quantitative assessments for any given conditions, including work material properties, tool geometries, chip-breaker types and cutting conditions. Chen and Savage [2001] used fuzzy-net based model to predict surface roughness with various combination of tool and job in end milling operation. The input parameters for the fuzzy system were speed, feed, depth of cut, vibration, tool diameter, tool material and work piece material. For the surface roughness, the authors observed prediction errors within 10%.

Abhuri and Dixit [2006] developed a knowledge base system using NN model and fuzzy set theory for the prediction of surface roughness in turning process. The trained network is used for generating a large amount of data that are fed to a fuzzy set based rule generation module. This rule-based module is used for predicting surface roughness for given process variables as well as for the inverse prediction of process variables for a given surface roughness. A fuzzy expert system was developed by Iqbal *et al.* [2007] for prediction of surface roughness and tool life in high speed milling operation.

Nandi and Pratihar [2004] developed a genetic-fuzzy system to predict surface finish. A genetic algorithm was used in the network for optimisation. Brezocnic *et*

al. [2004] proposed a genetic programming (GP) approach to predict surface roughness in end milling operations. The GP was first introduced by Koza [1992] in the year 1992. The aim of GP is to find out the computer programs (called as chromosomes) whose size and structure dynamically changes during simulated evolution that best solve the problem. Reddy *et al.* [2005, 2006] and Oktem *et al.* [2005] used genetic algorithm (GA) for various purpose of works in end milling *viz.* prediction of surface roughness with parameter-optimization, optimum cutting condition for minimum surface roughness, optimization of tool geometry *etc.* Jiao *et al.* [2005] developed a fuzzy adaptive neural network (FAN) for the prediction of dimensional deviation. In this model, first, an approximate model is established with the machining parameters that influence the dimensional deviation. This model is then improved by learning with the given training data. The author found that the model is very effective.

Samanta [2009] predicted surface roughness using adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithms (GA). The author used spindle speed, feed rate, depth of cut and the workpiece-tool vibration amplitude as inputs. The ANFIS with GAs (GA-ANFIS) are trained with a subset of the experimental data. The result of this model was found effective compared to other soft computing techniques such as genetic programming (GP) and artificial neural network (ANN). Lo [2003] used ANFIS to predict surface finish in end milling operation. The model was built using triangular and trapezoidal membership function. Speed, feed and depth of cut were considered as input parameter. Ho *et al.* [2008] also proposed ANFIS to predict surface finish in end milling operation of aluminium alloy with HSS tool. They used a hybrid Taguchi genetic learning algorithm in the ANFIS to determine the most suitable membership functions and simultaneously find optimal parameters by directly minimizing surface roughness error. The methodology performed better than the normal ANFIS method.

2.4.2 Tool Wear and Tool Life

In metal cutting, tool wear and tool life plays a major role from the viewpoint of economics. Tool wear monitoring and estimation of tool life are one of the hot research topics in machining. Ezugwu *et al.* [1995] studied the tool life and failure modes and trained an artificial neural network, which could be used for prediction of

tool lives and failure modes for different cutting conditions. In their experiment they used a black oxide ceramic cutting tool for turning of grey cast iron. The accuracy of prediction by the trained network was not very good and authors felt the need of carrying out more experiments for training the network. The authors had limited number of 25 data. With these data, they could predict the correct tool life (within 20%) in 58.3% cases and tool failure mode in 87.5% cases. A review of the work till 1988 on tool wear monitoring in turning process has been nicely carried out by Dan and Mathew [1990]. They have reviewed 128 papers and concluded that there was a need to develop reliable method for tool wear estimation. Sick [2002] reviewed neural network applications in the prediction of tool wear in a turning process.

Dutta *et al.* [2000] studied on-line tool condition monitoring using neural network. Speed, feed, depth of cut and three components of cutting force were input data in the network with flank wear as the output. The authors modified back propagation algorithm to make it faster than the standard back propagation algorithm. Ojha and Dixit [2005] proposed an economic and quicker method of tool life estimation using neural networks. The tool life is estimated by fitting a best-fit line for the data falling in the steady wear zone and finding the time till tool fails by extrapolation. For predicting the lower and upper estimates of tool life, the authors used the back propagation algorithm of Ishbuch and Tanka [1991]. The neural network model was found to be superior to regression model. Quiza *et al.* [2008] carried out the prediction of tool wear on ceramic cutting tool in the turning of hardened cold rolled steel by using a neural network model as well as a regression model. NN model was found more effective than regression model.

Morikawi and Mori [1993] used neural network based multi-sensor integration technique to determine tool wear states in a turning process. Ghosh *et al.* [2007] estimated tool wear during CNC milling using neural network based sensor fusion model. They took different signals of cutting force, spindle motor current and sound pressure levels as inputs for the network. Obikawa *et al.* [1996] made use of neural network to estimate tool wear states by using force signals. Das *et al.* [1996] used force signals and neural network modelling to predict tool wear. Lin and Lin [1996] used neural network and regression model to predict tool wear in face milling operation using cutting force, feed rate and work-piece geometry as input

parameters. The performance of neural network model is found superior to regression model. Dimla and Lister [2000] have presented a neural network based tool condition monitoring system. First they conducted some experiments on EN24 steel using coated cemented carbide inserts and measured different values of cutting force, vibration and tool wear length. All these values are used to train the neural network. The results of trained network are then cross-validated with some cutting conditions. Zhou *et al.* [2003] presented a method for tool wear monitoring using ANN model. The tool flank wear of a CBN tool is monitored and correlated with some measured parameters such as passive (radial) force, frequency energy and accumulated cutting time. All these parameters are integrated using ANN model to get an output of flank wear. Ozel *et al.* [2007] employed neural networks for the tool wear modelling for ceramic tools.

A number of other soft computing techniques have been used for the estimation of tool wear in machining. Feng [1995] developed knowledge-intensive fuzzy feature-state relationships matrices for the diagnosis of tool wear state in finish turning process using force signals and tool vibrations as input parameters. Chen and Black [1997] proposed a fuzzy-net model to monitor tool breakage during end milling. The model has self-learning capability and generates fuzzy rule base based on experimental data. Dutta *et al.* [2000] proposed a fuzzy controlled back propagation neural network model for prediction of tool wear in face milling operation. Susanto and Chen [2003] also developed a fuzzy logic based in-process tool wear monitoring system using feed, depth of cut and resultant cutting force as input parameter in predicting flank wear of cutter. The system monitored the wear condition with an average error of 8.7%. A tool wear monitoring system using genetic algorithm was proposed by Tansel *et al.* [2005] to estimate wear and local damages of the tool edge during micro end milling operation.

Natarajan *et al.* [2006] used a neural network model for the estimation of tool life, which was optimised by particle swarm optimisation (PSO). The use of PSO resulted in reduction of training time by 50%. Du *et al.* [1992] interpreted input parameters (cutting speed and feed motor current) using transition fuzzy probabilities to estimate wear conditions of a tool in a boring process. Silva *et al.* [1998] developed online tool condition monitoring based on neural network using

signals from various sensors. They used two types of learning algorithm in neural network, one is adaptive resonance theory (ART) and other is self-organising map (SOM). The authors found the NN with SOM performs better than ART.

Balazinski *et al.* [2002] described three artificial intelligence (AI) based methods to estimate tool wear in turning. These are: (a) Feed forward back propagation neural network (FFBPNN), (b) Fuzzy decision support system (FDSS) and (c) Artificial neural network-based fuzzy inference system (ANNBFIS). The tool wear estimation was based on the cutting force, feed force and feed. Tool wear was found increasing linearly with respect to feed force. All the three AI models give a similar result in estimation of tool life. Chungchoo and Saini [2002] proposed an on-line fuzzy neural network (FNN) model for wear estimation. They found that the model is better for the estimation of average width of flank wear and maximum depth of crater wear. Fang and Jawahir [1994] presented a methodology for assessing the aspects of total machining performance encompassing surface finish, tool wear rate, dimensional accuracy, cutting power and chip breakability. They quantified the effects of influencing process parameters on total machining performance by fuzzy-set method and developed a series of fuzzy-set models to give quantitative assessments for any given conditions, including work material properties, tool geometries, chip-breaker types and cutting conditions. Several authors have applied wavelet transform of various signals for the tool wear or machining condition estimation [Luo *et al.*, 2000; Li *et al.*, 2005]. In many of these researches, only a limited amount of experimental validation was conducted. In some cases, the tools were artificially ground.

2.4.3 Cutting Force

A review of some representative work concerning the prediction of forces and tool wear in machining is presented. Khanchustambham and Zhang [1992] used neural network to predict cutting force and surface finish in machining ceramic material putting speed, feed and depth of cut as input parameter. Lee *et al.* [1995] predicted cutting force components using feed forward neural network using undeformed chip thickness, chip width, cutting speed and tool rake angle as input parameters. The predictions matched with experimental data with a reasonable accuracy. Luong and

Spedding [1995] developed a neural network model to find out the cutting conditions for a given work material and required depth of cut to predict the cutting forces, surface roughness and tool life. With the help of a multi-layer perceptron network, Szecsi [1999] modelled the three components of cutting force in turning process as a function of process parameters, tool geometry, workpiece material and tool flank wear. He used 3200 training and 1500 testing data for designing the network. Very good prediction accuracy has been reported. However, there is no discussion about the statistical variation of the cutting forces. Ezugwu *et al.* [2005] used NN model to correlate between process parameter and performance parameters. The process parameters were speed, feed, depth of cut, cutting time and coolant pressure. The performance parameters were tangential force, feed force, consumption of spindle motor power, surface roughness, average flank wear, maximum flank wear and nose wear. The model gives a good performance and agrees well with experimental data.

A number of other authors have applied multi-layer perceptron neural network for the prediction of cutting forces in milling processes [Zuperl and Cus 2004; Radhakrishnan and Nandan, 2005; Zuperl *et al.*, 2006; Aykut *et al.*, 2007]. Tandon and El-Mounayri [2001] modelled the forces in end-milling process by a multi-layer perceptron network. The modelling was limited to one tool-work material combination (HSS tool and aluminium work piece) and a total of 96 data were used for training and testing. The output of the neural network model consisted of forces as well as standard deviation. However, this model does not take into account the tool wears. Hao *et al.* [2006] predicted the cutting forces in self-propelled rotary tool using a multi-layer perceptron neural network. Cutting speed, feed, depth of cut and tool inclination angle were input parameters in the network and thrust force, radial force and main cutting force were the output of the network. For improvement of the performance of the network, the authors used hybrid of genetic algorithm (GA) and back propagation (BP) algorithm.

Zuperl *et al.* [2006] found the radial basis function neural networks superior to the multi-layer neural network in modelling of machining forces in ball-end milling. Radhakrishnan and Nandan [2005] used neural network and regression model for prediction of cutting force. The regression model is used to filter out abnormal data

and the filtered data were used in neural network for better production. Briceno *et al.* [2002] also compared a multi-layer perceptron neural network with a radial basis function neural network for the prediction of machining forces in milling. The radial basis function neural network was found to be superior to multi-layer perceptron neural network in some aspects. Considering the statistical variation, the neural networks were used for predicting minimum, maximum, mean and standard deviation of the forces.

Researchers have put a lot of effort for indirect estimation of tool wear using cutting forces. It has been observed that the cutting force values are more sensitive to tool wear than other signals such as vibration or acoustic emission [Jemielniak, 1999; Byrne *et al.* 1995]. Choudhury and Kishore [2000] developed a mathematical model for the estimation of flank wear and concluded that force increases linearly with tool wear land width. Flank wear has been deduced indirectly by measuring an easily measurable quantity, ratio of the feed force to vertical cutting force. Lin *et al.* [2001] predicted cutting force and surface roughness using abductive neural network with speed, feed and depth of cut as input parameter. The abductive neural networks are composed of a number of polynomial function nodes organized into several layers and generate optimal network architecture automatically. It takes less iteration during training of the network.

Lin *et al.* [2003] employed radial basis function neural network in finding out the force-wear relationship in turning of composite materials. They compared the performance of the neural network model with a multiple regression model and observed that the neural network prediction is more accurate than the multiple regression model prediction especially when the functional dependency is nonlinear. They have found that feed force data gives a superior result than the cutting force data. Zhou *et al.* [2003] presented a method for tool wear monitoring using ANN model. The tool flank wear of a CBN tool is monitored and correlated with some measured parameters such as passive (radial) force, frequency energy and accumulated cutting time and all these parameters are integrated using ANN model.

The review of the literature in the area of soft computing applications to machining indicates the great potential of the soft computing techniques for the prediction and optimization of machining performance. In particular, neural

networks have been found very suitable for the modelling of machining process. However, the requirement of huge amount of training and testing data, the presence of the outliers and lack of one well-established standard method of training of neural network poses a challenge for the researchers.

2.5 Green Manufacturing and its Relvance to Turning Process

Of late there has been increasing concern about environmental consideration in manufacturing [Sheng and Srinivasan, 1995; Gungor and Gupta, 1999]. Green manufacturing, in particular, and green engineering, in general, has become popular in industrial processes and products. According to US Environmental Protection Agency, green engineering is the design, commercialization, and use of processes and products, which are feasible and economical while minimizing (a) generation of pollution at the source and (b) risk to human health and the environment [http://www.epa.gov/opptintr/greenengineering/pubs/whats_ge.html].

Green engineering embraces the concept that decisions to protect human health and the environment can have the greatest impact and cost effectiveness when applied early to the design and development phase of a process or product. In most of the factories, there is no comprehensive evaluation tool for green attribute of manufacturing process. Krishnan and Sheng [2000] presented an automatic process-planning agent for CNC machining for minimal environmental impact. The process planning system can accept web-based designs and offers feedback to the designer over the Internet. Yan *et al.* [2007] presented a process planning support system for green manufacturing (GMPPSS) to deal with the problems in optimization of environment-favorable process planning. The objective of the GMPPSS is to evaluate the green attributes of the process planning from the single process elemental level to the entire process project level, which include the raw material consumption, secondary material consumption, energy consumption and environmental impacts of the manufacturing process.

Machining is one of the most important and widely investigated manufacturing processes. Efficient utilization of cutting tool in machining is an important focus of the researcher. Efficiency of a cutting tool depends on the tool life and the cutting

environment. Many a times, a cutting fluid is used to enhance the tool life and/or improve the surface integrity. The fluids that are used to lubricate in metal forming and machining, especially of high alloy or stainless steels, contain environmentally harmful or potentially damaging chemical constituents. Prolonged exposure to coolants during machining may lead to respiratory irritation, asthma, pneumonia, dermatitis, cancer *etc.* [Burge, 2006]. Environmental concerns, market forces and legislative requirements are combining to make imperative a search for new solutions, which minimize environmental impact without compromising process economics.

Kevin *et al.* [2008] developed a detailed cost and performance based methodology for machining coolant/lubricant selection. However, the use of cutting fluid and disposal is a major concern for the environmental issue. Considering the costs of cleaning and disposal of used fluids, a general consensus has been grown up among the researchers for an alternative of the cutting fluid. As stated by Sreejith and Ngoi [2000], reduction of cutting fluid in metal cutting practice becomes an important objective in industry. Environmental concerns call for the reduction of cutting fluid either uses of minimal cutting fluid or dry machining. In the past, some researchers have developed the methods to minimize the cutting fluids [Wertheim *et al.*, 1992; Brockhoff and Walter, 1998]. Varadarajan *et al.* [2002] had adopted a method, which is intermediate between dry and conventional wet turning. The concept is pseudo dry turning with minimal cutting fluid where a mixture of some ingredients is injected in the cutting zone with variable pressure at some frequency of injection. The overall performance of this system is found to be superior to that of dry and conventional wet turning Wang *et al.* [2009] investigated the effect of flood coolant (FC), minimum quantity of lubricant (MQL) and dry cutting (DC) during continuous and interrupted turning of Ti6Al4V material. At low cutting speed and low feed, dry cutting in continuous turning was more effective than the MQL and FC, while at higher cutting speed and at high feed MQL seems to be more effective. Even, in interrupted cutting also, MQL was more effective than dry cutting and flood coolant. From these studies, it has been observed that, the overall performance of using minimum cutting fluid in turning is superior to that of dry and conventional wet turning. However, this process cannot be termed as fully eco-friendly

machining. The mist formed in the process is partly evaporated and remnants are carried away by the work and chip. The mist in the industrial environment can have serious respiratory effects on the operator. Moreover, one has to bear an additional cost in this technology.

The concept of dry machining has the advantages of non-pollution of the atmosphere or water, no residue or the swarf resulting in reduction of disposal and cleaning cost, no danger to health such as skin rupture and allergy *etc.* Moreover, it offers cost reduction in machining. However, to make the dry machining at par with wet machining, some investigations are needed. A number of researchers have started developing ceramic cutting tool materials with self-lubricating property [Jianxin *et al.*, 2005]. As such, dry machining is becoming popular with regards to safety of the environment as well as low production cost.

2.6 Optimization Techniques

The optimization problem in machining is highly non-linear and possesses multiple solutions. The selection and optimization of process parameters in machining are most important as it influences the production rate, tool life, surface finish *etc.* Optimization during metal cutting is the determination of the optimal set of operating conditions to satisfy an objective within the operation constraints. A number of objective functions to measure the optimality of machining conditions are: (1) minimum unit production cost, (2) maximum production rate, (3) maximum profit rate and (4) weighted combination of several objective functions. Several cutting constraints are to be considered in machining such as tool-life constraint, cutting force constraint, power constraint, stable cutting region constraint, chip-tool interface temperature constraint, surface finish constraint, roughing and finishing parameter relation constraint *etc.* Although more numbers of papers are available in the literature on the optimization of process parameters, the selection of suitable cutting tool and cutting fluid also forms an important part of optimization.

In an earlier work, Gilbert [1950] presented a theoretical analysis of the optimization of the machining process using two criteria, maximum production rate and minimum cost for single pass turning keeping feed and depth of cut fixed. In his analysis, he did not consider the surface roughness aspect. Ermer [1971] and

Petropoulos [1973] used geometric programming for the optimization of the constrained machining economics. In a geometric programming, the objective function and constraints are expressed as posynomials. Ermer [1971] considered the minimization of unit production cost of a turning operation subjected to different constraints like available speeds, feeds and horsepower as well as desired surface finish and dimensional deviation. Petropoulos [1973] also used geometric programming for optimal selection of machining rate variables and optimize the constrained unit cost problem in turning. He considered the following constraints: (a) the maximum cutting power available, (b) the surface roughness required, (c) the maximum cutting force permitted by the machine tool, (d) the maximum feed rate and rotational speed available from the machine tool. The author used the basic model describing the cost to produce a work piece (unit cost) by turning a job, as given by cost of operating time, tool cost and machining cost. Lambert and Walvekar [1978] used geometric programming for the optimization of machine variables to yield minimum production cost. They considered force, power and surface finish as constraints. The procedure developed by the authors provided simultaneous determination of the machining parameters that minimized the cost and satisfied constraints on the machining parameters.

Shin and Joo [1992] presented a model for the optimization of machining conditions in a multipass turning operation considering both rough and finish cutting operation. The authors adopted the minimum unit production cost as objective and cutting speed, feed and depth of cut were used as system variables. The constraints considered by them were parameter constraints (maximum and minimum values of process parameter), tool life constraints and operating constraints (cutting force constraint, power and surface finish constraint). Their model was verified with a hypothetical problem.

Gupta *et al.* [1995] achieved the minimization of total production cost by summation of the minimum cost of individual rough passes and finish pass. The authors used integer-programming model for obtaining the optimal subdivision of total depth of cut along with the selection of speed and feed. They used two steps for the minimization of total production cost considering fixed depth of cut and optimal combination of depth of cut for rough passes and finish pass. A new mathematical

model for determining machining parameters by minimizing total production cost in multipass turning with various constraints was presented by Al-Ahmari [2001]. The author had obtained the lowest minimum production cost compared to Shin and Joo [1992] and Gupta *et al.* [1995]. Yeo [1995] used sequential quadratic programming for optimizing the total production cost for obtaining optimal cutting parameters in finish pass and rough passes. Lee and Tarng [2000] used polynomial network and sequential quadratic programming to obtain the optimal cutting parameters in multipass turning. They considered the maximization of production rate and minimization of production cost.

Yang and Tang [1998] used Taguchi method, which is a special design of orthogonal array to find the optimal cutting parameters for turning operations. Signal to noise (S/N) ratio and analysis of variance (ANOVA) were used to investigate the cutting characteristics. The greatest S/N ratio level provides the optimal level of process parameters and ANOVA is performed to find out which process parameters are statistically significant.

In recent years, non-traditional optimization techniques have been applied to turning process optimization. Among the various techniques, neural network, simulated annealing, genetic algorithm, ant colony algorithm *etc.* have become more popular. Wang [1993] used neural network using manufacturer's fuzzy preferences to determine the optimum cutting parameters by solving the multi-objective problem. Productivity, operation cost and cutting quality were considered the objectives. Lee *et al.* [1999] and Hashmi *et al.* [1999] used fuzzy logic model to optimize cutting conditions for machining. Chen and Tsai [1996] and Baykasoglu and Dereli [2002] applied simulated annealing algorithm in turning for obtaining optimum process parameters. They had considered several practical constraints in their model. Alberti and Perrone [1999] used fuzzy probabilistic formulation in multipass turning and optimized the resulting possibilistic model using genetic algorithm. They considered a limited number of cutting constraints in their problems. Onwubolu and Kumalo [2001] had also used genetic algorithm for determining the optimal machining parameters that minimize the production cost. The authors had developed a new local search optimization based genetic algorithm

approach in their model. Finally, they validated the model taking some hypothetical example problems and compared their result with some other model.

An optimization technique based on ant colony algorithm was proposed by Vijaykumar *et al.* [2003] for solving multipass turning optimization problems. Optimum cutting parameters were obtained by minimizing the unit production cost considering various practical constraints. Karpat and Ozel [2005] developed a multi-objective optimization model using particle swarm optimization (PSO) based neural network for the prediction of surface roughness and tool wear during single pass turning. The PSO is used to obtain optimum cutting speed, feed and tool geometry. Sinivas *et al.* [2007] also used PSO technique to optimize multipass turning process to minimize total production cost using several cutting constraints. The PSO provides optimal feasible solutions within a reasonable computational time.

An optimization technique has been proposed by Amiolemhen and Ibadode [2004] based on genetic algorithms for the determination of the cutting parameters in multi-pass machining operations by simultaneously considering multi-pass roughing and single-pass finishing operations. The optimum machining parameters are determined by minimizing the unit production cost considering many practical constraints. The model is found effective and efficient when compared with experimental results. Abburi and Dixit [2007] developed an optimization method, which is a combination of a real-coded genetic algorithm (RGA) and sequential quadratic programming (SQP) to obtain Pareto-optimal solutions to minimize the production cost and production time. The model had a major advantage that various Pareto-optimal solutions are generated without the knowledge of the cost data. Kim *et al.* [2008] also explored the applicability of RGA in machining optimization. Ojha *et al.* [2009] optimized different parameters in multipass turning using neural network, fuzzy sets and genetic algorithms. Neural network has been used for the prediction of surface finish and tool life. The developed optimization model was applied for minimization of production cost and maximization of production rate.

The optimization of machining processes has been widely investigated with a number of techniques. However, the shop floor application of these methods is still a difficult task due to lack of proper machining model. For practical applicability of

the optimization methods, the robust machining models have to be integrated with these methods. Soft computing can play an important role in this task.

2.7 Challenging Issues

An integrated approach in machining produces a desired product with required finish and accuracies. This approach includes expert knowledgs in various aspects, such as proper selection of cutting tool for faster machining, reduced cycle times, increased control of machining, protection of the environment *etc.* Although the researchers have investigated various aspects of machining, there are only a few publications that attempt to provide an integrated user friendly solution. Some challenging issues that come in the way of the application of applying the research findings at the shop floor level are enumerated as follows:

- Machining performance is dependent on tool-work combination, the particular machine tool and a number of other factors. Although a number of experimental results are available in the literature, it is difficult to utilize these results in different settings.
- Neural networks have been found very useful in the modelling of machining processes. However, they require huge amount of training and testing data. The presence of outliers in the data creates a nuisance in the training process. Also, there is a need to develop a systematic, efficient and easy procedure for network training.
- The variety of the tool-job combinations, cutting fluids and machining requirements have increased tremendously. There is a need to develop efficient and simple methods that can optimize the process quickly on the shop floor. The environmental concerns are must during the optimization of the process.

2.8 Scope and Objectives of the Present Work

Based on the literature survey and major challenges identified in the last section, it is decided to investigate the following aspects of the turning process in this thesis:

1. **Exploring air-cooled turning:** The recent challenge before the researchers is to do machining in an environment-protected atmosphere. The application of air cooling in machining can achieve the conflicting goals of machining performance and green environment. Air is a freely available natural resource and it has no adverse effect on the health of the operator. Exploring the possibility of using air cooling in turning is the first and major objective of the thesis.
2. **A comparative study of dry and air-cooled turning of different tool-work material combinations:** The air cooling can be an effective substitute to cutting fluid. However, its effectiveness is dependent on the tool-work material combinations and use of proper cutting parameters. Therefore, it is decided to carry out experimental investigations on turning for the following combinations: (i) tool: HSS, work-material: grey cast iron (ii) tool: non-coated carbide, work-material: grey cast iron (iii) tool: mixed oxide ceramic, work material: grey cast iron (iv) tool: coated carbide, work-material: mild steel (v) tool: CBN, work-material: H13 steel. For the first two combinations only dry turning was carried out, while for the other three combinations both dry turning and air-cooled turning were carried out.
3. **Efficient use of neural network for modelling the turning process:** In the literature, various soft computing techniques have been used by different researchers for the prediction of surface finish, dimensional deviation, tool life, tool wear rate, cutting forces, cutting power *etc* during machining. Neural network is one of the most popular soft computing techniques which have different architectures. Multi-layer perceptron (MLP) and radial basis function (RBF) networks are two common networks. The RBF neural network can be trained at a faster rate, but requires more training data. On the other hand, a MLP neural network requires less training data compared to RBF neural network, but

takes more time in training. One of the objectives of the present thesis is to develop a strategy for using both MLP and RBF neural network in an efficient way. The emphasis is on using lesser number of data for network training and on providing some robustness against the presence of outlier.

4. **Development of strategies for efficient utilization of a cutting tool in a green manufacturing environment:** Efficient utilization of cutting tool and optimisation of process parameters is the last objective of this thesis. The optimization strategies should consider the statistical variation in the turning process. At the same time, one should be able to obtain the optimum solution in a simple way.

2.9 Summary

A review of literature was carried out for various aspect related to turning process. Following is the summary of major observations found from the literatures:

1. Surface finish, dimensional deviation, tool wear *etc* are the major performance parameters of turning process. Researchers have carried out different experimental studies using a variety of cutting tools and work piece materials. In most of the experiments, the turning process is carried out either with dry or wet or using minimum quantity of liquid as coolant. Cutting force, vibration *etc.* are some other important performance parameters, which have a direct relation with tool wear, surface roughness, work piece deflection *etc.* From the literature, it is seen that most of the researchers have tried to establish a correlation between machining performances with process parameters with the help of experimental data.
2. Modelling of machining process is a century old method with the pioneering work of Taylor [1907]. Taylor's empirical model relates cutting speed and tool life, which gives an average prediction. The first physics based model was introduced by Ernst and Merchant [1941] in an orthogonal machining. Since then, several mathematical models have been developed in turning for obtaining the optimum machining parameters.

Some of the important mathematical models used in metal cutting are multiple regression method, response surface method, FEM *etc.*

3. In general, there are large amount of statistical variation during data generation in an experimental study of turning process. Several researchers have carried out statistical analysis of the experimental data along with the mathematical modelling.
4. Application of soft computing techniques in machining has been reviewed in this chapter. Many of the researchers have incorporated soft computing techniques for the prediction of surface finish, dimensional deviation tool wear, tool life, cutting forces *etc.* in turning process. Some of the important soft computing techniques used by researchers are neural networks (NN), fuzzy systems (FS), evolutionary computation (EC), swarm intelligence (SI), genetic algorithm (GA), ant colony optimization (ACO), simulated annealing (SA) *etc.*
5. Nowadays, protection of environment during machining is a serious concern for researchers, environmentalist and industrialist. Literature review reveals that there is some awareness for the green engineering and green manufacturing. The concept of green engineering is the design, commercialization and use of processes and products, which are feasible and economical in the minimization of pollution at the source and protection to human health and the environment. Use of cutting fluid in machining is the major harmful object for the operator. Researchers are trying to minimize the use of cutting fluid for the safety of human and environment.
6. Study of literature reveals that various optimization techniques have been used for the turning process optimization. Both traditional and non-traditional algorithms have been used where minimum unit production cost, maximum production rate and maximum profit rate are considered as major objectives.

Some challenging issues have been identified. Finally, the scope and objectives of the thesis are presented.

Comparative Study of Dry and Air-cooled Turning with HSS, Carbide, Ceramic and CBN Tools

3.1 Introduction

Selection of proper cutting tool for turning of a material is of utmost importance. The objectives are to have minimum surface roughness, maximum tool life and maximum production rate. High-speed steel (HSS) tool is conventionally used as a traditional tool in most of the organizations for cutting different materials. Of late, cemented carbide tool, coated carbide tool, ceramic tool, cubic boron nitride tool are used mostly in the industries for better productivity and good quality. Initially, a series of experiment was conducted on grey cast iron with HSS and non-coated carbide tool in dry cut condition to make a comparative study for various cutting performances. Full factorial design was employed for selecting the operating conditions. From the study, it was found that the performance of non-coated carbide tool is better in terms of surface finish and tool life compared to HSS tools.

Another series of experiments with coated carbide tool was carried out on commercially available mild steel. The experiments were conducted for both dry and air-cooled conditions and the performances of coated carbide inserts were studied considering the parameters of surface roughness, tool wear and cutting forces. Full factorial design was employed with a number of replicates.

Alumina-based ceramic cutting tools are attractive alternatives to carbide tools for the machining of steels and cast irons, because of their higher hot hardness [Sadasivan and Sarathy, 1999]. Two main types of these ceramics are pure/white oxide ceramic and mixed/black oxide ceramic. White oxide ceramic containing Al_2O_3 with sintered additives and without metallic binder phase is relatively brittle. Its toughness can be improved by embedding of fine zirconia (ZrO_2) particles by an

amount of 3–5% into the aluminium oxide matrix. Such a ceramic is called dispersion ceramic. White oxide ceramic is used in rough machining of grey cast iron, nodular cast iron and chilled cast iron. Besides aluminium oxide, the black oxide ceramic contains titanium oxide and/or titanium carbonitride in the order of about 30% by weight. It is generally used for machining of hard materials and finish machining of cast iron. Compared to carbide tools, ceramic tools are expensive. Therefore, in order to manufacture the goods at competitive price, the proper selection of the cutting tool as well as cutting parameters is of utmost importance. A good tool may produce poor performance, if the operating conditions are not proper. The performance of a cutting tool is judged mainly by machining speed, tool life and quality of the machined surface. A comparative study was carried out to study the performance of dry and air-cooled turning of a grey cast iron with mixed oxide ceramic tool. The surface roughness of the machined surface, tool wear, cutting forces and vibrations are the parameters, which have been studied. It has been observed that at high speed, air-cooling is quite advantageous, where the dry turning provides a very low tool life.

The cubic boron nitride (CBN) is significantly harder material compared to ceramic or coated carbide tool. It is used to do machining on hard material due to its properties of chemical inertness, stability at high temperatures, hot hardness *etc.* The basic material of CBN is hexagonal boron nitride (HBN), which is converted to CBN grits by using a solvent catalyst under a high pressure and temperature. The structure of CBN does not change to hexagonal boron nitride below 1200°C at atmospheric pressure. CBN is used as a solid insert consisting of an upper layer of CBN laid onto a hard metal base (usually titanium nitride, TiN). Sometimes CBN is brazed on to a corner of a hard metal indexable insert. The main application of CBN tool is for machining of hardened steels of 45–68 HRC. Normally, these types of materials are ground rather than machined. However, when large amount of material is to be removed, machining with CBN proves to be economical. Machining of material with hardness less than 45 HRC with CBN does not prove to be economical as carbide and ceramics can also do the same machining without any significant difference in wear. Experimental work was carried out to study the turning of H13

steel with CBN tool with and without air-cooling. The effect of forced air-cooling on surface roughness of the job, tool wear and cutting forces was investigated. The observations indicate the effectiveness of environment-friendly air-cooling.

3.2 Experimental Procedure

3.2.1 Experimental Set-up

The experiments on turning were conducted on a high speed precision lathe of make HMT, model NH-26. A 3-phase 11 kW induction motor drives the spindle of the lathe. The machine provides 23 speeds between 40–2040 rpm and 27 different feeds ranging from 0.04 to 2.24 mm/rev. Compressed air was generated in a single stage air-cooled compressor of make: Ingersoll Rand India Ltd. The air was dried and delivered through a nozzle of diameter 5 mm at a pressure of 2 bars. The velocity of airflow was approximately 150 m/sec and air temperature was about 2°C less than the ambient temperature. Initially, the nozzle of air jet was adjusted with reference to the cutting tool by measuring the temperature of job on trial and error method. Even, opinions of expert operator were also taken for the location. Finally, the jet impinged on the tool-work interface at about 45° to the longitudinal direction.

The cutting forces were measured using a piezoelectric type 4-component dynamometer (Kistler make, type 9272), which was fitted on the tool holder. It has a threshold of 0.01 N in the measurement of forces in feed & radial direction and 0.02 N in the measurement of force in vertical direction. It has a linearity of $\pm 1\%$ of full-scale output. For measuring the centre line average (CLA) surface roughness values (R_a), Pocket Surf (Mahr, GMBH) was used. Its measuring range is 0.03–6.35 μm and accuracy is 0.01 micron. The surface roughness evaluation length in each case was kept as 2.4 mm. The flank wear was measured under an Optical Microscope (Axiotech^{vario} 100 HD, make: Carl Zeiss) of magnification range 5X to 200X and supported with KS-300 software for measurement of wear accurately. Two numbers of accelerometers (type 4396, sensitivity 10 mV/m/s², frequency 1Hz to 14 kHz, Make: Bruel & Kjaer) were connected on the tool holder of the lathe to measure the

vibrations in the radial and feed directions. These accelerometers were connected to a dynamic signal analyzer (Model: Single 3560D, Make: Bruel & Kjaer), which in turn was connected to the computer for taking the data with the help of B&K software, Pulse. The hardness of different cutting materials was measured by Brinells hardness tester and Rockwell hardness tester of make: Bluestar. Figure 3.1 shows a sketch of the experimental set up and Figure 3.2 (a) and 3.2 (b) shows the photograph of the different equipment used in actual machining process.

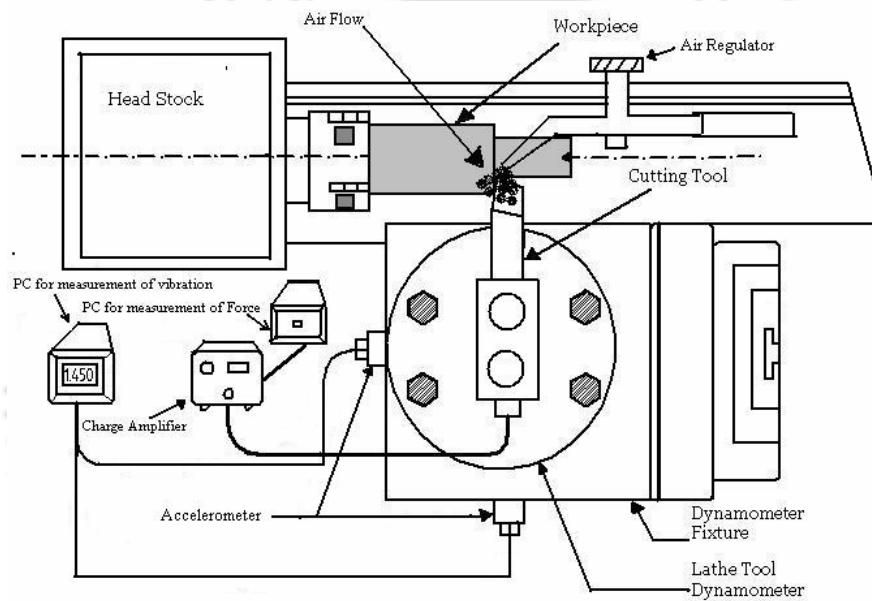
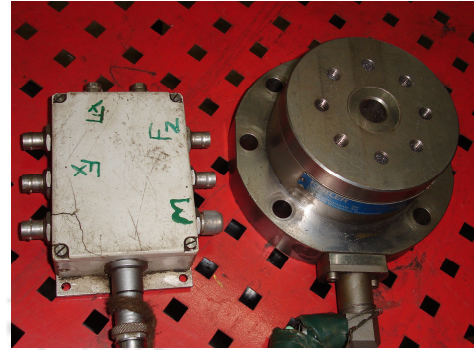
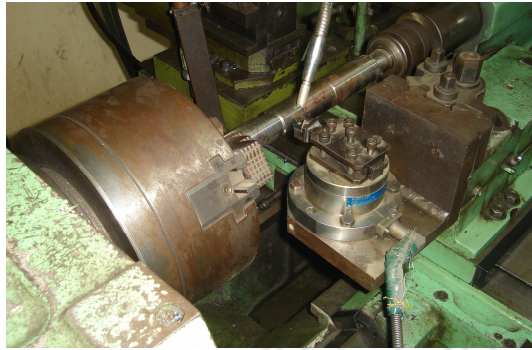


Figure 3.1. Sketch of experimental set up

3.2.2 Workpiece Materials

Following are some of work piece materials used for the turning operations.

(a) Grey cast iron: Most of the grey cast iron pieces were round bar of various diameters ranging from 50 to 100 mm. The length of each stock was 220 mm. The chemical composition for the cast iron includes carbon, silicon, manganese, sulphur and phosphorus. These were analyzed by Bureau of Indian Standard (BIS) method (IS: 228). The different chemical compositions and mechanical properties are listed in Table 3.1. Figure 3.3 shows the Scanning Electron Microscope (SEM) picture of the grey cast iron that is polished to show the darker flakes against the lighter background of the metal



Chuck, job, dynamometer with tool holder 4-component dynamometer



High speed precision lathe for conducting different turning operations

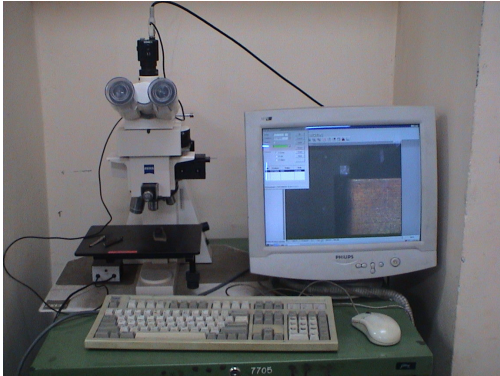


Air compressor



Different kinds of tool holders with inserts

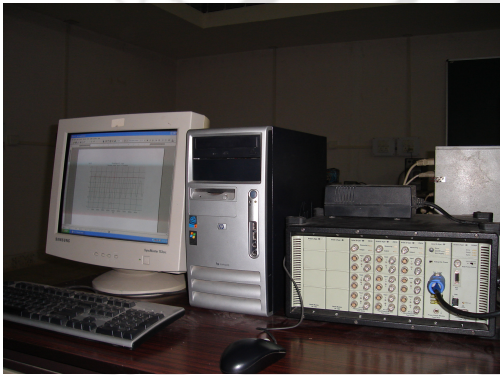
Figure 3.2 (a). Equipment used in turning operation



Optical microscope for measurement of Flank wear



Charge meter for measurement of forces



Dynamic signal analyzer for measurement of vibration



Surface roughness measuring instrument



Rockwell hardness tester



Brinell's hardness tester



Tool maker's microscope

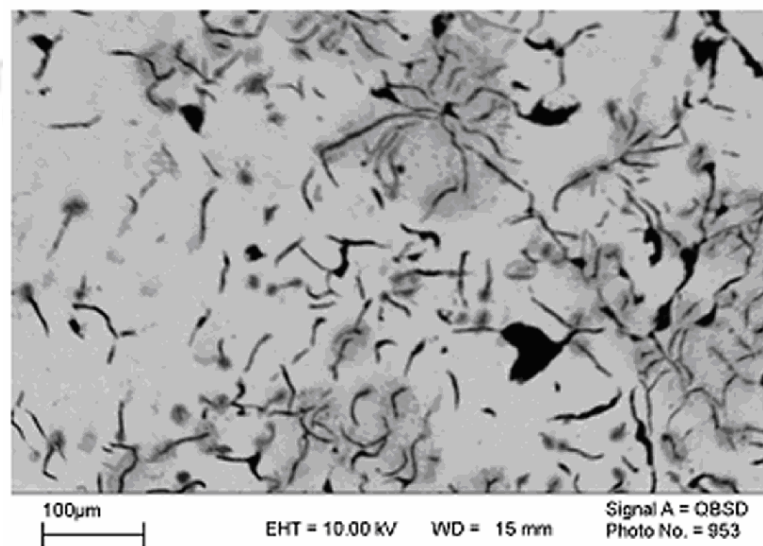
Figure 3.2 (b). Different measuring instruments used in turning operation

Table 3.1. Chemical composition and mechanical properties of grey cast iron

Work material	Chemical composition (%)				
	C	Si	Mn	S	P
Grey cast iron	3.2 approx	1.8	0.36	1.8	0.05
Hardness	143 BHN				
Tensile strength	86 MPa				
Compressive strength	512 MPa				

(b) Mild steel: Rolled mild steel containing 0.35% carbon was used for turning. The hardness of the work piece was 130 BHN, yield strength 290 MPa and ultimate tensile strength 477 MPa.

(c) AISI H13 steel: A number of experiments were carried out using AISI H13 hot-worked die steel. The basic composition of AISI H13 steel includes carbon, manganese, phosphorus, sulphur, silicon, chromium, vanadium, molybdenum *etc.* The diameter of the work piece was 75 mm and the length 300 mm. The work-pieces were heat treated at around 1040°C followed by air quenching for increasing the hardness of the material up to 46 HRC.

**Figure 3.3.** Scanning Electron Microscope (SEM) picture of the grey cast iron

3.2.3 Cutting Tools

Following are some of the cutting tools that were used during turning process. The measurements of different tool angles were carried out with tool-makers microscope of make Sipcon.

- (a) High speed steel (HSS) tool: The tool bit which contained 8% cobalt was designated as S200 by make: Miranda. The ASA tool signature was 8-18-20-25-20-25-1.
- (b) Non-coated brazed type carbide tool: Designated as ISO 5R 2525 K20 by make: Miranda. The ASA tool signature was (-10)-16-16-14-9-2-1.
- (c) Coated carbide tool: The TiN coated square shaped carbide inserts was used. The ISO code of the tool was SNMG 1204085 TN2000 of make: WIDIA and ASA tool signature was (-1)-(-1)-6-6-45-45-1.6. The compatible tool holder was R181.3 – 2020M-12 of make: Sandvik Coromant
- (d) Ceramic tool: Mixed oxide triangular ceramic insert of ISO code TNGA 16 04 08T01020 650 of make: Sandvik was used. The ASA tool signature was (-9)-(-5)-7-7-30-1-0.8. The compatible tool holder was PTG NR 2020 K16 of make: WIDAX.
- (e) Cubic Boron Nitride (CBN) tool: CBN 7020 square type insert of make Sandvik was used for turning. The ISO code of the tool was SNGA 090304S1020A. It was a low CBN content material with 60% CBN plus a titanium nitride (TiN) phase in its composition. According to the manufacturer, the tool is a highly wear-resistant material with high chemical stability and suitable for finish operation of hardened steel. The average hardness of the tool is ≥ 2900 HV₃ (Vickers hardness with 3 kg load). The tool holder used for holding the CBN insert is DSB NR 2020K 09 of make Sandvik. The ASA tool signature of the tool was (-6)-(-6)-6-5-12-15-0.4.

3.3 Design of Experiments and Comparative Study

The effects of various cutting factors during experimentation were considered for quantitative study. The experimental design consists of making an observation at

each of all possible combinations that can be formed for the different levels of the factors. The simplest and most common type of factorial design is one that uses the two levels of each factor *i.e.*, a 2^n factorial design. Here the effect of three parameters speed, feed and depth of cut on surface roughness was studied quantitatively. In order to investigate the main effect of these three factors, total $2^3 = 8$ experiments were carried out considering two levels (High and Low) of each the three factors.

Preliminary study was carried out according to full factorial design with a number of replicates. The comparative study of cutting performance was made for both dry and air-cooled turning. However, for HSS and non-coated carbide tool, the study was carried out only for dry turning.

3.3.1 Study of Cutting Performance of HSS Tool and Non-coated Brazed type Carbide Tool

Initially, HSS and non-coated brazed type carbide tool were considered for studying the performance parameter of surface roughness only. The experiments were carried out only in dry cut condition in the following ranges of speed, feed and depth of cut:

For HSS tools, the high and low levels of process parameters are, cutting speed: 20–60 m/min, feed: 0.04–0.32 mm/rev and depth of cut: 0.5–1.5 mm. For non-coated carbide tool, the high and low levels of process parameters are, cutting speed: 30–250 m/min, feed: 0.04–0.32 mm/rev and depth of cut: 0.5–1.5 mm

Experiments were conducted using cast iron material as work-piece and each test was conducted with a new cutting edge. The cutting was carried out for a length of 100 mm and the surface roughness were measured at several points and the average value was recorded. Table 3.2 shows different operating conditions of HSS tool along with the average R_a value for each cutting condition. The results of surface finish show that HSS tool cannot give a good surface finish in this operating condition. To see the possibility for obtaining a better surface finish, more experiments were conducted in different cutting condition within the same cutting ranges as shown in Table 3.3. However, the obtained surface roughness was more than 2.42 micron. It has been observed that, in some cutting combinations, the surface finish reaches nearly 6 micron corresponding to N9 finish.

Table 3.2. Operating conditions of HSS tool in dry turning with average R_a

v m/min	f mm/rev	d mm	R_a (μm)
20	0.04	0.5	3.42
20	0.04	1.5	3.40
20	0.32	0.5	5.79
20	0.32	1.5	5.49
60	0.04	0.5	2.81
60	0.04	1.5	3.03
60	0.32	0.5	5.92
60	0.32	1.5	5.70

Table 3.3. Additional experiments on HSS tool with average R_a during dry turning

v m/min	f mm/rev	d mm	R_a (μm)
22	0.08	1.2	4.07
34	0.12	0.6	3.06
53	0.20	1.0	4.87
46	0.28	1.3	5.70
42	0.16	1.3	5.89
37	0.16	1.3	3.19
47	0.05	0.9	2.42
35	0.06	0.6	3.21
27	0.07	1.0	4.33
48	0.10	1.1	3.57
53	0.12	0.8	3.40
39	0.14	0.7	3.70
55	0.24	1.2	5.88
50	0.08	1.0	2.75

Next, the experiments were carried out for studying the surface finish in turning of cast iron with non-coated carbide tool. Similar to the HSS tool, high and low level of process parameters were considered as shown in Table 3.4. The surface roughness values corresponding to different cutting conditions have been shown in the table.

It is observed that surface finish obtained in turning with non-coated carbide tool for the conditions shown in Table 3.4 is very poor and is always more than 2.22 micron. Hence, more experiments were conducted with non-coated carbide tool considering different cutting combination as shown in Table 3.5. This time, the resultant surface finish is found to be better than the results given in Table 3.4. For a combination of medium speed and low feed, non-coated carbide tool gives a good surface finish of around 1.84 micron. In general, carbide tool can operate at relatively higher feeds at reduced cutting speeds for obtaining better surface finish.

Table 3.4. Operating conditions of non-coated brazed type cutting tool in dry turning along with average R_a

v m/min	f mm/rev	d mm	R_a (μm)
30	0.04	0.5	3.78
30	0.04	1.5	3.46
30	0.32	0.5	4.74
30	0.32	1.5	4.42
250	0.04	0.5	3.28
250	0.04	1.5	2.22
250	0.32	0.5	4.64
250	0.32	1.5	4.66

Table 3.5. Additional experiments on non-coated carbide tool during dry turning

v m/min	f mm/rev	d mm	R_a (μm)
36	0.08	0.9	3.40
45	0.12	0.7	3.68
126	0.20	1.1	5.14
42	0.24	0.9	4.46
187	0.16	0.8	1.98
70	0.05	1.2	3.69
193	0.06	0.7	2.82
145	0.07	1.3	3.71
236	0.10	0.8	2.85
80	0.12	1.1	4.18
124	0.14	0.6	3.02
103	0.16	1.0	2.48
152	0.08	1.4	1.84
207	0.28	1.2	5.57

3.3.2 Study of Cutting Performance of Coated Carbide Tool

A number of experiments were carried out to find out the range of process parameters to predict surface finish in machining mild steel with coated carbide tool. The experiments were conducted for both dry and air-cooled cutting conditions and the performance of coated carbide insert was studied considering the parameters of surface roughness, tool wear and cutting forces. Full factorial design was employed with a number of replicates. Based on the study of literature and recommendation of manufacturer, the following ranges were chosen— cutting speed: 150–300 m/min, feed: 0.1–0.32 mm/rev and depth of cut: 1–3 mm. Two-level full factorial design corresponding to 3 process parameters gives 2^3 i.e., 8 experiments as shown in Table 3.6.

Table 3.6. Operating conditions in turning of mild steel with coated carbide tool

Experiment No.	Cutting speed, (m/min)	Feed, (mm/rev)	Depth of cut (mm)
1	150	0.1	1
2	150	0.1	3
3	150	0.32	1
4	150	0.32	3
5	300	0.1	1
6	300	0.1	3
7	300	0.32	1
8	300	0.32	3

In each cutting condition, a number of replicate experiments were carried out based on which the average performance of dry and air-cooled turning has been studied. New cutting edge was used for every cutting condition and a length of 100 mm was turned in one pass after which the tool wear and surface roughness were measured. The cutting times for different experiments were different depending on the feed and cutting speed.

Figure 3.4 compares the surface roughness for dry and air-cooled turning for eight different cutting conditions. Over 100 mm of machined length, the surface roughness was measured at 9–12 places and the mean values were calculated. These are plotted in Figure 3.4. Figure 3.4(a–d) represents the machining at lower speed and Figure 3.4(e–h) represents the machining at higher speed. In most of the cases, surface finish is found almost equal for both dry and air-cooled turning in all the cutting conditions. In some cases, there is a difference in surface roughness obtained in air-cooled and dry turning values. Increased temperature in metal cutting softens the material, but increases the tool wear. These have two opposing effects on metal cutting performance in general and surface roughness in particular. The net result depends on the relative influence of these opposing factors.

Figure 3.5 compares the progression of flank wear for dry and air-cooled turning. It is observed that at high cutting speeds (Figures 3.5 (e–h)), air has played a significant role in reducing the flank wear. However, at low cutting speeds (Figures 3.5 (a–d)) no-significant effect of air-cooling is seen. During low cutting speed heat generation is low and the effect of air cooling is marginal. In turning of mild steel with coated carbide tool, no crater wear has been observed during dry turning at high cutting speed.

Figures 3.6 and 3.7 depict the variation of cutting force and feed force with respect to cutting time for eight different cutting conditions. It is observed that in most cases, the value of cutting force or feed force is almost equal for both air-cooled and dry turning. Thus, no special effect has been seen for air-cooled turning. Comparing the cutting force with feed force for same cutting condition, the cutting force is found more than the feed force. It is a general phenomenon that cutting force is higher than the feed force. Indirect measurement of tool wear by cutting force or feed force may be employed during machining by coated carbide tool.

From this study it can be concluded that, air-cooled turning plays a vital role in reduction of tool wear at high cutting speed. However, the surface finish is found to be slightly better in air-cooled turning than in dry turning at low cutting speed. Seeing the overall performance, air-cooling may be used as an alternative to cutting fluid in machining.

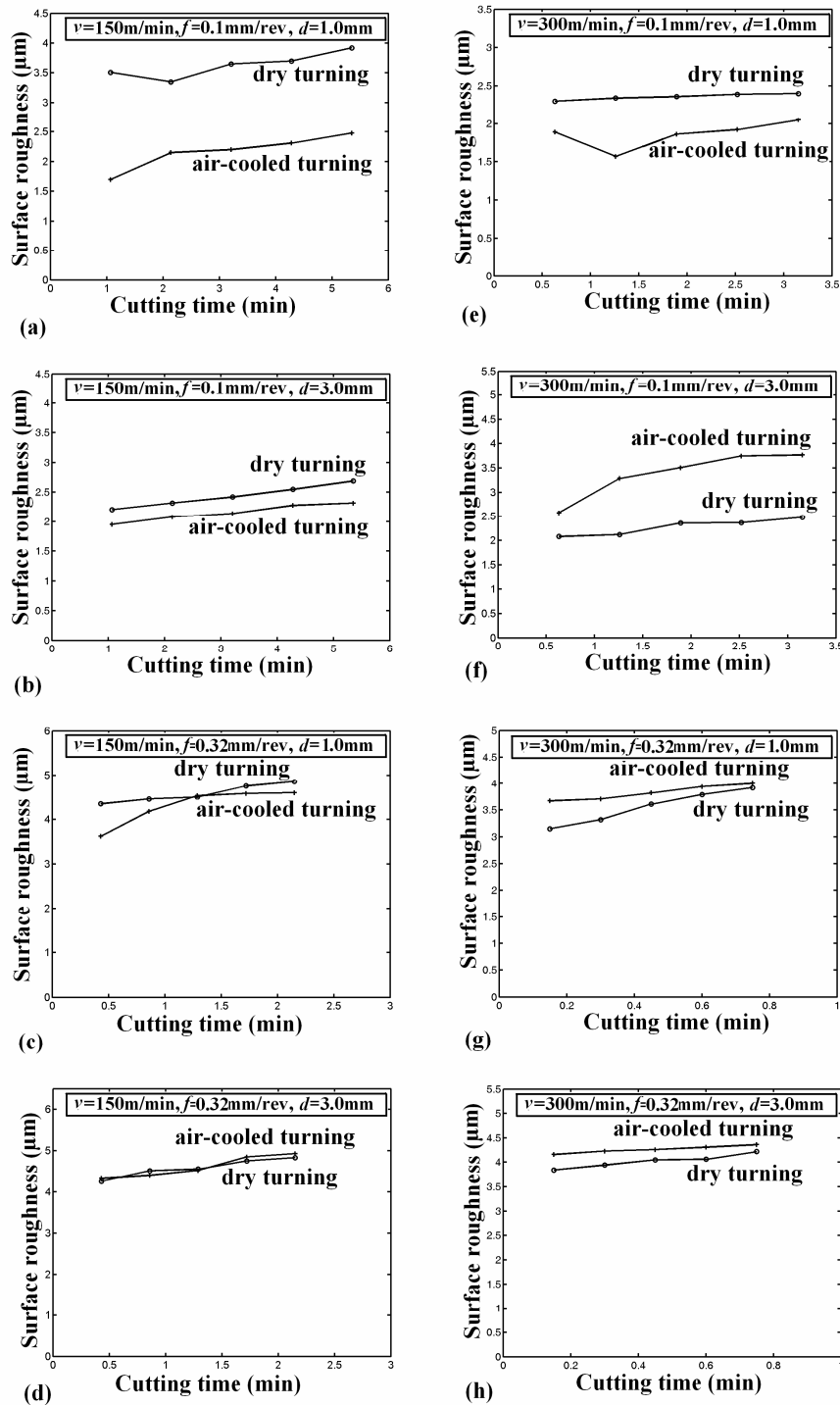


Figure 3.4. Variation of surface roughness with cutting time in turning of mild steel with coated carbide tool

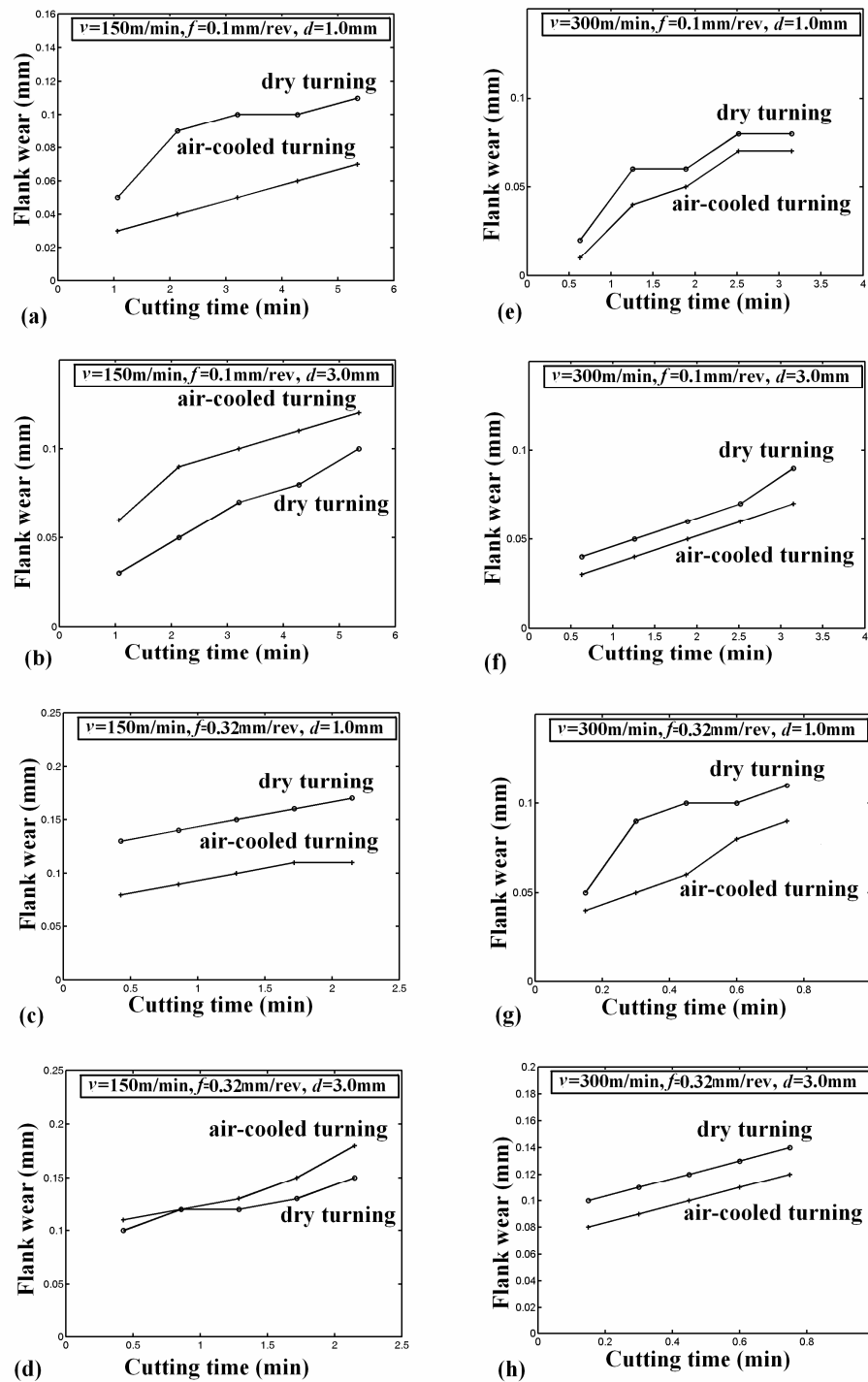


Figure 3.5. Variation of flank wears with cutting time in turning of mild steel with coated carbide tool

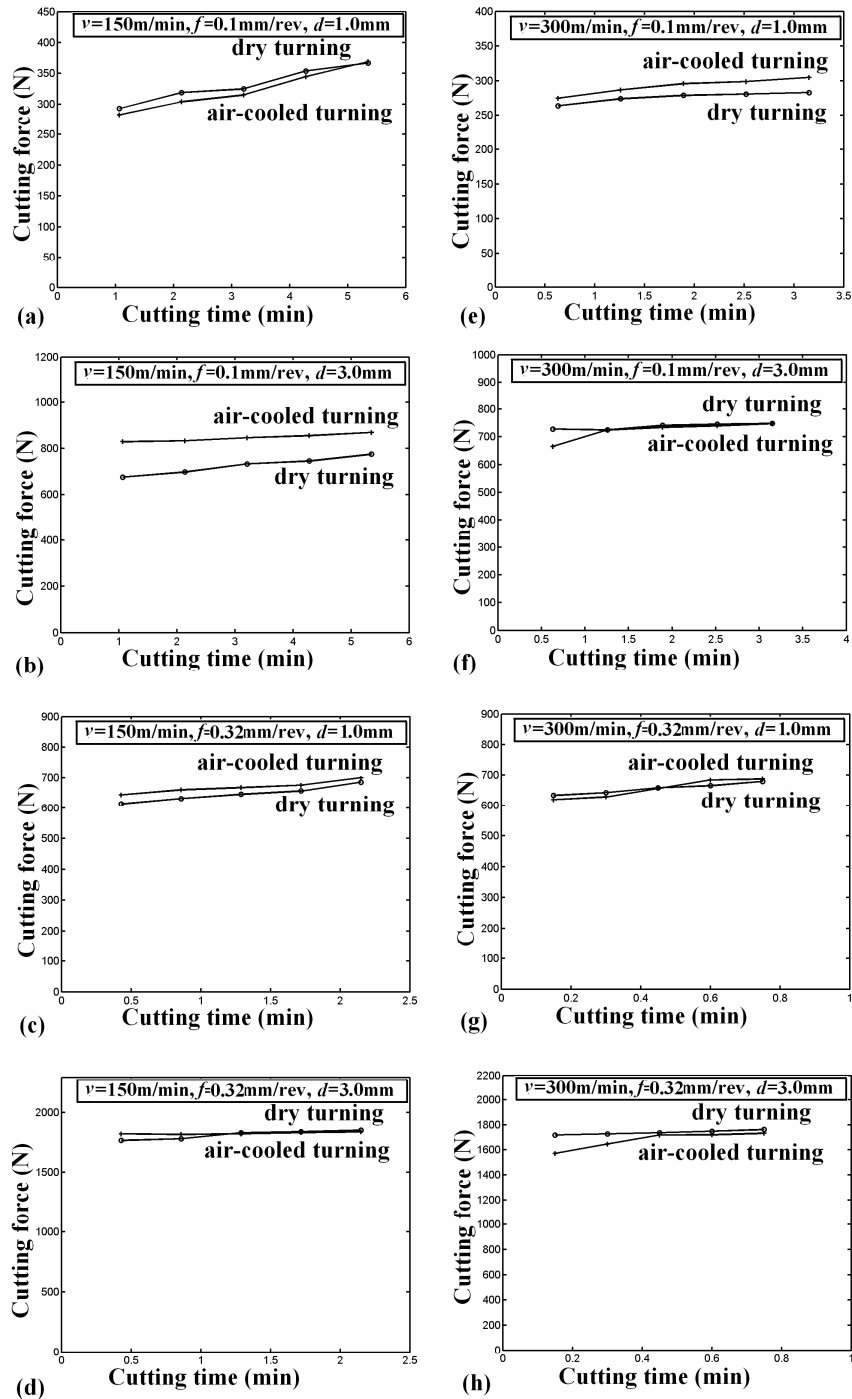


Figure 3.6. Variation of cutting force with cutting time in turning of mild steel with coated carbide tool

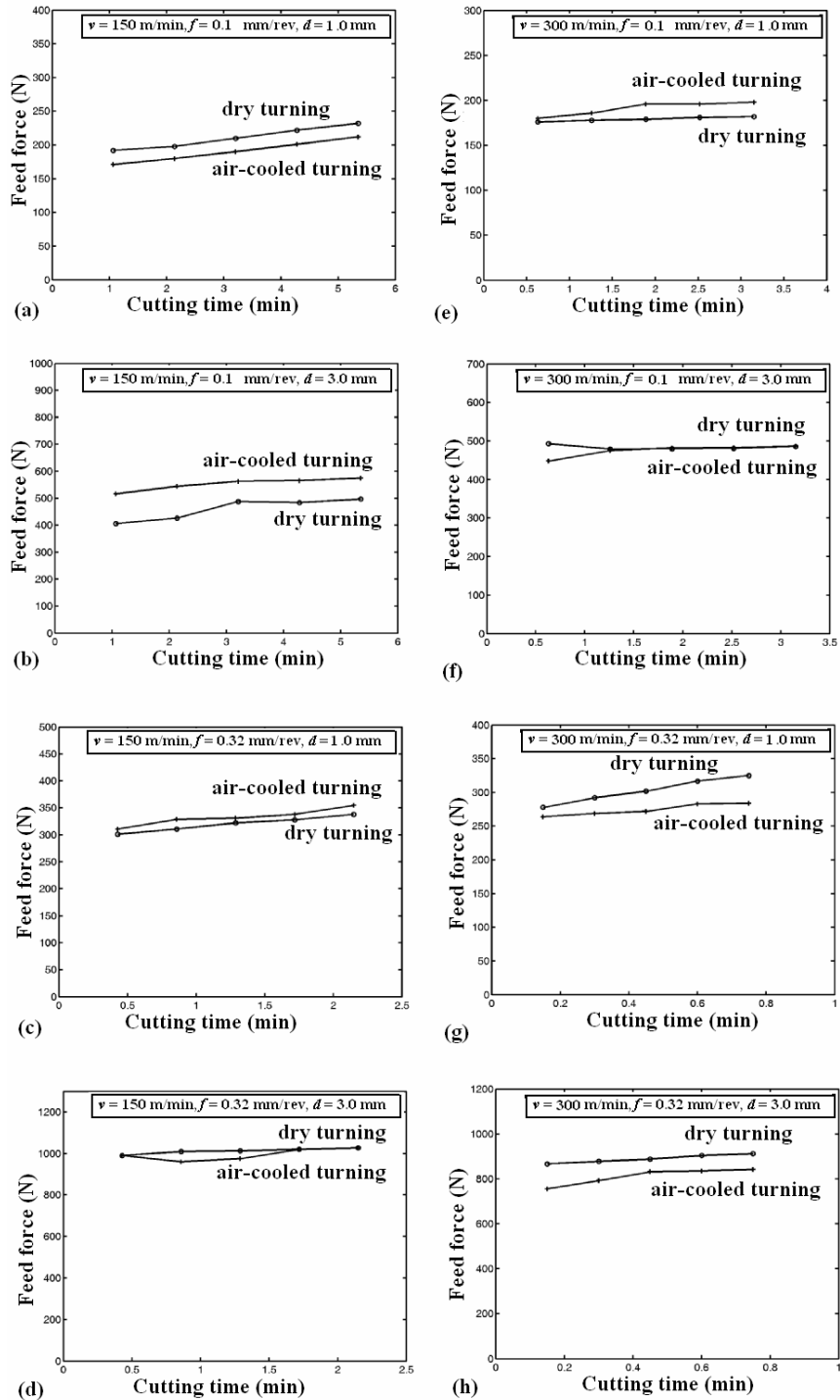


Figure 3.7. Variation of feed force with cutting time in turning of mild steel with coated carbide tool

3.3.3 Study of Cutting Performance of Ceramic Tool

3.3.3.1 Cutting performance of ceramic tool at high cutting speed using dry and air-cooled turning

The manufacturer recommends the cutting speed for mixed-oxide ceramic tool in the range of 500–670 m/min for turning of cast iron. Due to limitation of machine spindle speed, initially, a series of experiments were conducted for ceramic tool in the speed range of 480–600 m/min. The machining was carried out in both dry and air-cooled condition. The cutting speed (v), feed (f) and depth of cut (d) were taken as two-level factors using a full factorial design. Table 3.7 shows the different operating conditions.

Table 3.7. Operating conditions in turning of grey cast iron with ceramic tool at high cutting speed

Experiment No.	Cutting speed, (m/min)	Feed, (mm/rev)	Depth of cut (mm)
1	480	0.04	0.5
2	600	0.04	1.5
3	600	0.32	1.5
4	480	0.04	1.5
5	480	0.32	1.5
6	600	0.32	0.5
7	600	0.04	0.5
8	480	0.32	0.5

Each test was conducted with a new cutting edge and machining was stopped at a cutting length of 100 mm. The time was recorded for each cut. The vibration signals and cutting forces were measured during cutting operation. The maximum flank wear and surface roughness were measured after completion of each pass.

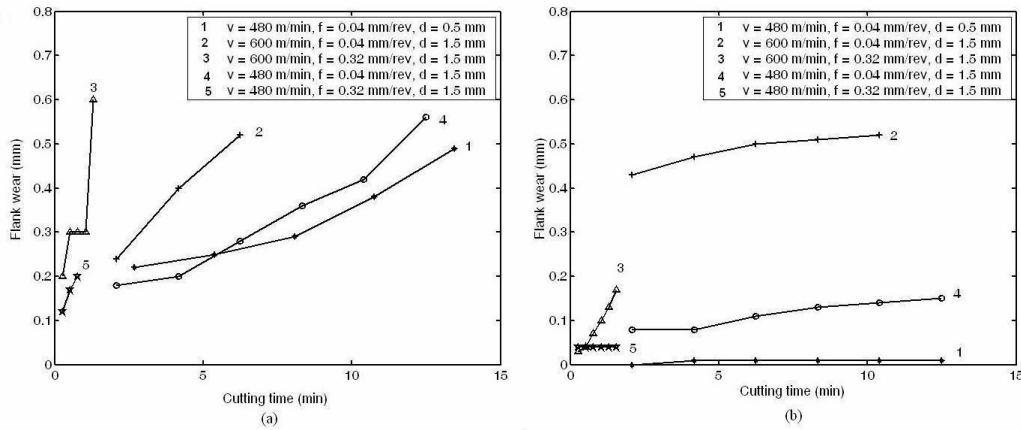


Figure 3.8. Progression of tool flank wear with cutting time: (a) dry turning (b) air-cooled turning of grey cast iron with ceramic tool at high cutting speed

Figure 3.8 shows the flank wear vs. cutting time for dry turning and air-cooled turning in the first five operating conditions of Table 3.7. During dry turning, crater wear was observed in the last three operating conditions *i.e.*, in experiment numbers 6, 7 and 8 which led to early tool breakage. The surface finish was also found to be very poor at these conditions and a large amount of heat was generated. However, in air-cooled turning, no crater wear was seen in experiment number 7 and combination of crater wear and flank wear were seen in experiment numbers 6 and 8. It indicates that air-cooling plays a vital role in reducing the temperature at high-speed turning on ceramic tool. Both surface finish and tool life were found to be satisfactory in experiment numbers 6, 7 and 8 during air-cooled turning (not shown in figure). For the first five operating conditions, air-cooled turning would provide better tool life as is evident from Figure 3.8(a) and Figure 3.8(b). Also, during dry turning, for conditions 2, 3 and 5, tool breakage occurred after 3-4 passes. However, in air-cooled turning, the tool breakage was not observed up to even 6 passes (each pass consisting of a length of 100 mm), after which the experiment was stopped.

Figure 3.9 shows the variation of surface roughness of the turned component with cutting time for dry and air-cooled turning. It is observed that the surface roughness at operating conditions 3 and 5 is quite high in both dry and air-cooled

turning. These cases pertain to a high feed of 0.32 mm/rev. For the cases, 1, 2 and 4, air-cooling reduce the surface roughness significantly.

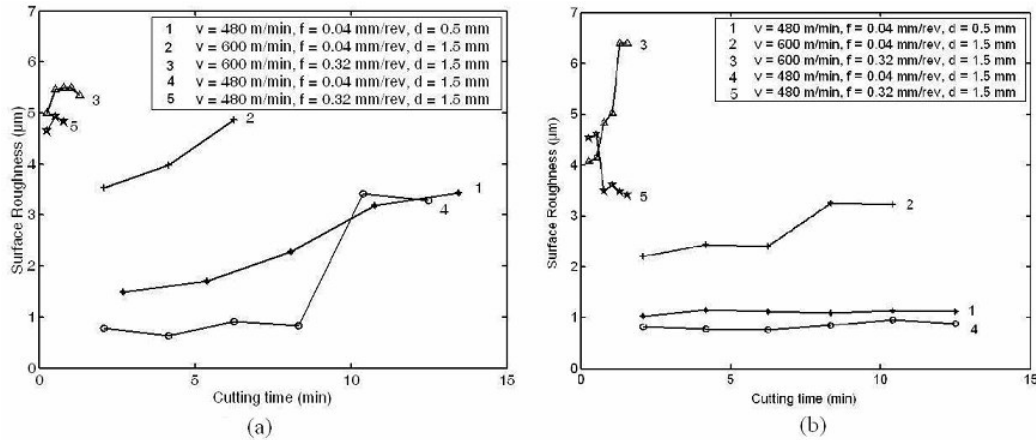


Figure 3.9. Progression of surface roughness with cutting time: (a) dry turning (b) air-cooled turning of grey cast iron with ceramic tool at high cutting speed

For the conditions 1 and 4, which pertain to cutting speed of 480 m/min and feed of 0.04 mm/rev, a very low and almost constant surface roughness was observed in air-cooled turning. Tool wear was also very low in these conditions. This shows that in high-speed turning, the air-cooling improves the surface roughness as well as tool life apart from the reduction in cutting forces.

Thus, it is seen that high speed turning of grey cast iron with mixed alumina ceramic tools provides a low tool life. This observation is in line with the observations of Ghani *et al.* [2002] for high speed turning of nodular cast iron by mixed alumina ceramic. However, air-cooled turning provides an enhanced tool life and may be adopted by industries for high speed machining by ceramic tools.

3.3.3.2 Study of cutting performance of ceramic tool at medium cutting speed using dry and air-cooled turning

In the previous sub-section, a series of experiments were conducted for ceramic tool in the speed range of 480–600 m/min. However, in this range excessive tool wear was observed, the tool life ranging between 2–15 minutes. Moreover, due to tool wear, the machined surface roughness value reached more than 3 µm after first few turning passes. Therefore, a number of experiments were carried out to find out the

range of process parameters giving a reasonable tool life and surface finish. Based on experimental study, the following ranges were chosen— cutting speed, 100–400 m/min, feed, 0.04–0.16 mm/rev, depth of cut, 1.0–1.5 mm.

Following the factorial design for 2-level and 3 process parameters, a total of 2^3 *i.e.*, eight experiments were carried out as shown in Table 3.8. For each cutting condition, a number of replicate experiments were carried out based on which the average performance of dry and air-cooled turning has been studied (Figures 3.10–3.15). For each cutting condition, a new cutting edge was used and 100 mm length was turned in one pass after which the tool wear and surface roughness were measured. Cutting times for different experiments were different depending on the feed and cutting speed.

Table 3.8. Operating conditions in turning of grey cast iron with ceramic tool at medium cutting speed

Conditions	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)
1	100	0.04	1.0
2	100	0.04	1.5
3	100	0.16	1.0
4	100	0.16	1.5
5	400	0.04	1.0
6	400	0.04	1.5
7	400	0.16	1.0
8	400	0.16	1.5

Figure 3.10 compares the surface roughness for dry and air-cooled turning for eight different cutting conditions. Over a length of 100 mm, the surface roughness was measured at 9–12 places and the mean value was taken. Finally, the mean value of all replicates at a cutting condition was taken and the same have been plotted in Figure 3.10. It is observed that in general the surface roughness is lower at higher

cutting speeds compared to lower cutting speeds. However, at high speed, a combination of low feed and high depth of cut provided a relatively poorer surface finish (Figure 3.10(f)) with air-cooling. It is observed that air-cooling does not improve the surface finish. For one condition (Figure 3.10(f)), air-cooling generated more surface roughness compared to dry turning. At this condition, which is low feed and high depth of cut, air-cooled turning produces more vibrations compared to dry turning.



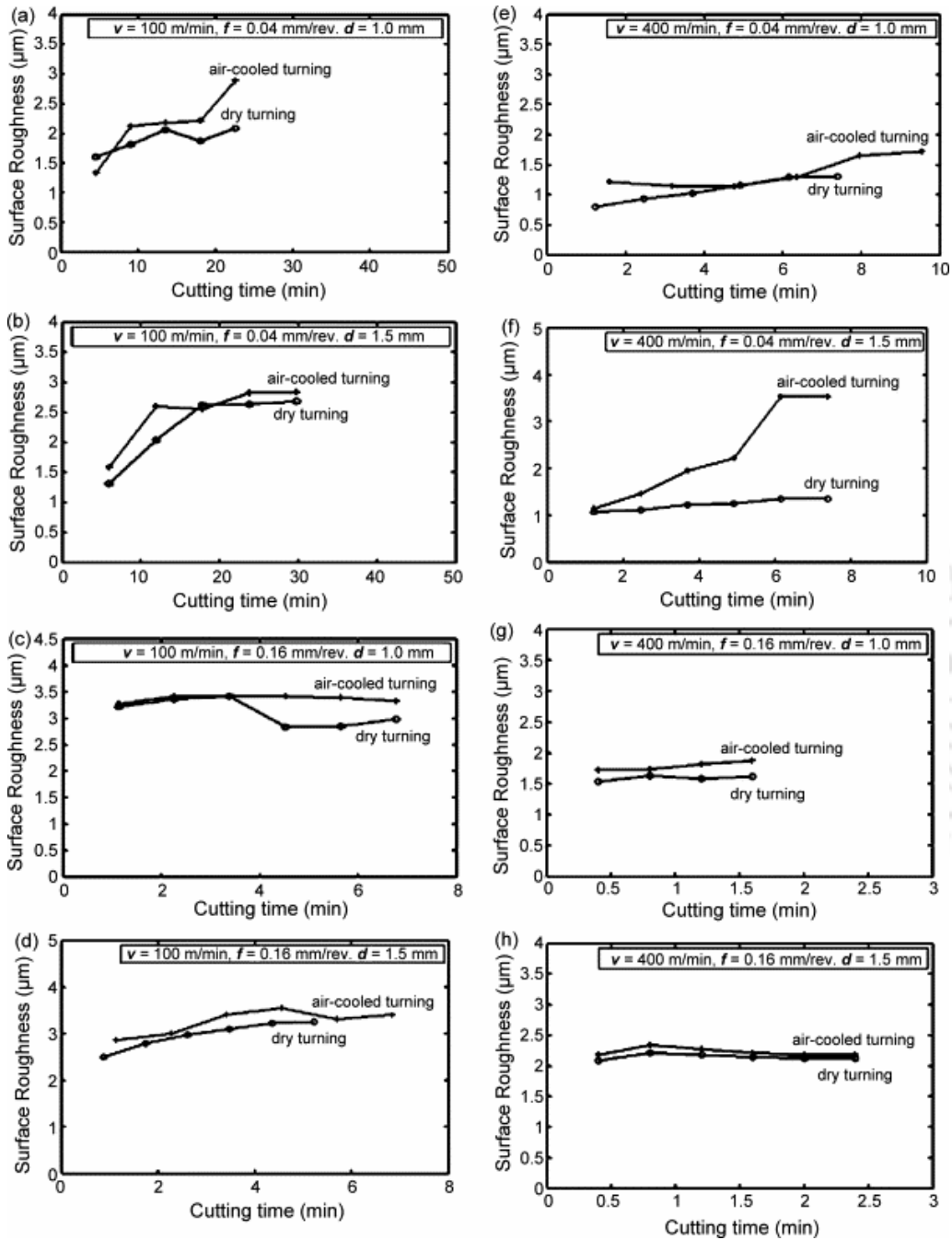


Figure 3.10. Variation of surface roughness with cutting time in turning of grey cast iron with ceramic tool

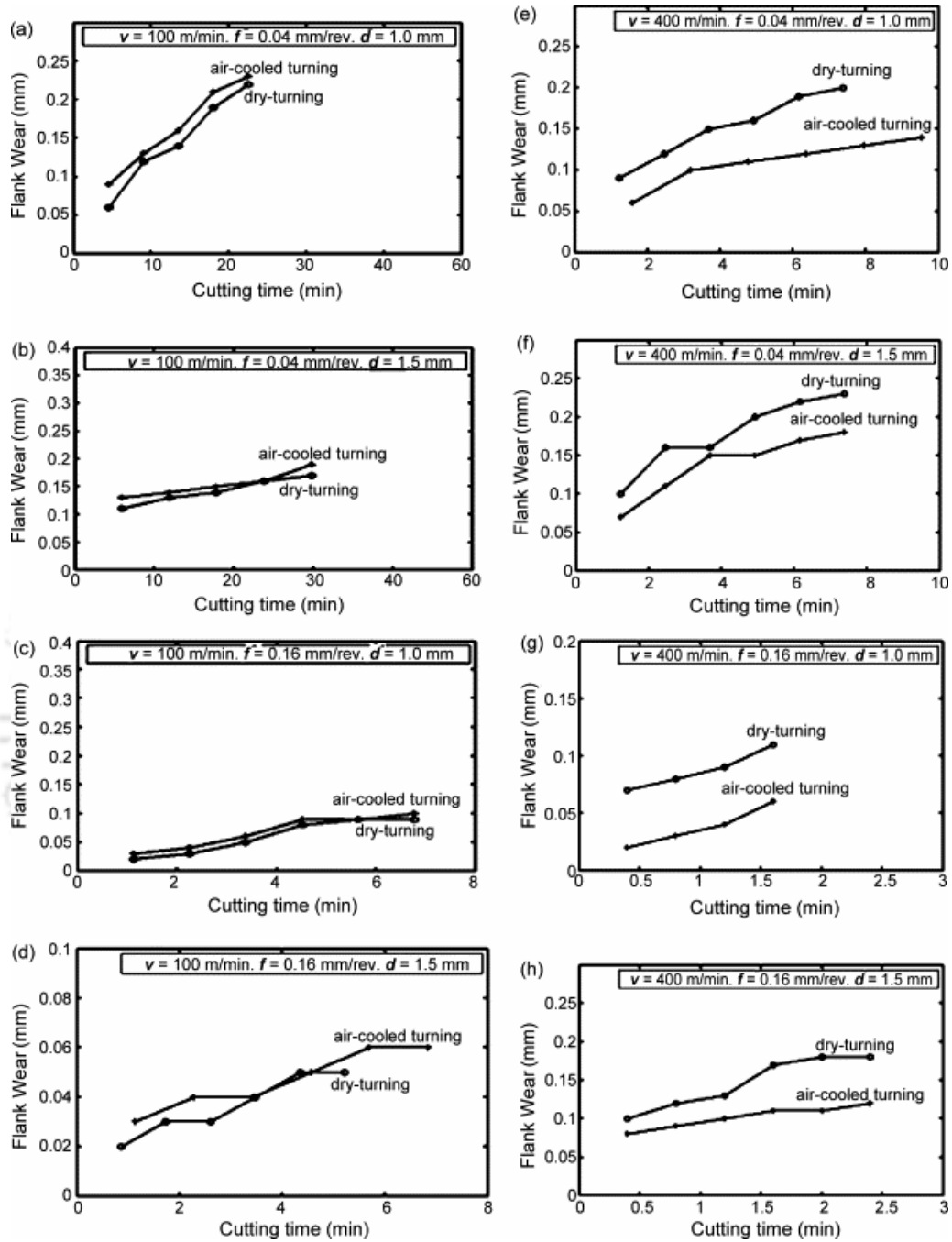


Figure 3.11. Progression of tool flank wear with cutting time in turning of grey cast iron with ceramic tool

Figure 3.11 compares the progression of flank wear for dry and air-cooled turning. It is noted that at high cutting speeds (Figs. 3.11 (e-h)), the air-cooling reduces the flank wear. This is not the case at low cutting speeds (Figs. 3.11(a-d)). In fact, at low cutting speed, for some cases, the air-cooling slightly increases the flank wear. At low cutting speed, the heat generation is low and tool-job temperature is not as high as in high speed machining. Therefore, the forced convective heat transfer is not as effective as in high speed machining and one should not expect any significant reduction in tool wear due to reduction of tool-tip temperature. Instead, sometimes in dry turning at low speed, a slight increase of job temperature causes a slight reduction in tool wear due to softening of the material.

Figure 3.12 shows the variation of main (vertical) cutting force with the cutting time for eight cutting conditions. Interestingly, in some cases of low speed turning, the cutting force in dry turning was found more compared to air-cooled turning, although the tool wear in dry-turning was less than that in air-cooled turning. In all the cases of high speed turning, the vertical cutting force is less in air-cooled turning due to less flank wear.

Figure 3.13 shows the variation of feed force with cutting time for eight cutting conditions. Here, also it is observed that forces in air-cooled turning are lower, although the difference is less pronounced than in the case of cutting force (Fig. 3.12). Unlike cutting force, feed force increases significantly with the progression of cutting particularly at high cutting speed, thus making it more suitable for indirect measurement of tool wear. It is also noted that percentage increase of force due to tool wear is more at low feed than at high feed. This observation is in line with the theoretical analysis of Smithy *et al.* [2000], who showed that for a given tool and work-piece combination, the incremental increase in the cutting forces due to tool flank wear is solely a function of the amount and nature of the wear and is independent of cutting condition in which tool wear was produced. Thus, it may be a good strategy to carry out the indirect measurement of tool wear at low feeds, because the relative effect of wear is more prominent at low feeds.

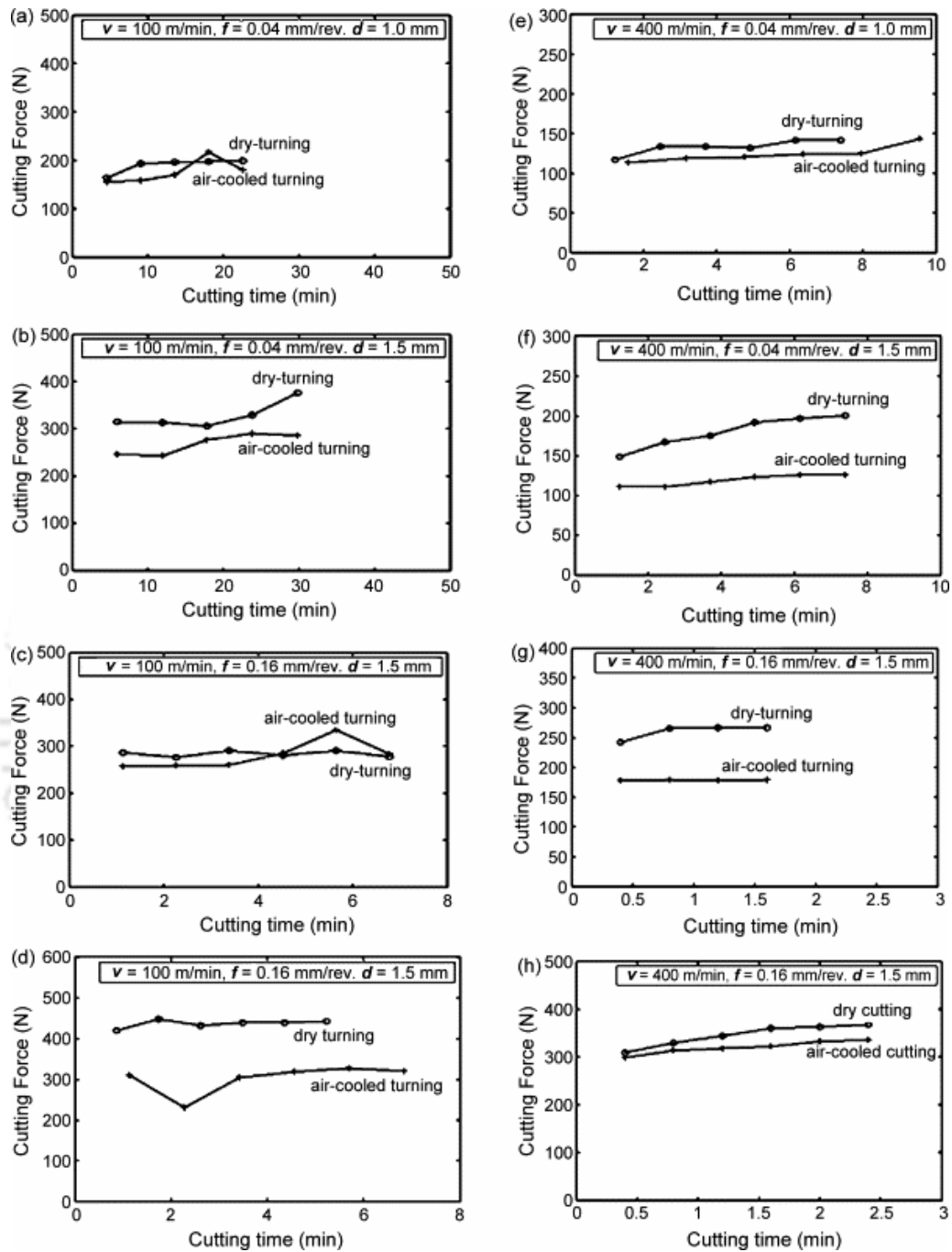


Figure 3.12. Variation of cutting force with cutting time in turning of grey cast iron with ceramic tool

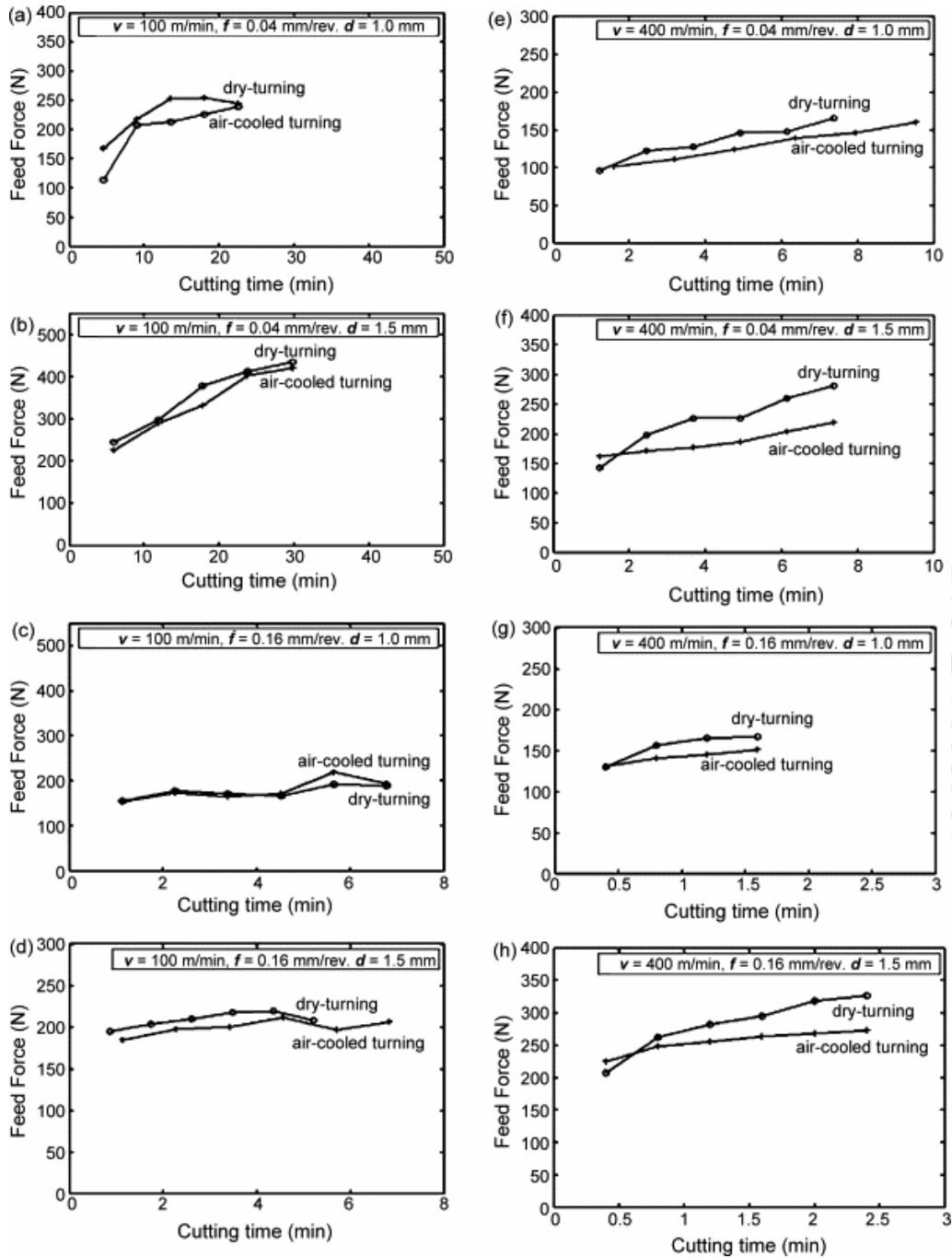


Figure 3.13. Variation of feed force with cutting time in turning of grey cast iron with ceramic tool

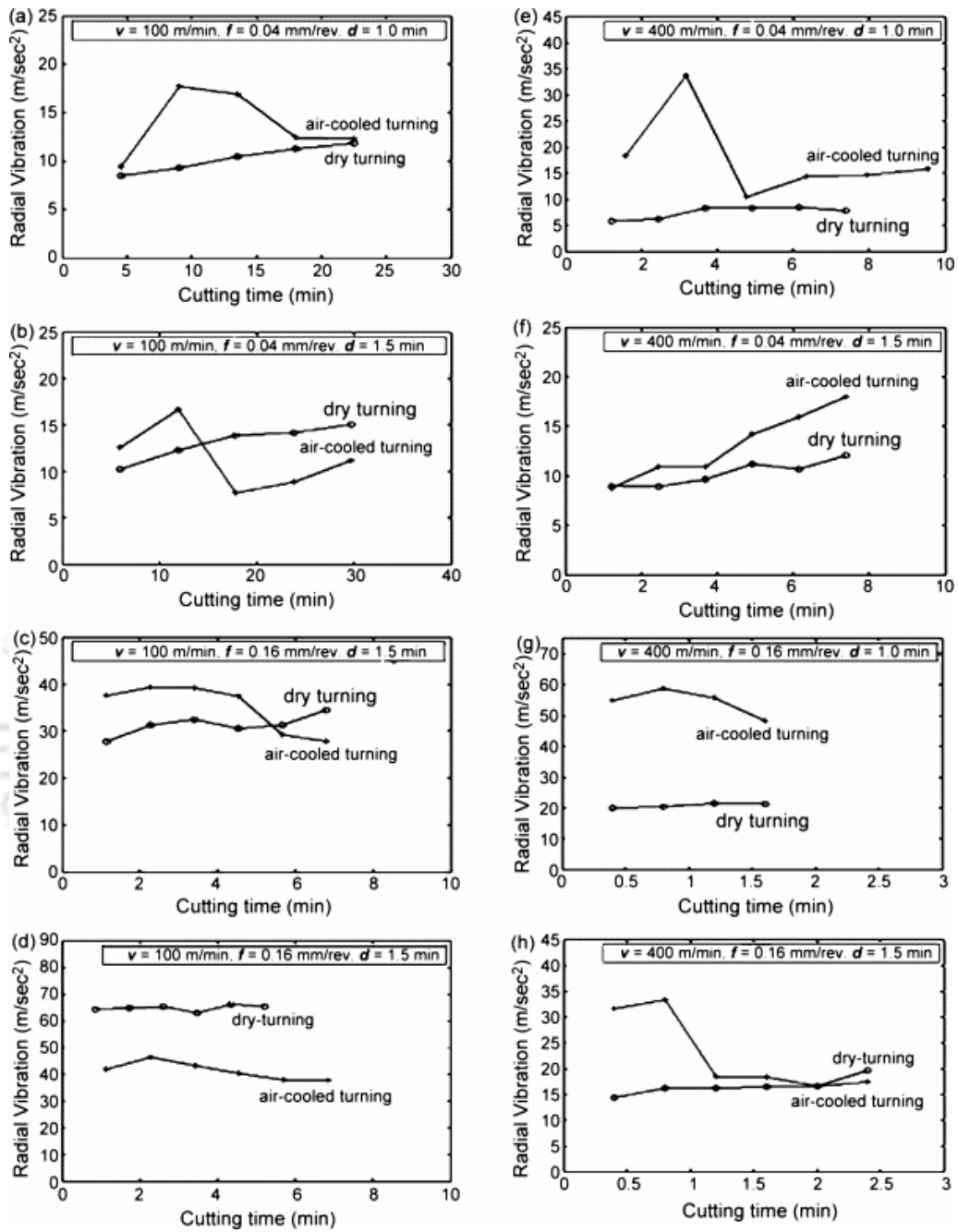


Figure 3.14. Variation of acceleration of radial vibration with cutting time in turning of grey cast iron with ceramic tool

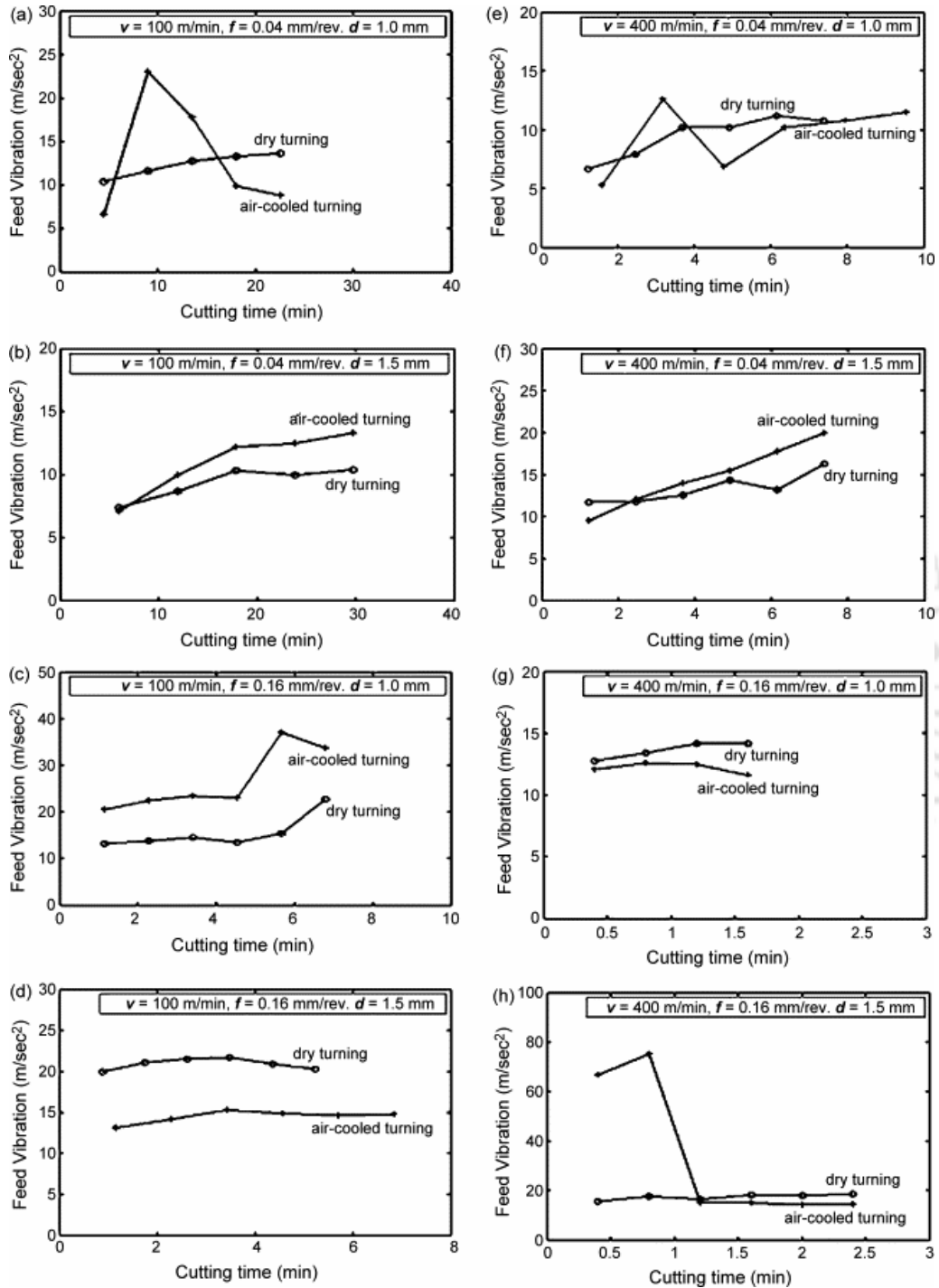


Figure 3.15. Variation of acceleration of feed vibration with cutting time in turning of grey cast iron with ceramic tool

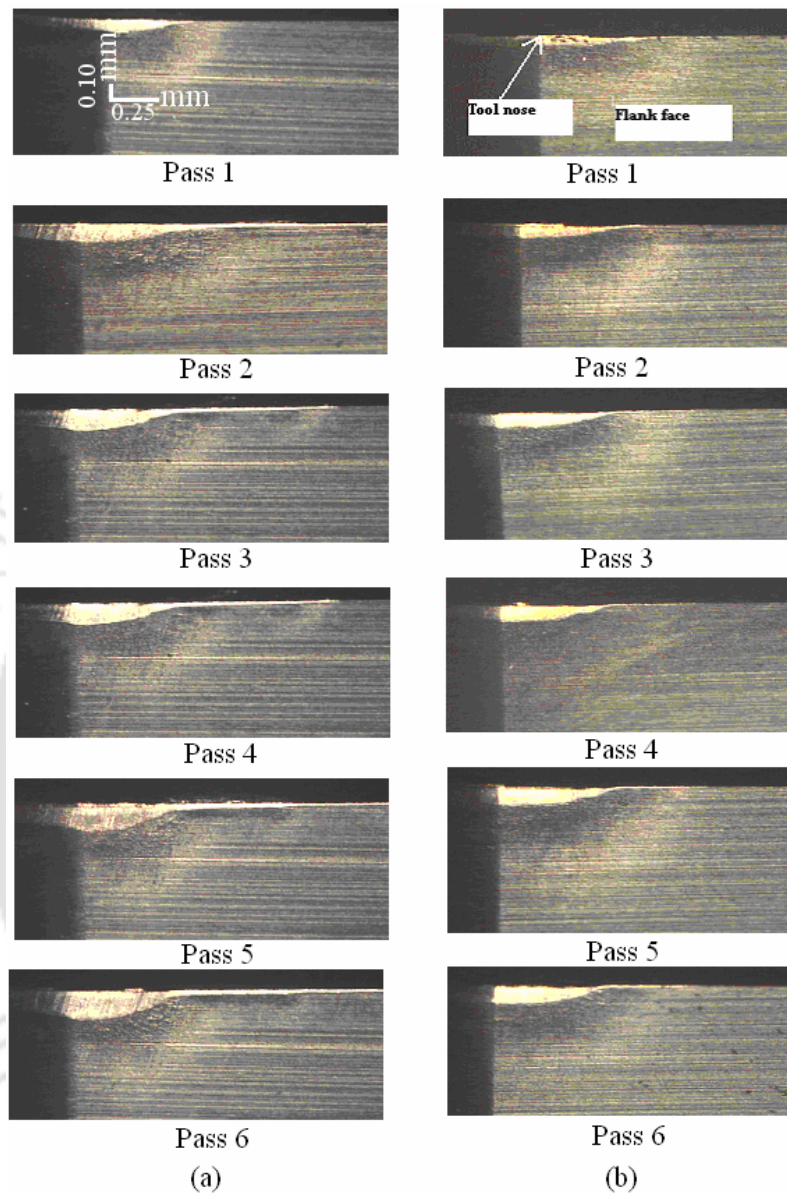


Figure 3.16. Progression of tool flank wear in turning passes: (a) dry turning and (b) air-cooled turning of grey cast iron with ceramic tool

Figures 3.14 and 3.15 show the plot of acceleration of vibrations in radial and feed direction with the change of cutting length. No specific pattern has been observed. In some cases, the vibrations increase with the progression of flank wear, whilst in some cases they decrease. Also there seems to be no correlation between the accelerations of vibration in both the directions. Thus, any inference on the basis of the acceleration of vibration might be deceptive.

The major advantage of air-cooled turning seems to be reduction of tool wear at high speed. Figure 3.16 shows the photographs of the progression of flank wear in dry and air-cooled turning for a cutting condition of speed 400 m/min, feed 0.04 mm/rev and depth of cut 1 mm. It is seen that with air-cooling the growth of wear land is minimized. Other advantage is the lowering of cutting and feed forces. However, there is very slight reduction in surface roughness in air-cooled cutting. Thus, air-cooled turning using ceramic tool offers an attractive alternative to dry turning.

3.3.4 Study of Cutting Performance of CBN Tool

The tool manufacturer recommends the following cutting conditions for machining of hardened steel of around 45 HRC by CBN 7020 tool:

- Cutting speed less than 250 m/min
- Feed in the range of 0.05–0.25 mm/rev
- Depth of cut in the range of 0.06–0.40 mm

Based on manufacturer's recommendations and review of the literature, the following ranges of the process parameters were chosen- cutting speed (v): 125–215 m/min, feed (f): 0.05–0.16 mm/rev and depth of cut (d): 0.06–0.16 mm. The total numbers of full factorial experiments are $2^3=8$ as shown in Table 3.9.

Table 3.9. Operating conditions in turning of hardened steel with CBN tool

Conditions	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)
1	125	0.05	0.06
2	125	0.05	0.16
3	125	0.16	0.06
4	125	0.16	0.16
5	215	0.05	0.06
6	215	0.05	0.16
7	215	0.16	0.06
8	215	0.16	0.16

Similar to the ceramic tool, each test was conducted with a new cutting edge and machining was stopped at a cutting length of 100 mm. The time was recorded for each cut as for different experiments the cutting time will be different depending upon the cutting speed and feed. The cutting forces in cutting direction and feed forces in feed direction were measured during cutting operation. Maximum flank wear and surface roughness were measured after completion of each pass of machining. The tool rejection criteria were considered as follows:

- Maximum flank wear ≥ 0.2 mm
- Nose wear ≥ 0.3 mm
- Notching at the depth of cut line ≥ 0.6 mm
- Surface roughness value ≥ 3.0 μm
- Excessive chipping or catastrophic failure

Figure 3.17 represents a comparison of surface roughness for dry and air-cooled turning for eight different cutting conditions. It can be noticed that the R_a values increase with cutting time irrespective of the cutting conditions.

In general, the surface finish for air-cooled turning is found slightly better than dry turning. However, at a combination of high feed and low depth of cut (Figures 3.17(c) and (g)) the surface finish for dry turning is found better compared to air-cool turning. Improvement in the surface finish for these conditions may be attributed to the change in cutting tool geometry. For the conditions pertaining to Figure 3.17(c), *i.e.*, at low speed, high feed and low depth of cut, a built up edge (BUE) was formed near the chamfered edge of the insert during dry turning (Figure 3.18).

The built up edge was not observed at high speed. As expected, the R_a value at lower feed rate (0.05 mm/rev) is found to be lower than the R_a value at higher feed rate (0.16 mm/rev). Figures 3.17(a), 3.17(b), 3.17(e) and 3.17(f) correspond to low feed rate with R_a values ranging from 1 to 2 μm and Figures 3.17(c), 3.17(d), 3.17(g) and 3.17(h) correspond to the high feed rate with R_a values ranging from 1.7 to 2.8 μm .

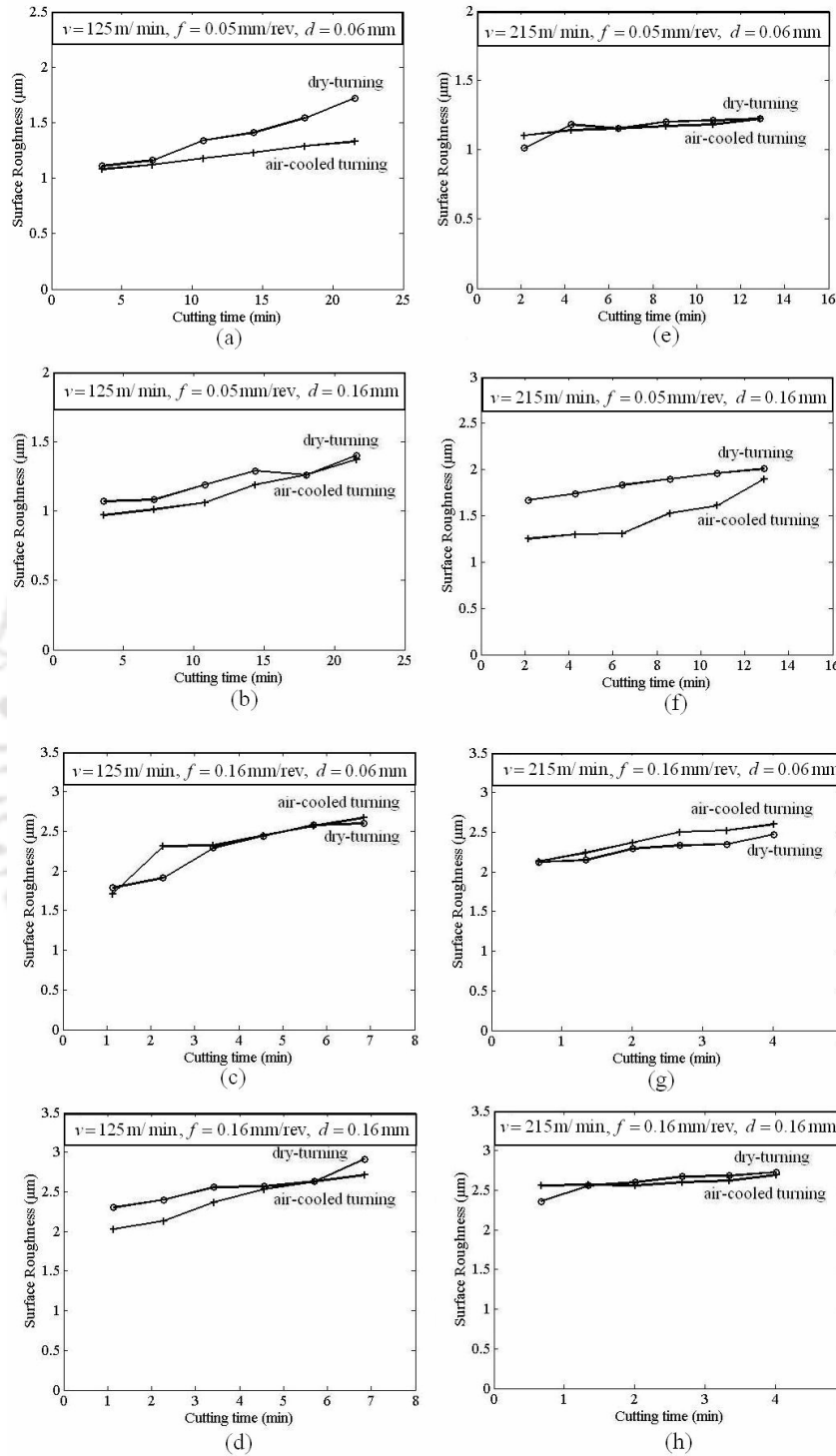


Figure 3.17. Surface roughness variation with cutting time in turning of hardened steel with CBN tool

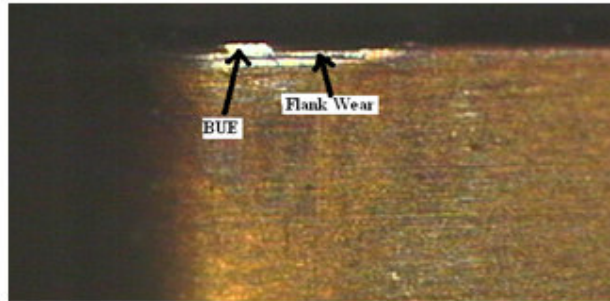


Figure 3.18. Tool flank wear with built up edge (BUE) in the CBN insert

Generally, the surface finish in machining operations improves with increasing cutting speed. However, at conditions corresponding to Figure 3.17(f), the surface finish is found slightly higher compared to the condition at low speed (Figure 3.17b). At this cutting condition (215 m/min, 0.05 mm/rev, 0.16 mm), nose wear occurred (Figure 3.19) for both dry and air-cooled turning. The presence of nose wear deteriorates the surface finish during the turning operation.

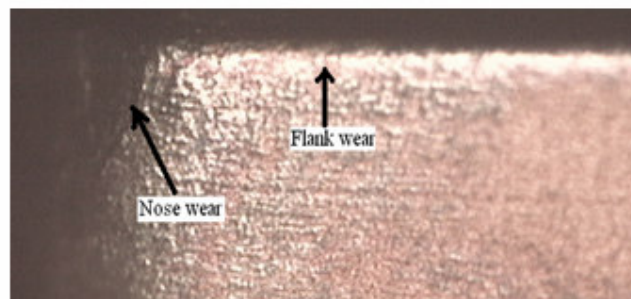


Figure 3.19. Tool flank wear with nose wear in the CBN insert

Figure 3.20 represents a comparison of propagation of flank wear with cutting time for dry and air-cooled turning for eight different cutting conditions. In each condition, it has been observed that tool flank wear is higher during dry turning compared to air-cooled turning. This shows that air-cooling has a direct influence in reducing tool flank wear and thus increasing the tool life. The tool rejection criteria based on maximum flank wear was kept as 0.2 mm, but in actual turning, after the flank wear of about 0.07 mm, the surface roughness of the machined surface came out to be more than $3.0 \mu\text{m}$ and the tool was rejected based on maximum surface roughness criterion.

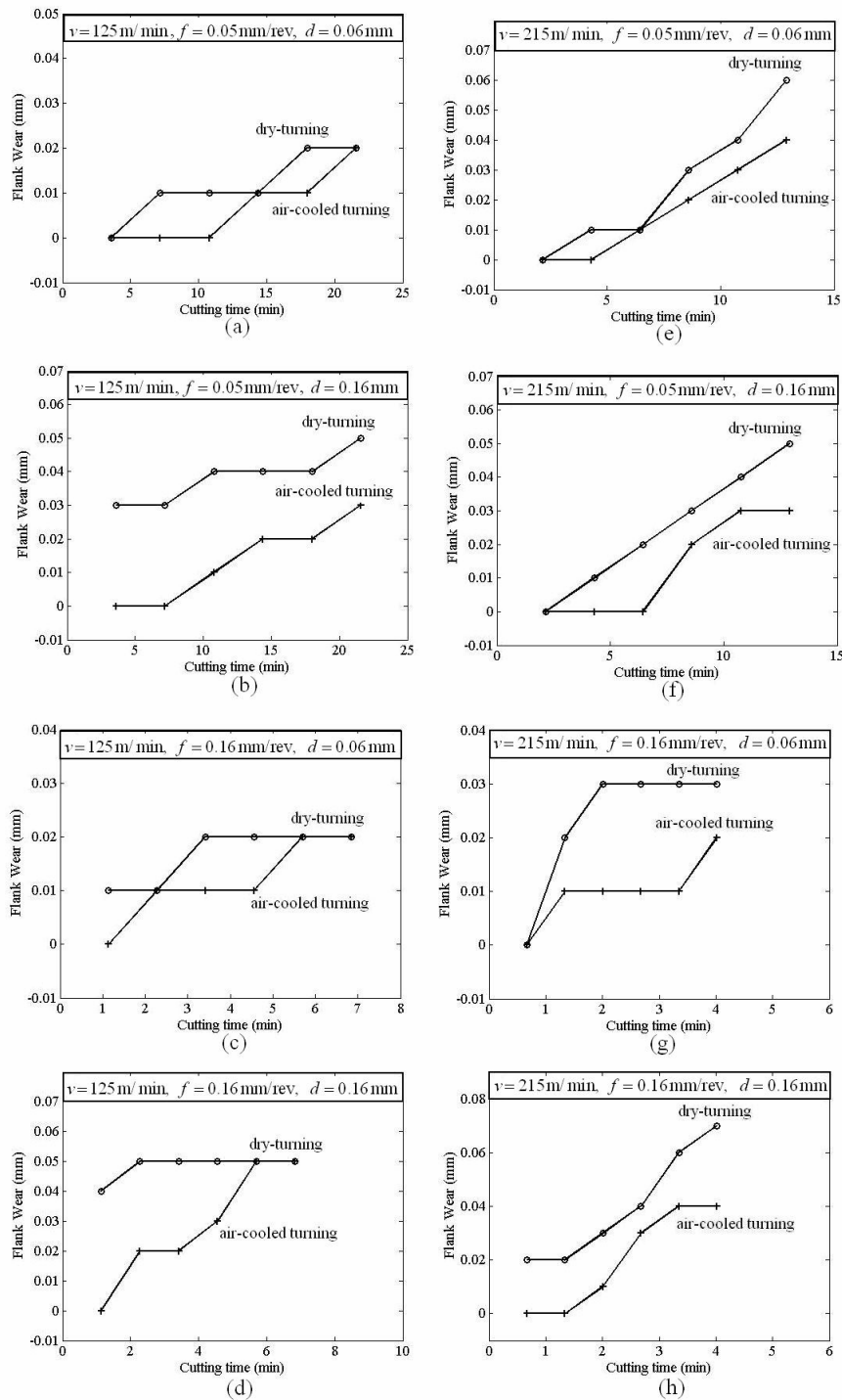


Figure 3.20. Flank wear progression with cutting time in turning of hardened steel with CBN tool

For the condition of high cutting speed (Figs. 3.20(e-h)), the tool flank wear is found to be more as compared to the low cutting speed case (Figs. 3.20(a-d)). During high speed machining, temperature becomes high causing partial burning near the cutting edge and sometimes crater wear in the rake face. Burning of cutting edge accelerates the tool flank wear rate and deteriorates the surface finish. It has been observed that at high cutting speed, high feed and high depth of cut (Fig. 3.20h), flank wear as well as crater wear (Fig. 3.21) was formed during dry turning but not in air-cooled turning.

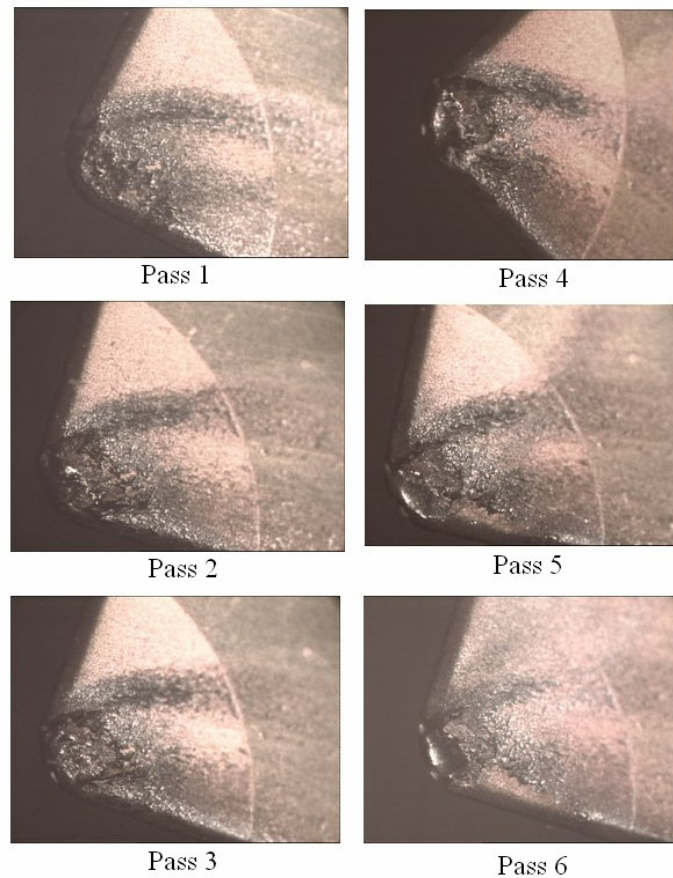


Figure 3.21. Progression of crater wear on CBN tool for the condition of high speed, high feed and high depth of cut during dry turning

On the other hand, at high speed and low feed (Figs. 3.20(e-f)), flank wear as well as nose wear was seen during dry turning, but not in air-cooled turning. Chou and Evans (1999) suggested that there are different dominant wear modes at

different cutting speed ranges such as mechanical wear at low cutting speed, and thermal wear at high cutting speed during turning with CBN tool. The experimental results show that air-cooling may be used as a preventive measure to reduce the thermal wear.

Figures 3.22 and 3.23 represent a comparison of feed force (F_x) and cutting force (F_z) for dry and air-cooled turning for eight different cutting conditions. In general, the values of cutting force are higher than the feed force for the same cutting condition. In another observation, feed force and cutting force is found to be more during air-cooled turning except for the conditions pertaining to Figures 3.22 (e-f) and Figures 3.23(e-f). The reason is that during air-cooled turning air carries away the heat through convective heat transfer method and reduces the temperature. Therefore, the mechanical strength of the job material becomes high in comparison to dry turning due to which more feed/cutting force is required to do machining in air-cooled turning. However, for conditions of Figures 3.22(e-f) and 3.23(e-f), nose wear occurred along with flank wear during dry turning. It is generally believed that the forces are lower when machining at higher cutting speed. However, here, in some cases, the forces are found more in high cutting speed. In these cases, besides flank wear, the nose wear or built up edge was observed.

Figure 3.24 shows the images of progression of tool flank wear in dry and air-cooled turning of H13 steel with CBN tool for a condition of cutting speed 125 m/min, feed 0.16 mm/rev and depth of cut 0.16 mm. Each image was taken after machining a cutting length of 100 mm. As seen in the images, the wear land keeps on increasing with time at almost constant rate. Comparing Figures 3.24(a) and 3.24(b), the growth of wear land is found to be lower during air-cooled turning. Thus, air-cooling has played an important role in reducing the growth of wear land.

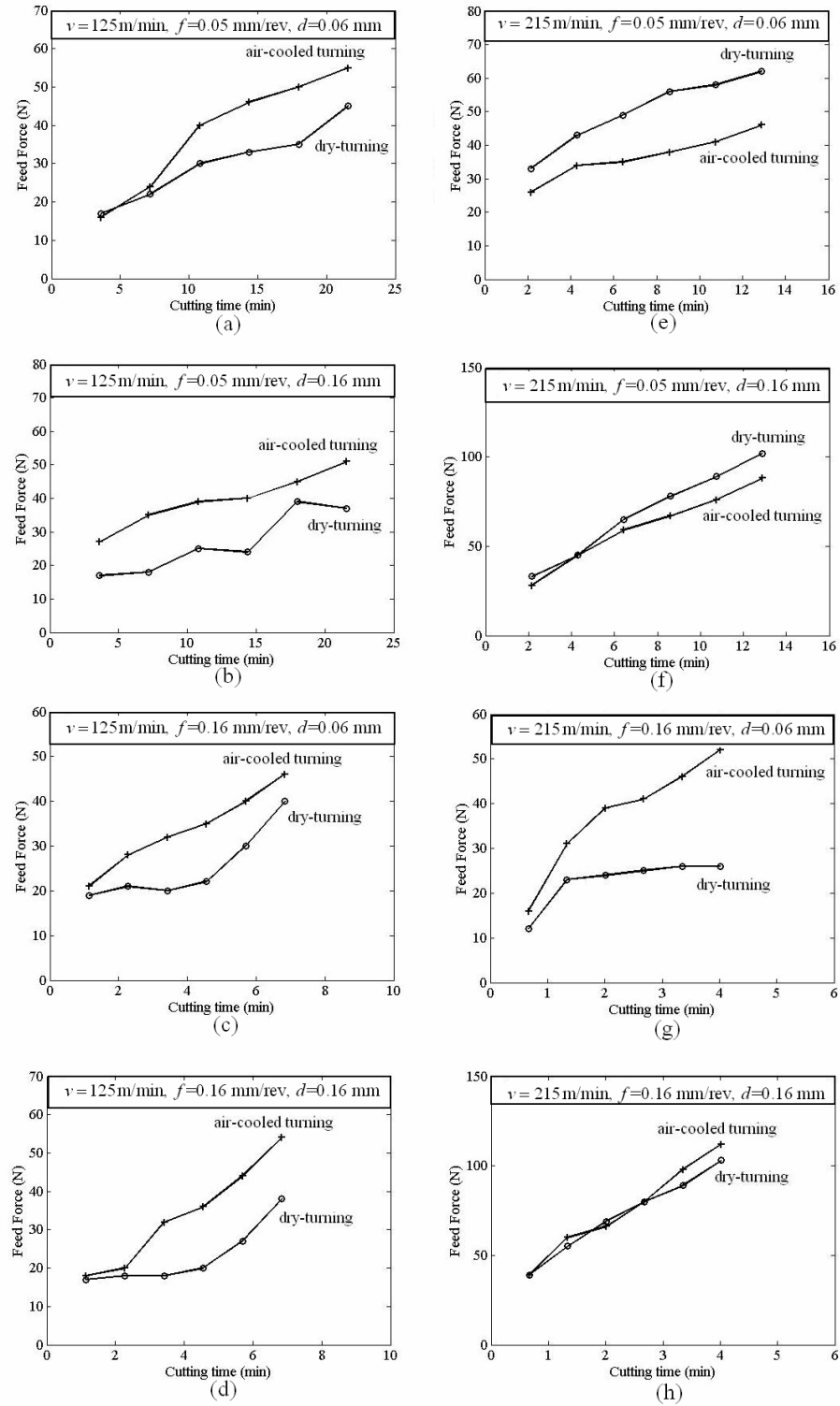


Figure 3.22. Feed force variation with cutting time in turning of hardened steel with CBN tool

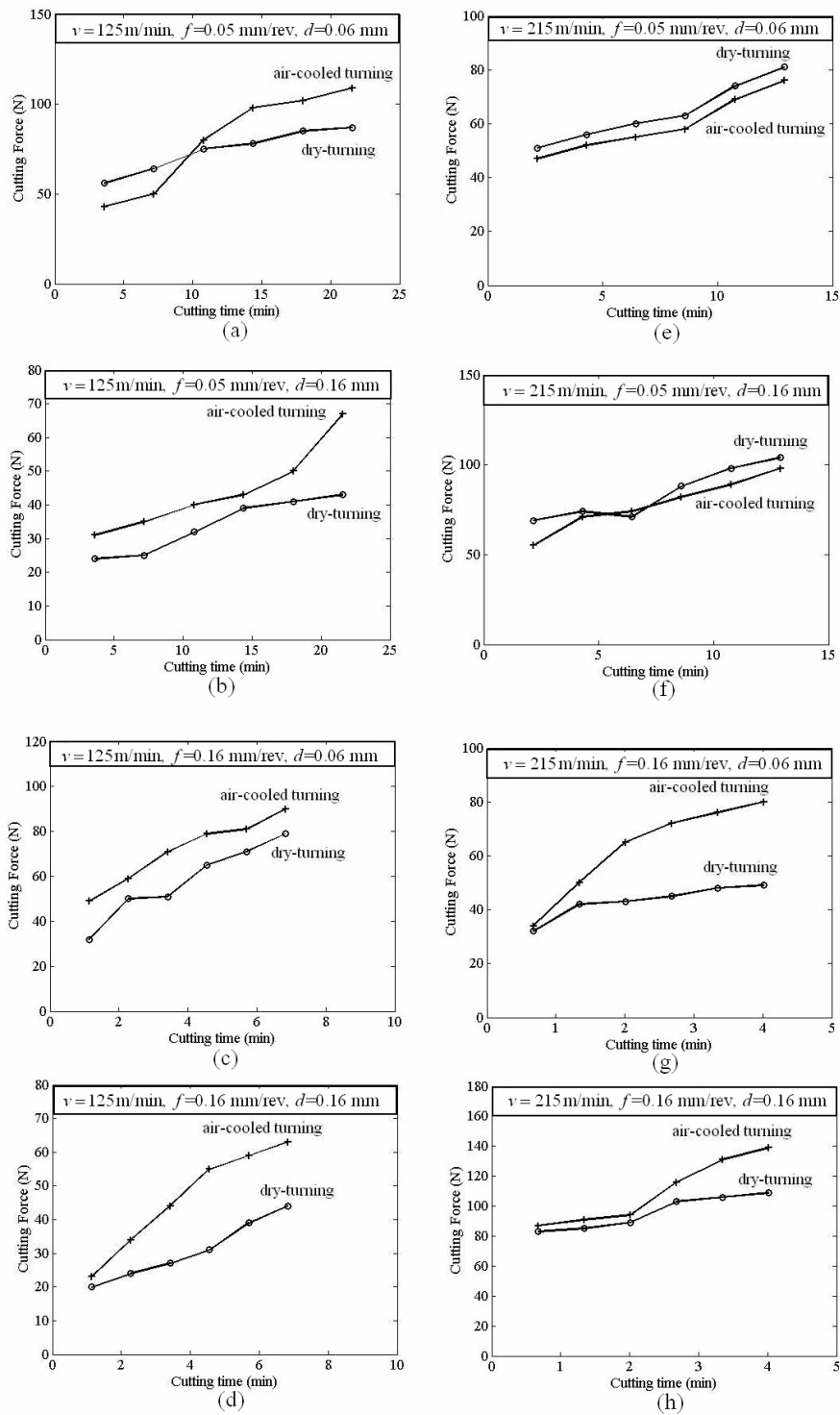


Figure 3.23. Cutting force variation with cutting time in turning of hardened steel with CBN tool

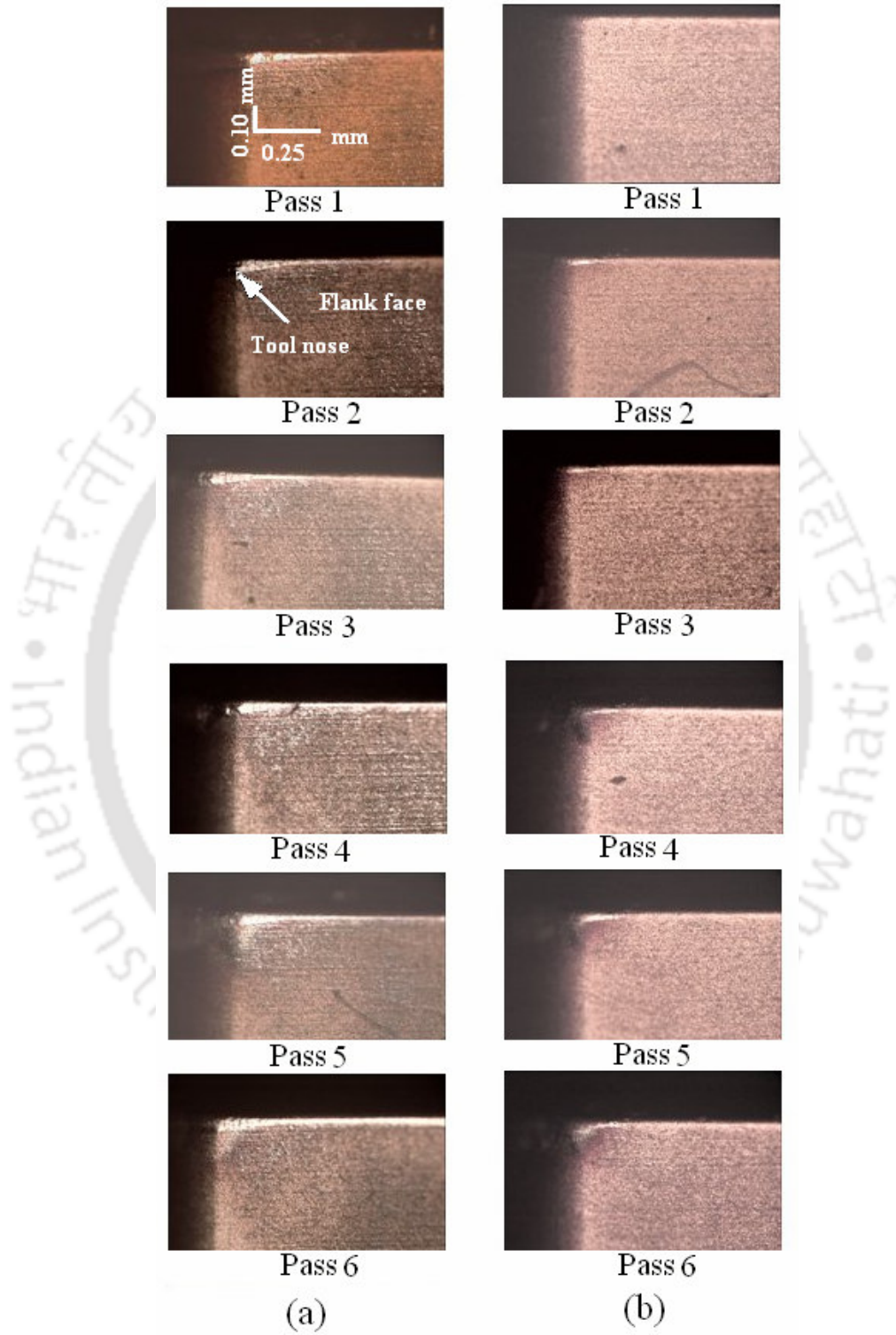


Figure 3.24. Tool wear progression during (a) dry turning and (b) air-cooled turning of hardened steel with CBN tool

3.4 Summary

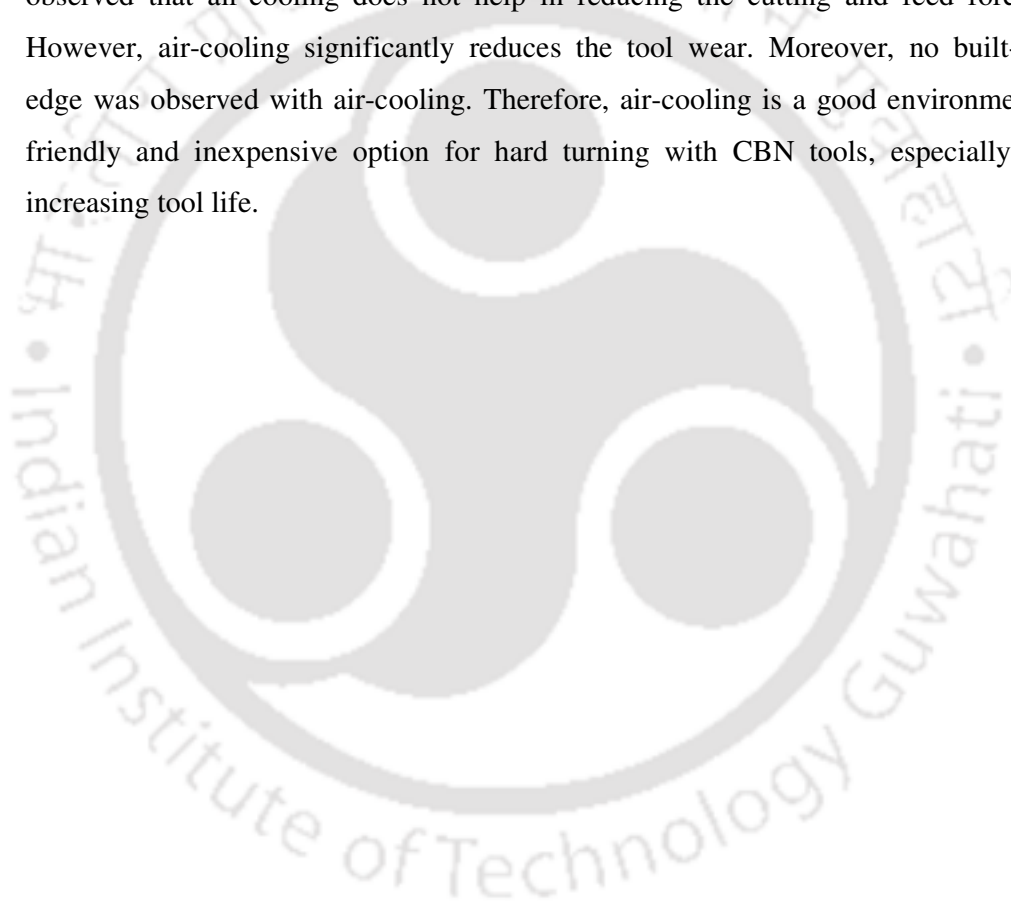
An experimental study on the performance of HSS, non-coated carbide, coated carbide, ceramic and CBN cutting tool was carried out on different workpiece materials. HSS tool was not found suitable in finish turning of grey cast iron in dry turning. However, non-coated carbide tool provides a better surface finish and it can be employed for finish turning of grey cast iron. For a combination of medium speed and low feed, non-coated carbide tool gives a good surface finish of around 1.84 micron.

The performance of dry and air-cooled turning of mild steel with coated carbide tool was studied. It was observed that air has no effect in improvement of surface finish during high cutting speed (300 m/min). However, air reduces the tool flank wear during high cutting speed. At low cutting speed (150 m/min), air-cooling has random effect in reduction of flank wear. It was observed that in most of the cases, the value of cutting force or feed force is almost equal for both air-cooled and dry turning. Thus, no special effect has been seen for air-cooled turning. However, for same cutting condition, cutting force is more than the feed force. It is a general phenomenon that cutting force is higher than the feed force.

A study was also carried out for the performance of the dry and air-cooled turning of grey cast iron with a mixed oxide ceramic cutting tool. It was observed that at a low cutting speed of 100 m/min air-cooling did not offer any advantage. However, at higher cutting speeds (400 m/min and above), it significantly reduced the tool flank wear and increased the tool life. Although no improvement in the surface finish was observed at a cutting speed of 400 m/min compared to dry turning, however at a cutting speed of 480 m/min, where the dry turning provides a very poor surface finish due to rapid tool wear, the air-cooling provided a very good surface finish. In all the cases, air-cooled turning lowered the cutting and feed forces compared to corresponding forces in dry turning. Thus, air-cooled turning seems to be a good environment-friendly option for high speed turning. This study also brought out some interesting and useful observations for future researches. For example, acceleration of vibrations during cutting does not provide any direct

correlation with flank wear or surface roughness. It is, however, yet to be explored whether vibration data can be processed to provide useful information regarding surface roughness and tool wear. The work presented in Chapter 5 concentrates in optimizing the process parameters of air-cooled turning process.

Another work in this chapter was comparison of dry-turning and air-cooled turning of H13 die steel with CBN tool. It was observed that air-cooling does not influence surface roughness of the machined surface significantly. It was also observed that air-cooling does not help in reducing the cutting and feed forces. However, air-cooling significantly reduces the tool wear. Moreover, no built-up edge was observed with air-cooling. Therefore, air-cooling is a good environment-friendly and inexpensive option for hard turning with CBN tools, especially in increasing tool life.



Neural Network Modelling of Turning Process

4.1 Introduction

Selection of proper cutting tool for turning of a material is of utmost importance. Initially, a comparative study was carried out on the cutting performance of high speed steel, carbide and ceramic tools in turning of grey cast iron at dry cut condition. Due to non-linear nature of turning process, wider ranges of cutting parameters were chosen. It was observed that when machining was carried out using a ceramic tool at manufacturer's recommended process parameters, there was a rapid tool wear and/or breakage. The performance was found better at other process parameters. Hence, it was felt necessary to obtain functional relationships between process parameters and performance parameters for different tool-workpiece combinations. Neural network was employed as a tool for modelling. A well-trained neural network requires less number of experiments. This helps in selecting the proper operating conditions for each tool in order to derive the maximum benefit.

Initially, neural network modelling was carried out for the prediction of surface finish in turning of grey cast iron with HSS tool, non-coated carbide tool and mixed oxide ceramic tool in dry cut condition. Multi-layer perceptron neural network was used for modelling. The details of the results of the surface roughness prediction are presented in the paper of Sarma *et al.* (2005). A brief report of this work has been presented in Section 4.3.

As reported in the previous chapter, the use of air during turning helps in reduction of tool wear and in some cases it lowers the surface roughness and cutting forces as well. A detailed study was carried out to compare the performance of coated carbide tool while turning mild steel in dry and air-cooled condition. Neural

network modelling was carried out for the prediction of surface roughness and tool life. The details of the work have been presented in Section 4.4.

Next, the neural network model was developed for the prediction of surface roughness and tool life in turning of grey cast iron with mixed oxide ceramic tool in dry and air-cooled condition. Considering the limitation of experimental data and inherent noise, a novel procedure of neural network modelling was developed utilizing both multi-layer perceptron and radial basis function network. The contours of surface roughness and tool life were plotted with the help of trained neural networks.

Neural network modelling was carried out for predicting cutting and feed forces in turning of grey cast iron with mixed oxide ceramic tool. The radial basis function neural network was used for this purpose. Indirect estimation of tool wear based on the force measurements was also attempted. It was observed that rate of change of tool wear with respect to forces can be used for the estimation of tool wear.

4.2 Background on Neural Networks

A neural network can be defined as a model of reasoning based on the human brain. A human brain can be considered as a highly complex, nonlinear and parallel information-processing system; information is stored and processed in a neural network simultaneously throughout the whole network, rather than at specific locations. An artificial neural network (ANN) is also an information processing model that is inspired by the way biological nervous systems process information. It is composed of highly interconnected processing elements (neurons) working in unison to solve specific problems. A typical neuron receives one or more input signals and provides an output signal depending on the processing function of the neuron. This output is transferred to connected neurons in varying intensities, the signal intensity being decided by the weights. Neural networks can be used for finding out the relationship between independent and dependent variables. For this purpose, a set consisting of input and output vector pairs is needed. From this set,

some pairs are used for the training of the network that is used for adjusting the parameters of the network in order to minimize the predicted error. After that the network is tested or cross-validated with the remaining pairs. A properly fitted network should provide very less amount of training as well as testing error.

Neural network can be classified based on their architecture and the method of training. The most commonly used neural network architectures are (a) feed-forward neural network, (b) feedback neural networks and (c) self-organizing neural networks. Feed forward neural networks are most popular and widely used ones. Two most common networks in this category are multi-layer perceptron (MLP) neural network and radial basis function (RBF) neural network.

A multi-layer perceptron (MLP) neural network is a feed-forward neural network with one or more hidden layers. Typically a network consists of an input layer, one or more hidden layer, and an output layer (Figure 4.1). The input signals are propagated in a forward direction on a layer-by-layer basis. A feed-forward neural network has a sequence of layers consisting of a number of neurons in each layer. The output of neurons of one layer becomes input to neurons in the succeeding layer. Presence of hidden layer is needed in order to provide complexity to network architecture for modelling non-linear functional relationships. During the training process, the network adjusts its weights to minimize the error between the predicted and actual outputs. Most common algorithm available for adjusting the weights is back propagation algorithm which is based on the steepest-descent algorithm. The algorithm used the concept that the maximum decrease in the function is in a direction opposite to the direction of the gradient of the function. Another commonly used backpropagation algorithm is based on the Levenberg-Marquardt method, which is a combination of the steepest-descent method and the quasi-Newton method.

The training process involves two passes. In the forward pass, the input signals propagate from the network input to output. In the reverse pass, the calculated error signals propagate backward through the network where they are used to adjust the weights. The calculation of output is carried out, layer by layer, in the forward direction. As an input pattern is presented to the neural network, the output response

is calculated on a forward pass through the network. Assume that a typical j -th artificial neuron in a layer receives n input signals x_i emitted by the neurons of the previous layer. The weighted sum of these input signals alongwith the bias b_j is accepted as the input by the j -th neuron. The output o_j of the neuron will be given by

$$o_j = f\left(\sum w_{ji}x_i + b_j\right), \quad (4.1)$$

where w_{ji} is the weight associated with the j -th neuron of the layer and the i -th neuron of the previous layer. The function f is called the activation function. Some commonly used activation functions are:

$$\text{logsig} : o = f(t) = \frac{1}{1 + e^{-ct}}, \quad (4.2)$$

$$\text{tansig} : o = f(t) = \tanh(ct/2), \quad (4.3)$$

$$\text{identity} : f(t) = t, \quad (4.4)$$

where c is a constant.

The output of a layer reaches as a weighted input in the neurons of the succeeding layer. The weights and biases for each neuron are different. This process is carried out starting from the input layer to output layer. The final output is compared with the desired (target) output and error terms are calculated for each output neuron. This error is used to adjust weights connecting the layers. First, the weights connecting the output and immediately preceding hidden layer are adjusted. Then, the error is propagated backwards to the neurons of immediately preceding hidden layer. This propagated error is used to adjust the weights connecting these neurons with the neurons of the previous layer. This procedure of weight adjustment is continued till we reach from output to input layer. Because of this method of weight adjustment (moving from output to input), the algorithm of weight adjustment is called the backpropagation algorithm.

The architecture of a typical MLP neural network used for modelling of the surface roughness in the turning process is shown in Figure 4.1. It consists of one input layer with 3-inputs *viz.* cutting speed (v), feed (f) and depth of cut (d) as input neurons, one hidden layer and one output layer with one neuron representing the

surface roughness (R_a). Input and output parameters were normalized to lie between 0.1-0.9.

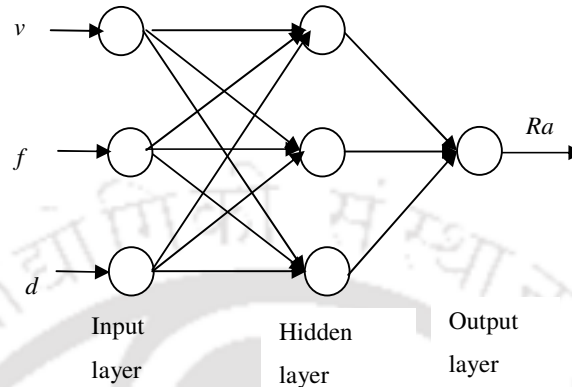


Figure 4.1 MLP neural network architecture

The radial basis function (RBF) neural network consists of one input layer having neurons corresponding to the input vector, one hidden layer having a number of neurons that process the input using the radial basis functions and one output layer corresponding to the parameter being modelled. The architecture of a typical RBF network is shown in Figure 4.2.

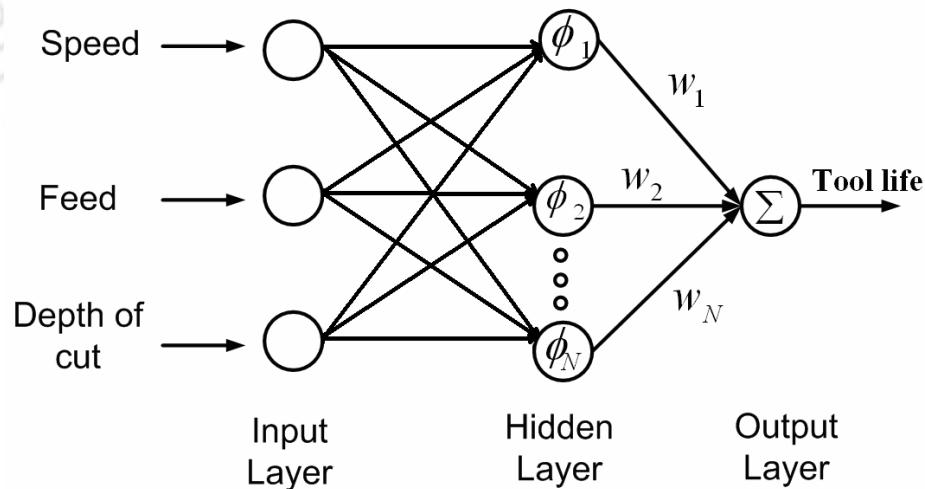


Figure 4.2. A typical RBF neural network architecture

A neuron of the hidden layer receives the input vector and emits the output, which is a function of the Euclidian distance of the input vector and a centre

associated with that particular neuron. This function is a radial basis function having a radial symmetry. The radial basis function used in this work is a Gaussian function (bell-shaped) of the following form:

$$\phi(x) = \exp(-x^2 / \sigma^2), \quad (4.5)$$

where x is the Euclidian distance between the centre and the input vector and σ is known as the spread parameter that controls the domain of influence of the radial basis function. The weighted addition of the outputs of neurons of the hidden layer is sent to the output neuron, which processes it by adding a constant term b called bias. Thus the output of the RBF neural network is approximated as

$$f(\mathbf{x}) = b + \sum_{k=1}^N w_k \phi_k(\|\mathbf{x} - \mathbf{c}_k\|_2), \quad (4.6)$$

where $\mathbf{x} = \{f, v, d\}^T$ is the input vector, $\phi_k(\cdot)$ is the processing function of the k^{th} neuron in the hidden layer, $\|\cdot\|_2$ denotes Euclidean norm, w_k are the associated weights, N is the number of neurons in the hidden layer and \mathbf{c}_k are the RBF centres obtained from the input vector space. For fixed centres and spread parameter, applying Equation 4.6 for each training data provides a linear system of equations with N unknown weights w_k and one unknown bias b , which can be solved using the least square method. Hence, the training procedure takes lesser computational time, as compared to multi-layer perceptron neural network.

The dimensional values of the input variables lie in different ranges. Due to this, normalization has been carried out for these input variables such that their values lie from 0.1 to 0.9. In MATLAB, the NEWRB function is used for the training of the network. The function works on the algorithm of starting with zero neurons in the hidden layer and keep on adding the input vector with the greatest error as the centre in the successive runs till the error goal is achieved. The selection of spread parameter is based on a simple heuristic relationship [Haykin, 1996]:

$$\sigma = \frac{d_{\max}}{\sqrt{K}}, \quad (4.7)$$

where d_{\max} is the maximum Euclidian distance between the centres and K is the number of centres. However, the relation expressed by Equation 4.7 is a heuristic relation. In this work, to fine-tune the value of spread parameter, the value calculated by Equation 4.7 is multiplied by a factor β . A number of numerical experiments were carried out to find out the optimum value of β . In most of the cases, the optimum β is obtained around 1.5.

4.3 Comparative Study of Cutting Performance of HSS, Carbide and Ceramic Tools using Neural Network

To study the cutting performance of HSS, non-coated carbide and ceramic tools in turning of grey cast iron at dry cutting condition, a large number of experiments are required, which is expensive and time consuming. Also, it is not possible to find out the exact cutting conditions of those tools to achieve a desired surface roughness. Hence, a decision was taken to conduct a series of experiments in wider ranges of cutting parameters and search for a better performance zone. Neural network was used for training the network with the experimental data. Considering the best network topology (network which gives the least effective error), contour plots were generated for surface roughness. The contour plots give a wider zone of operating conditions for each tool for a good surface finish.

To obtain the process parameters for getting a surface finish of ISO N7 (1.6 micron), detailed study was carried out by selecting the process parameters in a zone with a value up to $\pm 40\%$ of the optimum parameter values, thus narrowing the search space. More experiments were conducted considering the new chosen ranges of process parameters and the experimental data were again put in the network for training. From the trained network, the best network was selected and a refined contour was plotted. From the plot, it was observed that HSS tool could not achieve the target of 1.6 micron (N7) finish at any operating condition. Hence, this tool is not suitable for finish turning operation. Carbide and ceramic tools could achieve the target of N7 finish and ceramic tool provides better production rate compared to carbide tool. Moreover, for the same production rate, ceramic tool provides better

surface finish and tool life compared to carbide tool. The details of this work are available in the paper of Sarma *et al.* [2005].

The procedure employed in this work helps in assessing the effectiveness of a tool in machining of a material. Also, it identifies the zones where detailed investigation should be carried out to study the performance parameter of carbide and ceramic tool.

4.4 Modeling of Cutting Performance of Coated Carbide Tool in Dry and Air-cooled Turning

Two important performance parameters in turning process are surface roughness of the machined surface and tool life of cutting tool. The center line average (CLA) surface roughness (R_a) value is obtained by measuring the mean deviation of the peaks from the center line. On the other hand, tool life is dependent on the wear of cutting tool with respect to cutting time. This wear may be either flank wear or crater wear or nose wear or notch wear. This study mainly focuses on the effect of the air-cooling in improving the surface finish and the tool life.

For the experiments, TiN coated square shaped carbide inserts were used. The ISO code of the tool was SNMG 1204085 TN2000 of make: WIDIA. The work material was rolled steel.

4.4.1 Design of Experiments and Prediction of Surface Roughness by Neural Network

The simplest and most common type of factorial design is one that uses the two levels of each factor i.e. a 2^n factorial design. Here the three parameters speed, feed and depth of cut are used to study their effects quantitatively on surface roughness and tool life. In order to investigate the main effect of these three factors, total $2^3 = 8$ experiments were carried out as per factorial design of experiments considering two levels (High and Low) of each of the three factors. The high and low levels of process parameters for the coated carbide tool are as follows.

Cutting speed: 150–300 m/min

Feed: 0.1–0.32 mm/rev

Depth of cut: 1–3 mm.

The main effect of a factor is the change in response produced by a change in the level of the factor. The parameter which has higher effect on the surface roughness value should have more representation in the dataset to be used. The effect of factor for an input variable can be evaluated as [Dieter, 1991]

$$\text{Effect of a factor} = \frac{\sum \text{responses at high levels} - \sum \text{responses at low levels}}{\text{half the number of runs in the experiment}} \quad (4.8)$$

The total number of experiments is decided by the effect of factor. In order to compute the effect of each process parameter initially factorial design of 8 experiments are carried out. Factor with least influence is assigned level 2. The levels of other factors are taken in proportion to their effect, and additional experiments are performed to represent these levels in the data set. For example, if the influence levels for depth of cut, feed, and cutting speed come out to be 2, 3 and 5 respectively, then one additional level of feed and three additional levels of cutting speed have to be generated. Thus for feed, one value in the middle of range should be chosen and other process parameters corresponding to this may be taken at random. Similarly, in the case of cutting speed, three additional levels should be chosen to have a total of five equally spaced levels in the range. Thus, initial training dataset of 2^3 should be increased by one level of feed and three levels of cutting speed, making the training data set to be 12. If the magnitude of effect of factor is less than one fifth of the magnitude of effect of most influential parameter, the factor is considered insignificant and is eliminated from the consideration. All these data sets are used to train the neural network.

The size of testing data set is very important from the point of view of reliability of the network. A guideline regarding this has been provided in [Kohli and Dixit, 2005]. The method to decide the minimum number of testing data in a network is as follows. Supposing that in the validation data, the percentage of data having an error greater than a prescribed value is p_f . The network is always fitted in such way so that in no prediction, the error is more than the prescribed value. For a testing data size of k , the probability that in this dataset, all of the predictions fall within the limit is given by

$$P_0 = \left(1 - \frac{p_f}{100}\right)^k \quad (4.9)$$

Using this expression, one can find the testing dataset size k , if P_0 and p_f are known. For example, let us suppose that requirement is that, in general, 75% of the time the prediction error should come out to be less than the prescribed value and that the probability that a network will have poorer predictive capability is 0.1. Then, putting $p_f = 25$ and $P_0 = 0.1$ into the expression at Equation 4.9 gives $k = 8$. Hence, in the present work, eight random testing datasets were chosen for testing the NN models.

In a properly fitted neural network, the network gives nearly equal training and testing errors. The network parameters are arranged to achieve higher accuracy. The error measures used to assess the performance of fitted neural network are presented below.

Let Ra_i is the experimentally observed value of surface roughness, and \hat{Ra}_i is the neural network predicted value of surface roughness.

$$\text{Absolute error in prediction for } i^{\text{th}} \text{ data} = (Ra_i - \hat{Ra}_i) \quad (4.10)$$

$$\text{Percentage fractional error in prediction for } i^{\text{th}} \text{ data (or \% deviation)} = \frac{(\hat{Ra}_i - Ra_i)}{Ra_i} \times 100 \quad (4.11)$$

$$\text{Mean square error (MSE)} = \frac{1}{n} \sum_{i=1}^n (Ra_i - \hat{Ra}_i)^2 \quad (4.12)$$

$$\text{Root mean square fractional error, } (RMS_{err}^f) = \sqrt{\sum_{i=1}^n \frac{(Ra_i - \hat{Ra}_i)^2}{nRa_i^2}} \quad (4.13)$$

$$\text{Effective error} = \max \text{ of } [RMS_{err}^f \text{ of training data, } RMS_{err}^f \text{ of testing data}] \quad (4.14)$$

Table 4.1 and Table 4.2 represent the training and testing data set for air-cooled turning for the prediction of surface finish. Altogether, there are 21 data for training and 8 data for testing. The network was trained using TRAINLM function in MATLAB. The activation function was LOGSIG. The best trained network gives

the RMS errors in training and testing as 5.89% and 14.80% respectively. The maximum effective percentage deviation was found to be 24.52 %. Out of total 29 data, only 2 data were found to have error more than 20%. Considering the inherent statistical variation in machining, 20% deviation in prediction may be deemed acceptable.

Similarly, Table 4.3 and Table 4.4 represent the training and testing data sets for dry turning for the prediction of surface finish. Here also, total 21 data were used for training and 8 data for testing. The RMS errors in training and testing were found to be 3.55% and 12.26% respectively. The maximum effective percentage deviation was found to be 17.47%, *i.e.* less than 20%.

To assess the performance of a predictive model in the presence of statistical deviations, hypothesis testing may be employed. In this work, hypothesis testing has been carried out. Before describing the results of the hypothesis testing for the present work, a brief description of the hypothesis testing is provided below.

Many a times, some results are strongly believed to be true. But after taking a sample, it is noticed that data of one sample does not wholly tally with the results. The difference is due to (i) the original belief being wrong and (ii) the sample being slightly one sided. Tests are, therefore, needed to distinguish between the two possibilities. These tests tell about the likely possibilities and reveal whether or not the difference can be due to chance elements. If the difference is not due to chance elements, it is significant, and therefore these tests are called test of significance. The whole procedure is known as *testing of hypothesis*. A hypothesis is a statement supposed to be true till it is proved false. It may be based on previous experience or derived theoretically. First, a statistician forms a research hypothesis. Then he derives a statement, which is the opposite of the research hypothesis. The approach here is to set up an assumption that there is no contradiction between the believed results and the sample results and the difference can be described solely to chance. Such a hypothesis is called a *null hypothesis* (H_0).

Table 4.1. Training data set for prediction of surface roughness in turning of mild steel with coated carbide tool during air-cooled turning

v m/min	f mm/rev	d mm	R_a (μm)
148	0.10	1.0	2.17
149	0.10	3.0	2.15
145	0.32	1.0	4.30
149	0.32	3.0	4.81
327	0.10	1.0	1.86
320	0.10	3.0	3.38
327	0.32	1.0	3.82
320	0.32	3.0	4.26
211	0.10	1.1	2.32
273	0.12	1.1	2.16
229	0.20	1.3	2.23
272	0.24	1.5	2.86
269	0.28	1.6	3.83
207	0.32	1.7	3.99
165	0.10	1.8	2.43
207	0.12	1.9	2.36
240	0.14	2.0	2.63
202	0.20	2.2	4.49
290	0.12	2.9	2.55
211	0.14	1.1	1.62
204	0.16	2.2	2.65

Table 4.2. Testing data set for prediction of surface roughness in turning of mild steel with coated carbide tool during air-cooled turning

v m/min	f mm/rev	d mm	R_a (μm)
245	0.12	3.0	2.60
250	0.14	1.2	2.38
179	0.20	1.4	2.27
232	0.24	2.5	3.46
268	0.28	2.6	3.47
162	0.32	2.7	4.70
185	0.10	2.8	2.55
270	0.16	1.2	1.93

Table 4.3: Training data set for prediction of surface roughness in turning of mild steel with coated carbide tool during dry turning

v m/min	f mm/rev	d mm	R_a (μm)
145	0.10	1.0	3.63
158	0.10	3.0	2.44
145	0.32	1.0	4.58
158	0.32	3.0	4.78
303	0.10	1.0	2.36
305	0.10	3.0	2.34
285	0.32	1.0	3.56
289	0.32	3.0	4.02
167	0.10	1.1	2.47
273	0.12	1.1	2.15
225	0.20	1.3	1.97
280	0.24	1.5	3.16
261	0.28	1.6	3.37
215	0.32	1.7	4.38
160	0.10	1.8	2.69
197	0.12	1.9	2.86
255	0.14	2.0	2.87
201	0.20	2.4	3.73
291	0.12	2.9	2.84
197	0.14	1.1	2.38
203	0.16	2.2	2.85

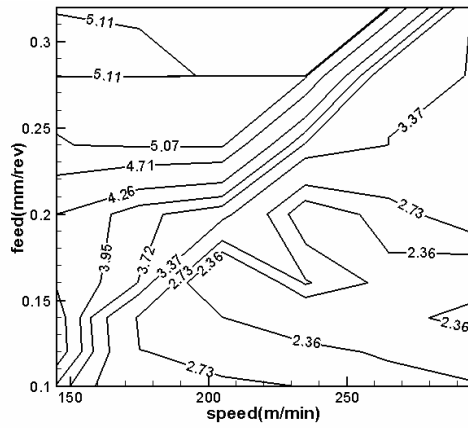
Table 4.4: Testing data set for prediction of surface roughness in turning of mild steel with coated carbide tool during dry turning

v m/min	f mm/rev	d mm	R_a (μm)
247	0.12	3.0	2.72
254	0.14	1.2	2.19
183	0.20	1.4	3.53
247	0.24	2.5	2.67
272	0.28	2.6	3.35
166	0.32	2.7	5.34
209	0.10	2.8	2.32
259	0.16	1.2	2.07

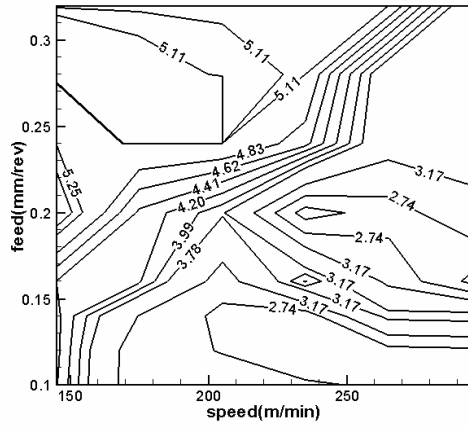
Here, a test of hypothesis using Student's t -test at 95% confidence level was carried out for the assessment of prediction accuracy of surface finish. Generally,

Student's t -test is used when the size of sample is less than 30. The main application of t -distribution is to test if the sample mean (\bar{x}) differs significantly from the hypothetical value of population mean (μ) and to test the significance of the difference between two sample means. In the present work, some replicate experiments were carried out for both the dry and air-cooled turning. Each replicate experiment was carried out for 5-6 passes and the surface roughness values were than used in student's t -test calculation. The result showed that prediction accuracy up to 15% is sufficient at 95% confidence level [Appendix A].

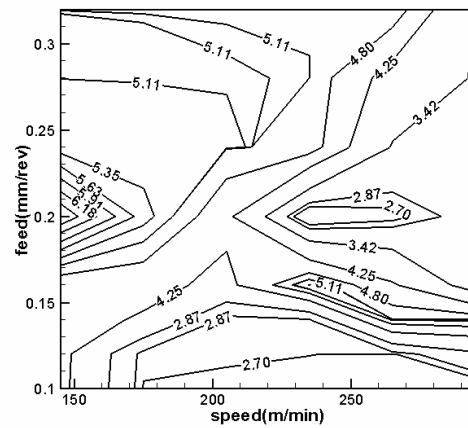
The trained networks were used to generate some contour plots of surface roughness. Figure 4.3 and Figure 4.4 show the contour plot of surface roughness for dry turning and air-cooled turning. In each case, (a), (b) and (c) depict the contour for 3 depths of cut *viz.* 1 mm, 2 mm and 3 mm. It is seen that in general the surface roughness in air-cooled turning is lesser compared to the dry turning. During air-cooled turning at 1 mm depth of cut, ISO grade N7 (1.6 μm) surface finish could be achieved. Comparing both Figures 4.3 and 4.4, it is observed that surface roughness increases at low speed and at moderate feed of 0.2 mm/rev. However, the surface roughness decreases as speed increases. During dry turning, the surface finish is found to be better as compared to air-cooled turning at high speed. It has also been noticed that increase in depth of cut has slight influence in increasing the surface roughness. The interaction of speed and feed affects the surface finish significantly. From both the figures, it can be concluded that coated carbide tool can be used at high feed to obtain a reasonable surface finish.



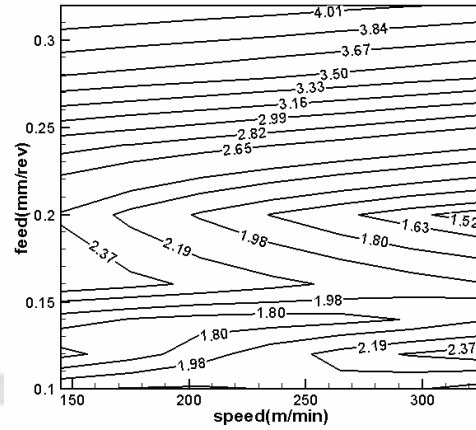
(a) doc = 1 mm



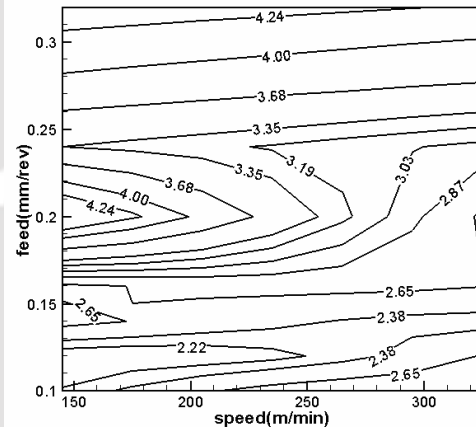
(b) doc = 2 mm



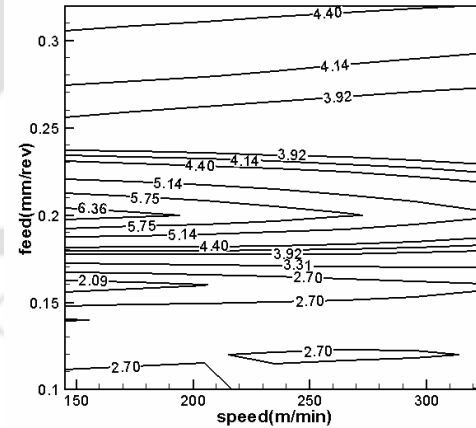
(c) doc = 3 mm



(a) doc = 1 mm



(b) doc = 2 mm



(c) doc = 3 mm

Fig. 4.3. CLA surface roughness (micron) for different depths of cut in turning of mild steel with coated carbide tool for dry turning

Fig. 4.4. CLA surface roughness (micron) for different depth of cut in turning of mild steel with coated carbide tool for air-cooled turning

4.4.2 Estimation of Tool Life using Neural Network Model

Estimation of tool life during machining is a time consuming process, where machining by the cutting tool is continued till it fails. This procedure consumes a number of tools, work material and time. Usually, the flank wear is taken as a basis of tool life. The wear developed in the flank face is easier to measure as compared to the wear occurring at the rake face. Moreover, the flank wear has direct influence on the accuracy of the machining. Compared to crater wear, it is more commonly observed. Conventional method of tool life determination consumes a number of tools and requires a lot of time and work-piece material. Hence, the procedure suggested by Ojha and Dixit [2005] is adopted to obtain a rough estimate of tool life. Accordingly, at different cutting conditions, the machining is carried out for 5-6 passes. The wear after each cutting pass is noted and the time for a limiting flank wear is estimated by extrapolating the wear-time curve till a maximum flank wear of 0.6 mm. The maximum flank wear of 0.6 mm is chosen as a criterion for tool failure based on the literature and experience gained in this work. The wear time curves for most cutting tools follow a pattern as shown in Fig. 4.5, having three distinct wear zones. These are initial wear zone, steady wear zone and severe wear zone.

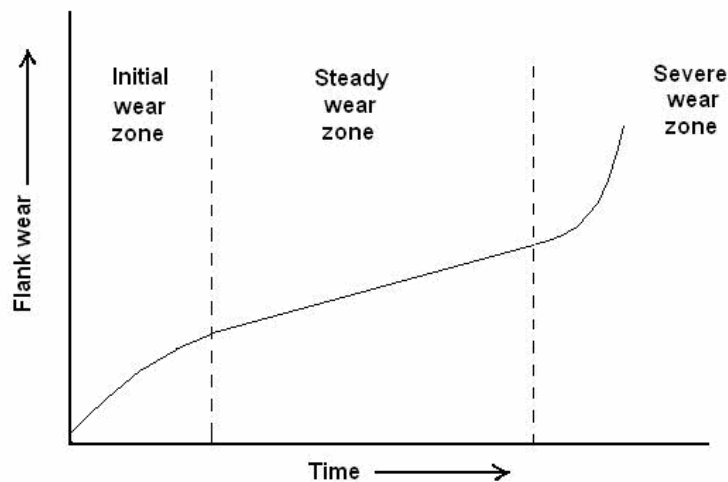


Fig. 4.5. Flank wear verses Cutting time for a typical tool

Tool life is estimated by fitting a best-fit line on the data falling in the steady wear zone. Mathematically, if the best-fit equation is

$$w = a + bt, \quad (4.15)$$

where w is the flank wear, t is the time and a and b are constants, then the tool life T is given by

$$T = \frac{w_{\max} - a}{b} \quad (4.16)$$

where w_{\max} is the maximum flank wear.

By conducting a few tests till tool failure, it is verified that wear-time curve is almost linear up to maximum flank wear of 0.6 mm, thus justifying the use of linear interpolation based on the best fit line. The tool life values are then put in the neural network model to develop a model for the prediction of tool life in machining of steel with coated carbide tool.

For air-cooled turning, 21 training and 8 testing sets are used (Tables 4.5 and 4.6) and for dry turning, 23 training and 8 testing sets are used (Tables 4.7 and 4.8). A multi layer perceptron (MLP) neural network using Levenberg-Marquardt algorithm is used for weight adjustment. The RMS error for training and testing was found to be 9.89% and 24.82% respectively and the maximum effective percentage deviation was found to be 32.37% for air-cooled turning. Only three data were found to have error of more than 25%. Similarly for dry turning, the RMS error for training and testing is found to be 8.79% and 23.50% and the maximum effective percentage deviation is found to be 32.53%. In this case, only two data were found to have error of more than 25%.

The test of hypothesis using Student's t -test at 95% confidence level was carried out for the assessment of prediction accuracy of tool life (considering the flank wear value). Same procedure was followed to carry out the replicate experiments as in the case of surface finish. The result showed that prediction accuracy up to 21% is reasonable at 95% confidence level [Appendix A]. A few more random experiments ascertained that fitted neural network models could achieve this accuracy.

Table 4.5: Training data set for prediction of tool life in turning of mild steel with coated carbide tool during air-cooled turning

v m/min	f mm/rev	d mm	<i>Tool life</i> (min)
148	0.10	1.0	84
149	0.10	3.0	57
145	0.32	1.0	39
149	0.32	3.0	18
327	0.10	1.0	28
320	0.10	3.0	49
327	0.32	1.0	16
320	0.32	3.0	21
211	0.10	1.1	53
273	0.12	1.1	21
229	0.20	1.3	38
272	0.24	1.5	16
269	0.28	1.6	19
207	0.32	1.7	19
165	0.10	1.8	66
207	0.12	1.9	44
240	0.14	2.0	29
202	0.20	2.2	20
290	0.12	2.9	22
211	0.14	1.1	60
204	0.16	2.2	31

Table 4.6: Testing data set for prediction of tool life in turning of mild steel with coated carbide tool during air-cooled turning

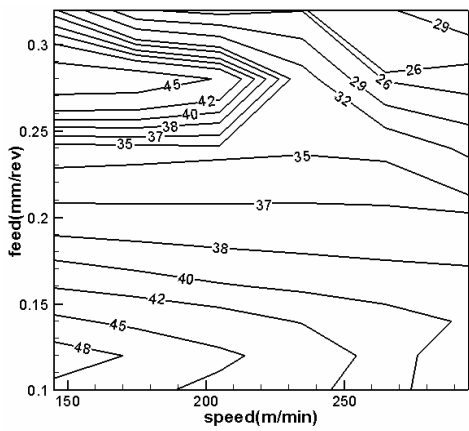
v m/min	f mm/rev	d mm	<i>Tool life</i> (min)
245	0.12	3.0	35
250	0.14	1.2	57
179	0.20	1.4	32
232	0.24	2.5	22
268	0.28	2.6	27
162	0.32	2.7	14
185	0.10	2.8	54
270	0.16	1.2	30

Table 4.7: Training data set for prediction of tool life in turning of mild steel with coated carbide tool during dry turning

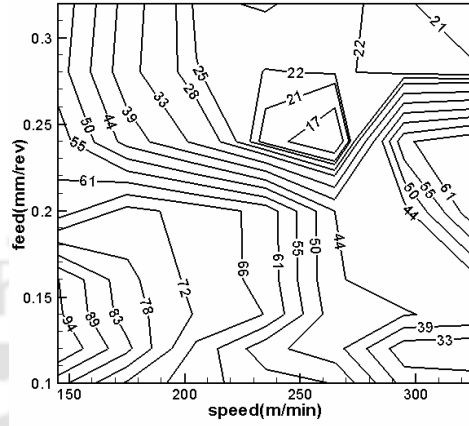
v m/min	f mm/rev	d mm	<i>Tool life</i> (min)
145	0.10	1.0	62
158	0.10	3.0	38
145	0.32	1.0	23
158	0.32	3.0	16
303	0.10	1.0	27
305	0.10	3.0	41
285	0.32	1.0	18
289	0.32	3.0	20
167	0.10	1.1	43
273	0.12	1.1	21
225	0.20	1.3	28
280	0.24	1.5	13
261	0.28	1.6	10
215	0.32	1.7	12
160	0.10	1.8	52
197	0.12	1.9	38
255	0.14	2.0	17
201	0.20	2.4	15
291	0.12	2.9	37
197	0.14	1.1	33
259	0.16	1.2	28
160	0.28	1.14	53
164	0.16	1.0	35

Table 4.8: Testing data set for prediction of tool life in turning of mild steel with coated carbide tool during dry turning

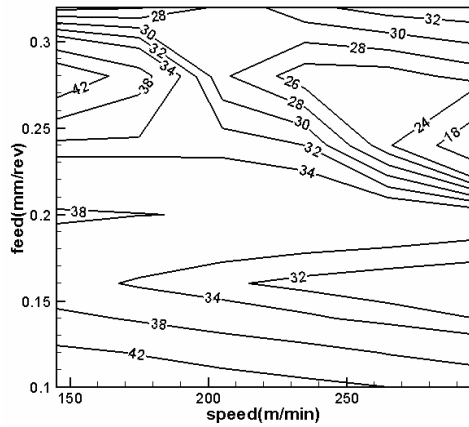
v m/min	f mm/rev	d mm	<i>Tool life</i> (min)
247	0.12	3.0	39
254	0.14	1.2	37
183	0.20	1.4	23
247	0.24	2.5	16
272	0.28	2.6	16
166	0.32	2.7	16
209	0.10	2.8	58
203	0.16	2.2	23



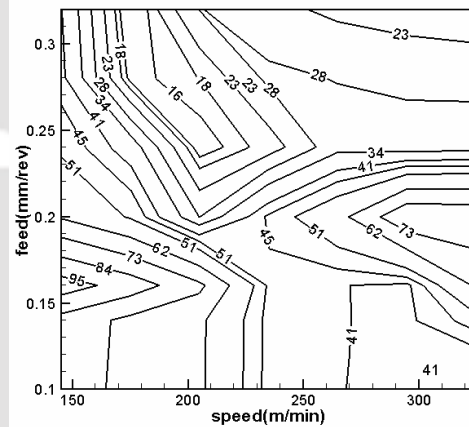
(a) doc = 1 mm



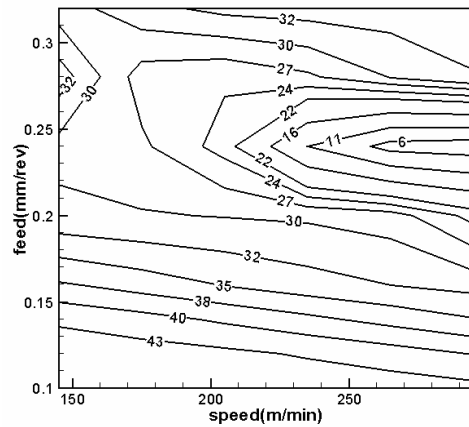
(a) doc = 1 mm



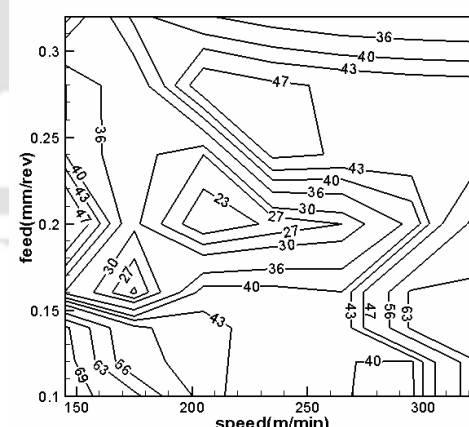
(b) doc = 2 mm



(b) doc = 2 mm



(c) doc = 3 mm



(c) doc = 3 mm

Fig. 4.6. Tool life (minutes) for different depth of cut in turning of mild steel with coated carbide tool in dry turning

Fig. 4.7. Tool life (minutes) for different depth of cut in turning of mild steel with coated carbide tool in air-cooled turning

Based on the trained networks, contours of tool life were plotted as shown in Figure 4.6 and Figure 4.7 respectively for dry turning and air-cooled turning. In each case, (a), (b) and (c) define the contours for various depth of cut *viz.* 1 mm, 2 mm and 3 mm. It is clearly seen that the tool life gets improved due to air-cooling. In certain cases, tool life increases by more than a factor of 2 during air-cooled turning. Generally, in all the cases, the tool life decreases with cutting speed. It is also seen that tool life decreases with increase of feed. The effect of the depth of cut on the tool life is not uniform. Increasing the depth of cut increases the tool life some times and decreases it at some other times depending on the value of feed

4.5 Modelling of Cutting Performance of Ceramic Tool in Dry and Air-cooled Turning

The present work compares the performance of a mixed oxide ceramic tool in dry and air-cooled turning of grey cast iron. The surface roughness of the machined surface, tool wear and cutting forces are the parameters which have been studied. Preliminary study was carried out according to a full factorial design with a number of replicates. Neural network model was trained with a number of experimental data. Considering that the data is noisy and it is not possible to have a large number of training and testing data, a novel procedure is employed for the training of the network. With the help of the trained network, contours of dependent variables have been plotted to compare the performance of dry and air-cooled turning.

4.5.1 Neural Network Modelling for Prediction of Surface Roughness and Tool Life

In Section 4.4, MLP neural network was used for modelling of surface roughness and tool life in turning of mild steel with coated carbide tool. In the present work, MLP network is first used for the prediction of surface finish and tool life in turning of grey cast iron with mixed oxide ceramic tool. However, neural network was not able to predict the RMS error within 10% during training and also the prediction the RMS error during testing is found to be more than 25%. This is due to limited number of experimental data and inherent noise in the data set. Considering these, a

new procedure has been employed to predict the surface roughness and tool life by combining both MLP and RBF network. The RBF neural network can be trained at a faster rate, but requires more training data. The MLP network needs relatively less training data, but takes more time in training. The noise in the experimental data creates problem in both the types of network. Hence, considering the limitation on the number of experimental data and inherent noise, a novel neural network modelling procedure is employed in this work. The procedure follows the following steps:

Step 1: Initially, to run the MLP neural network, the following ranges of cutting speed, feed and depth of cut are chosen to generate training and testing data during dry and air-cooled turning with ceramic tool:

Cutting speed: 96–448 m/min

Feed: 0.04–0.16 mm/rev

Depth of cut: 1.0–1.5 mm.

The surface roughness was measured with the help of surface roughness gage after every pass of each of the experiment. Each experiment consists of 5-6 passes. The CLA surface roughness was measured at 9 to 12 places for each pass, the average value is found out for each pass. The final surface roughness value of each experiment is the average value of all the passes in that experiment. The tool life was measured considering the flank wear of the cutting tool following the procedure of Ojha and Dixit [2005] as explained in the Section 4.4.2. The tool failure criterion for maximum flank wear was considered as 0.4 mm in this work.

The initial training data set is selected based on the influence of the process parameters on the performance. Some testing data is also generated. The MLP network was trained with TRAINLM function in MATLAB using LOGSIG activation function. The trained network was tested. The testing data providing more than specified errors of prediction are transferred from testing set to training set. In lieu of the transferred data, fresh data are generated from experiment for the testing data set. This procedure is repeated till the neural network is able to predict reasonably in the entire domain.

Thus in the present work, 19 training data and 8 testing data were generated for air-cooled turning and 16 training data and 9 testing data were generated for dry turning for prediction of surface roughness. Table 4.9, Table 4.10, Table 4.11 and Table 4.12 represent the training and testing data set respectively for air-cooled turning and dry turning.

Table 4.9: Training data set for prediction of surface roughness in turning of grey cast iron with ceramic tool during air-cooled turning

v m/min	f mm/rev	d mm	R_a (μm)
96	0.04	1.0	2.54
106	0.04	1.5	1.70
112	0.16	1.0	2.30
115	0.16	1.5	3.25
400	0.04	1.0	1.48
419	0.04	1.5	2.30
448	0.16	1.0	1.79
420	0.16	1.5	1.70
209	0.06	1.1	1.38
361	0.08	1.4	1.31
234	0.10	1.2	1.36
140	0.12	1.3	1.76
297	0.14	1.2	1.41
126	0.08	1.3	2.24
316	0.12	1.5	2.67
292	0.05	1.46	1.18
330	0.06	1.34	1.31
141	0.07	1.14	1.54
154	0.10	1.22	2.19

Table 4.10: Testing data set for prediction of surface roughness in turning of grey cast iron with ceramic tool during air-cooled turning

v m/min	f mm/rev	d mm	R_a (μm)
303	0.05	1.44	1.40
195	0.14	1.18	2.26
255	0.10	1.28	1.56
386	0.06	1.36	1.42
282	0.07	1.12	1.19
194	0.10	1.24	1.70
259	0.08	1.42	1.23
295	0.12	1.38	1.51

Table 4.11: Training data set for prediction of surface roughness in turning of grey cast iron with ceramic tool during dry turning

v m/min	f mm/rev	d mm	R_a (μm)
119	0.04	1.0	1.37
100	0.04	1.5	1.78
106	0.16	1.0	2.46
113	0.16	1.5	3.01
393	0.04	1.0	1.12
433	0.04	1.5	1.23
417	0.16	1.0	1.61
400	0.16	1.5	2.90
156	0.08	1.4	1.38
246	0.10	1.1	1.69
107	0.12	1.0	1.98
333	0.05	1.2	2.33
184	0.12	1.5	2.44
210	0.04	1.5	1.46
332	0.14	1.2	2.27
213	0.04	1.4	1.05

v m/min	f mm/rev	d mm	R_a (μm)
149	0.06	1.5	1.65
100	0.08	1.3	1.97
260	0.10	1.4	1.73
233	0.16	1.0	2.50
100	0.12	1.3	2.51
354	0.16	1.2	1.97
113	0.04	1.5	1.44
205	0.09	1.4	2.28
406	0.14	1.1	1.36

The tables show the experimentally observed CLA surface roughness (R_a) for the given speed (v), feed (f) and depth of cut (d). From the trained network, the RMS errors for air-cooled turning in training and testing were found as 10.90% and 13.93% respectively. The maximum effective percentage deviation observed is 30.48%. For dry turning, the RMS errors in training and testing were found as 5.39% and 27.47% respectively. The maximum effective percentage deviation

observed is 38.69%. Similarly, for prediction of tool life, 19 training data and 8 testing data were generated for air-cooled turning and 11 training data and 7 testing data were generated for dry turning.

Table 4.13: Training data set for prediction of tool life in turning of grey cast iron with ceramic tool during air-cooled turning

v m/min	f mm/rev	d mm	Tool life (μm)
96	0.04	1.0	60.9
106	0.04	1.5	50.7
112	0.16	1.0	24.6
115	0.16	1.5	68.2
400	0.04	1.0	49.7
419	0.04	1.5	19.7
448	0.16	1.0	12.2
420	0.16	1.5	9.1
209	0.06	1.1	60.9
361	0.08	1.4	23.2
234	0.10	1.2	46.9
140	0.12	1.3	44.2
297	0.14	1.2	28.9
126	0.08	1.3	53.2
316	0.12	1.5	47.3
292	0.05	1.46	30.6
330	0.06	1.34	37.0
141	0.07	1.14	76.1
154	0.10	1.22	41.9

Table 4.14: Testing data set for prediction of tool life in turning of grey cast iron with ceramic tool during air-cooled turning

v m/min	f mm/rev	d mm	Tool life (μm)
332	0.14	1.2	14.2
213	0.04	1.4	63.7
149	0.06	1.5	25.0
100	0.08	1.3	32.1
260	0.10	1.4	11.7
233	0.16	1.0	13.0
113	0.04	1.5	34.7

Table 4.15: Training data set for prediction of tool life in turning of grey cast iron with ceramic tool during dry turning

v m/min	f mm/rev	d mm	Tool life (μm)
119	0.04	1.0	67.0
100	0.04	1.5	57.1
106	0.16	1.0	45.4
113	0.16	1.5	53.5
393	0.04	1.0	18.0
433	0.04	1.5	15.2
417	0.16	1.0	8.6
400	0.16	1.5	7.0
333	0.05	1.2	32.8
184	0.12	1.5	13.1
210	0.04	1.5	39.0

Table 4.16: Testing data set for prediction of tool life in turning of grey cast iron with ceramic tool during dry turning

v m/min	f mm/rev	d mm	Tool life (μm)
149	0.06	1.5	1.65
100	0.08	1.3	1.97
260	0.10	1.4	1.73
233	0.16	1.0	2.50
100	0.12	1.3	2.51
354	0.16	1.2	1.97
113	0.04	1.5	1.44
205	0.09	1.4	2.28
406	0.14	1.1	1.36

Table 4.13, Table 4.14, Table 4.15 and Table 4.16 show the number of training and testing data set respectively for tool life estimation in air-cooled and dry turning. Same procedure was followed as in surface roughness to train the network in MATLAB. For air-cooled turning, the RMS errors in training and testing were found as 6.87% and 18.97% respectively. The maximum effective percentage deviation observed is 29.86%. For dry turning, the RMS errors in training and testing were found as 6.44% and 22.17% respectively. The maximum effective percentage deviation observed is 35.52%.

Step 2: In this step, all the training and testing data is merged to make the combined data sets of sizes 27 and 25 for surface roughness prediction and 27 and 18 for tool life prediction in air-cooled and dry turning respectively. For testing data sets, 10 data are generated from the neural network trained in Step 1. In this step, more

attention is paid to the reduction of training error, RMS training error being limited to 5%. The testing error is allowed to go up to 20%, as the testing data is not the real experimental data. The testing data only serves the purpose of avoiding excessive over-fitting. Using the fitted network, in this step, a total of 64 data are generated by the network to be used in an RBF network subsequently. The 64 data were generated as per factorial design, considering four levels of each of the three factors speed (v), feed (f) and depth of cut (d).

Step 3: The data set generated in Step 2 is used to train an RBF network. All experimental data serve the role of testing data in this case. The three-dimensional domain of cutting speed, feed and depth of cut is divided into 27 cubic elements, with 64 data forming the corners of the cube. Table 4.17 and Figure 4.8 show a 3-D domain of cutting speed, feed and depth of cut.

Table 4.17: Levels of cutting speed, feed and depth of cut for generation of data for RBF network in turning of grey cast iron with ceramic tool

Speed (m/min)	96 (air-cooled) 100 (dry)	200	300	448 (air-cooled) 433 (dry)
Feed (mm/rev)	0.04	0.08	0.12	0.16
Depth of cut (mm)	1.0	1.17	1.33	1.50

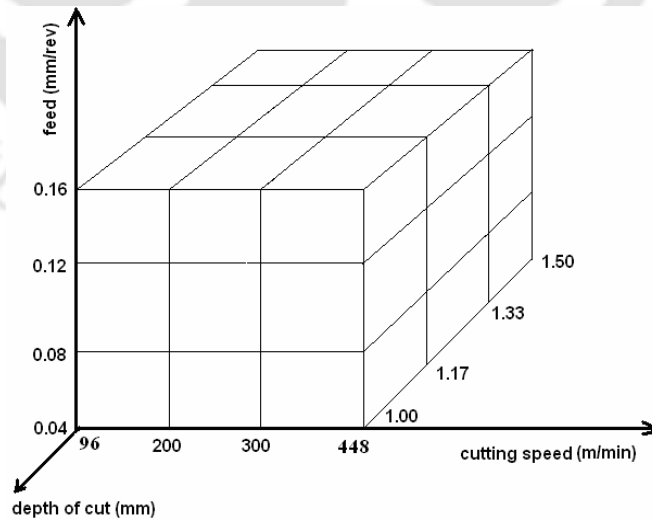


Figure 4.8: Cubic cell of 3-dimensional domain

Whenever the error in the prediction of testing data in any element is more, the corresponding corner data is modified by providing up to 10% perturbation. The modification in the corner data is carried out as follows.

The entire domain of process parameters is divided into a number of cubic cells. This cell can be transformed into natural coordinates having the eight corner nodes as $(\pm 1, \pm 1, \pm 1)$. The relation between physical parameters and natural coordinates is

$$\xi = \frac{2 \left(v - \frac{(v_{\max} + v_{\min})}{2} \right)}{v_{\max} - v_{\min}}, \quad \eta = \frac{2 \left(f - \frac{(f_{\max} + f_{\min})}{2} \right)}{f_{\max} - f_{\min}}, \quad \zeta = \frac{2 \left(d - \frac{(d_{\max} + d_{\min})}{2} \right)}{d_{\max} - d_{\min}} \quad (4.17)$$

Assume that error in the prediction of an experimental data is E . This error is distributed at the nodes such that error at the i^{th} node is e_i . Assuming that error function is tri-linear in natural coordinates, the corner errors are related to the error at a particular point in the cell in the following way:

$$E = \sum_{i=1}^8 N_i e_i \quad (4.18)$$

where

$$N_i = (1 + \xi_i \xi)(1 + \eta_i \eta)(1 + \zeta_i \zeta) \quad (4.19)$$

are called shape functions. Further, we assume that the error at a particular corner node is proportional to corresponding shape function value at the point of the cubic cell *i.e.*,

$$e_i = k N_i \quad (4.20)$$

Substituting it in Equation 4.18, the constant k is found equal to

$$k = \frac{E}{\sum_{i=1}^8 N_i^2} \quad (4.21)$$

Thus, error in a corner node is

$$e_i = \frac{N_i}{\sum_{i=1}^8 N_i^2} E \quad (4.22)$$

In order to reduce the error in prediction, the value of the parameter to be predicted is modified at the corner by subtracting the corresponding error value calculated from Equation 4.22.

Step 4: Based on the modified 64 data, RBF network is trained. If the error in prediction for all the experimental data is less than 20% and RMS error is less than 10%, the network is frozen. Otherwise the process of modifying the data and the training of RBF neural network is repeated.

Following are the results obtained using this methodology for surface roughness and tool life in air-cooled and dry turning.

Surface roughness:

For air-cooled turning, the RMS errors in training and testing were found as 4.75% and 11.18% respectively. The maximum effective percentage deviation was found to be 23.29% (only in one case the value was more than 20%).

For dry turning, the RMS errors in training and testing were found as 2.84% and 10.56% respectively. The maximum effective percentage deviation was found to be 20.62% (only in one case the value was more than 20%).

Tool life:

For air-cooled turning, the RMS errors in training and testing were found as 3.05% and 13.32% respectively. The maximum effective percentage deviation was found to be 28.56% (only in one case the value was more than 20%).

For dry turning, the RMS errors in training and testing were found as 4.46% and 14.63% respectively. The maximum effective percentage deviation was found as 32.28% (only in one case the value was more than 20%).

Table 4.18 shows a comparison of the result of RMS error in training and testing and maximum effective percentage deviation that was obtained from MLP network and combined MLP and RBF network for both surface roughness and tool life. The novel modelling procedure employed for combined application of both MLP and RBF network gives a better result compared to individual application of MLP network. In each case, the RMS error and maximum effective percentage deviation have been found to be reduced with the help of novel modelling procedure.

Table 4.18: Comparison of the result obtained from MLP and combined MLP and RBF network for prediction of surface roughness and tool life in turning of grey cast iron with ceramic tool

		MLP			Combined MLP and RBF		
		Training (RMS error) %	Testing (RMS error) %	Maximum effective % deviation	Training (RMS error) %	Testing (RMS error) %	Max. effective % deviation
Surface roughness	Air-cooled turning	10.90	13.93	30.48	4.75	11.18	23.29
	Dry turning	5.39	27.47	38.69	2.84	10.56	20.62
Tool life	Air cooled turning	6.87	18.97	29.86	3.05	13.32	28.56
	Dry turning	6.44	22.17	35.52	4.46	14.63	32.28

A test of hypothesis using Student's *t*-test showed that prediction accuracy up to 20% in case of surface roughness and 25% in the case of tool life is reasonable from a statistical point of view at 95% confidence level [Appendix A]. By carrying out a few more random experiments, it was ascertained that fitted neural network models could achieve this accuracy. In the machining of the cast iron, this much variation in the machining performance is common due to variation in material quality.

Based on these steps, neural networks were fitted for the prediction of the average surface roughness and tool life. Figures 4.9 and 4.10 show the contours of CLA surface roughness (in microns) of machined surface for turning with 1 mm and 1.5 mm depth of cut where (a) and (b) indicates for dry and air-cooled turning respectively. It is seen that, in general, the surface roughness in dry turning is less

compared to the air-cooled turning. Both the dry turning and air-cooled turning are capable of providing N7 (1.6 μm) surface roughness.

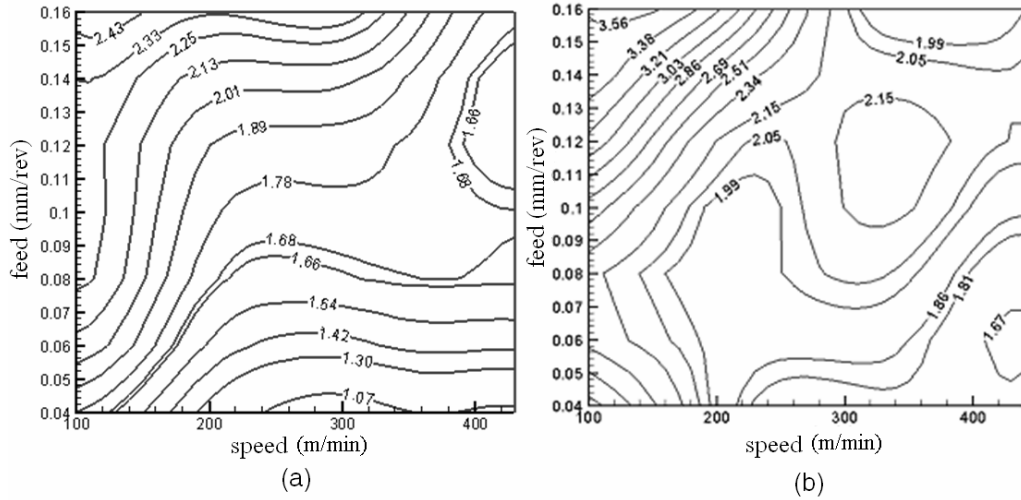


Figure 4.9: CLA surface roughness (in micron) of machined surface for turning of grey cast iron with ceramic tool at 1 mm depth of cut (a) dry turning (b) air-cooled turning

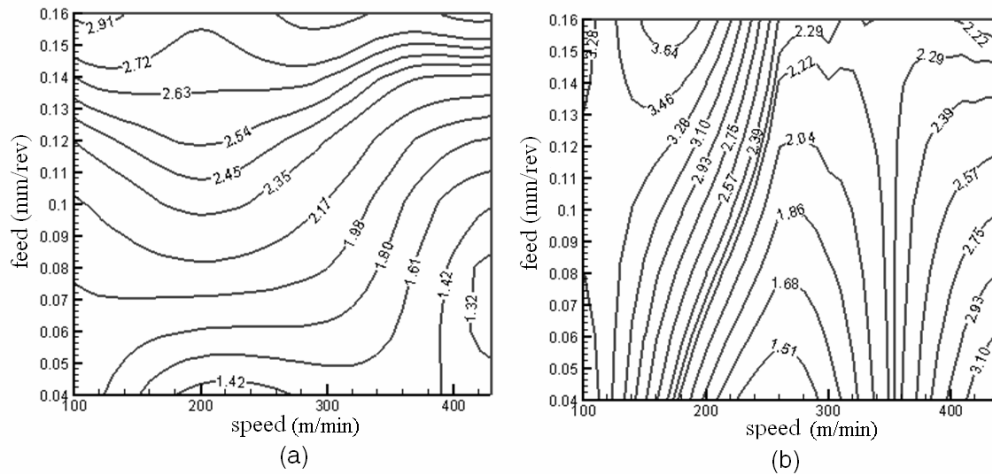


Figure 4.10: CLA surface roughness (in micron) of machined surface for turning of grey cast iron with ceramic tool at 1.5 mm depth of cut (a) dry turning (b) air-cooled turning

Figures 4.11 and 4.12 show the contours of tool life (in minutes) for turning with 1 mm and 1.5 mm depth of cut for dry and air-cooled turning respectively. It is

clearly seen that the tool life gets improved due to air-cooling. In certain cases, the improvement in tool life is more than 50%.

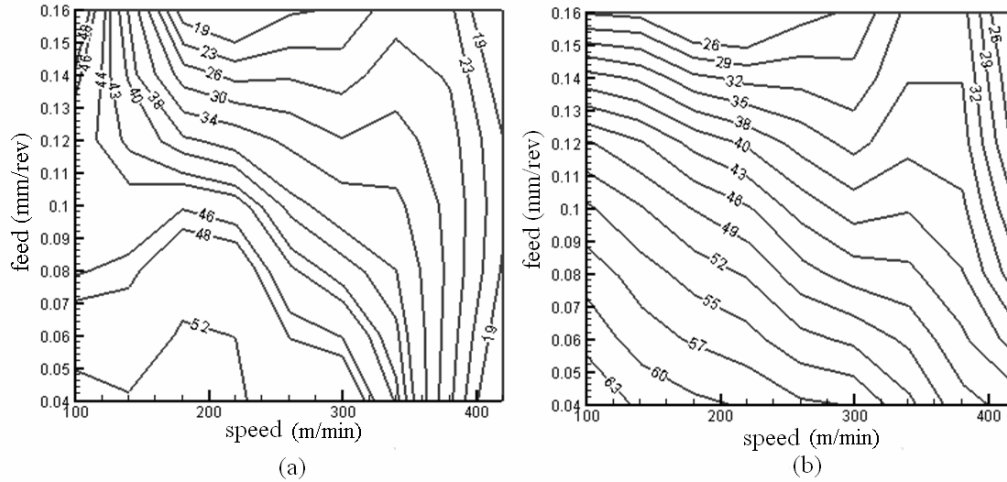


Figure 4.11: Tool life (in minutes) for turning of grey cast iron with ceramic tool at 1 mm depth of cut (a) dry turning (b) air-cooled turning

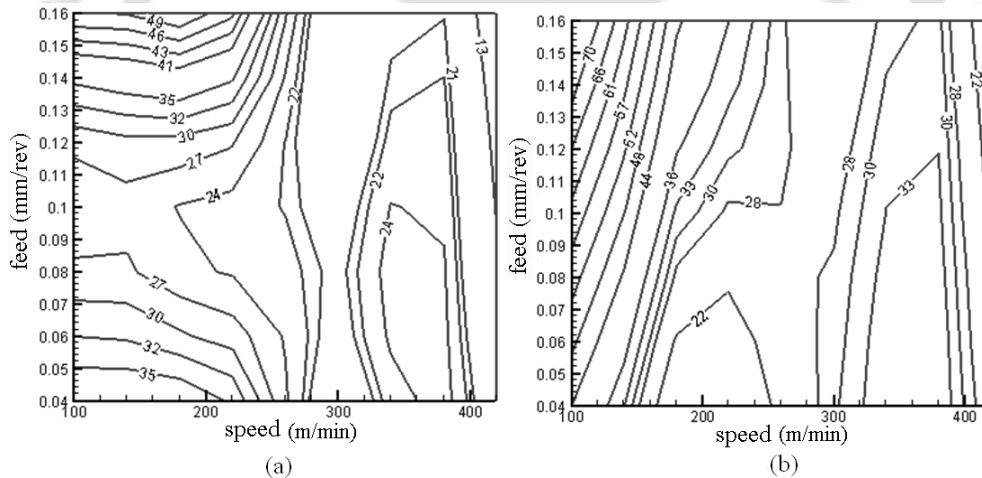


Figure 4.12: Tool life (in minutes) for turning of grey cast iron with ceramic tool at 1.5 mm depth of cut (a) dry turning (b) air-cooled turning

Generally, in all the cases, the tool life decreases with decrease in cutting speed. For most of the cases, it does decrease with increase in feed. However, for some cases of machining at high depth of cut and low speed, tool life is found to increase

with increase in feed. The effect of the depth of cut on the tool life is not uniform particularly at low speed. Increasing the depth of cut increases the tool life some times and decreases it in some other cases depending on the value of feed. The physics governing this phenomenon is complex; however, some explanation can be given on the basis of Markarow's law [Markarow, 1976]. Way back in 1976, Markarow introduced the concept of optimal cutting temperature based on experimental studies on metal cutting, which has been presented as the first metal cutting law in the book by Astakhov [1998]. According to it, the tool wear will be the minimum at an optimal cutting temperature. Thus, the combination of process parameters providing optimum temperature gives maximum tool life.

4.5.2 Neural Network Modelling of Cutting Forces

In the present work, a radial basis function (RBF) neural network is used for prediction of cutting forces in feed direction and cutting direction for machining of cast iron with ceramic tool in dry and air-cooled condition. Figure 4.13 shows the architecture of the RBF network for prediction of cutting forces.

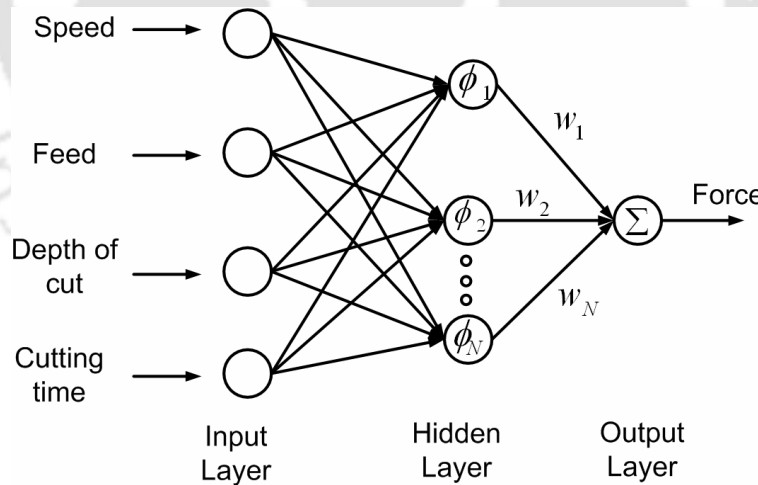


Figure 4.13. RBF neural network architecture used in the modelling of force

The operating conditions for cutting speed, feed, depth of cut and cutting time are chosen from the following cutting ranges. The generated data were put later on

as training and testing data in the network. Cutting speed: 96-448 m/min, Feed: 0.04-0.16 mm/rev and Depth of cut: 1.0-1.5 mm.

The cutting time is dependent on the cutting length, feed and spindle rpm. As such, for each operating condition the cutting time will be different. Tables B-1 to B-6 in Appendix B show the training and testing data set for different operating conditions. There are total 108 data in training set for the prediction of cutting force and feed force in air-cooled condition. For testing, 38 and 26 data were considered for both air-cooled and dry turning conditions. Similarly, 86 data were put in training set for prediction of cutting force and feed force in dry cut condition. For testing, a total 30 and 33 data were considered for both air-cooled and dry turning conditions.

The performance data of the fitted neural network is shown in Table 4.19. In the prediction of feed force in air-cooled turning, the maximum error in prediction is 26.16%, although the root-mean squared percentage error is only 14.81%. In other cases, the prediction accuracy is better than this.

Table 4.19: Performance of RBF network in modelling of cutting and feed forces in turning of grey cast iron with ceramic tool for dry and air-cooled turning

Network output	Number of Training Data	Number of Testing Data	RMS %error (training)	RMS %error (testing)	Maximum %deviation (training)	Maximum %deviation (testing)
Cutting force in dry turning	86	30	2.20	12.02	5.96	19.01
Cutting force in air-cooled turning	108	38	2.33	9.88	9.84	18.62
Feed force in dry turning	86	33	2.86	9.53	10.37	18.93
Feed force in air-cooled turning	108	26	2.33	14.81	9.98	26.16

Realizing the statistical nature of the problem, a test of hypothesis using Student's t -test was carried out at 95% confidence level for air-cooled turning. For different conditions, 5-6 replicates were obtained for applying the t -test. The test results revealed that the expected prediction accuracy of the feed force is in a range of 6–30% [Appendix A]. This means that for some cutting conditions, results of replicates did not differ much and the t -test showed that an error of around 6% was significant. On the other hand, for certain cutting conditions, there was a wide variation in the results of the replicates, indicating that the error of the order of even 30% may not be significant from the view point of statistics. As per the Student's t -test, similar order of expected prediction accuracy is observed for cutting force. A slightly lesser statistical deviation was obtained in the case of dry turning as compared to the air-cooled turning.

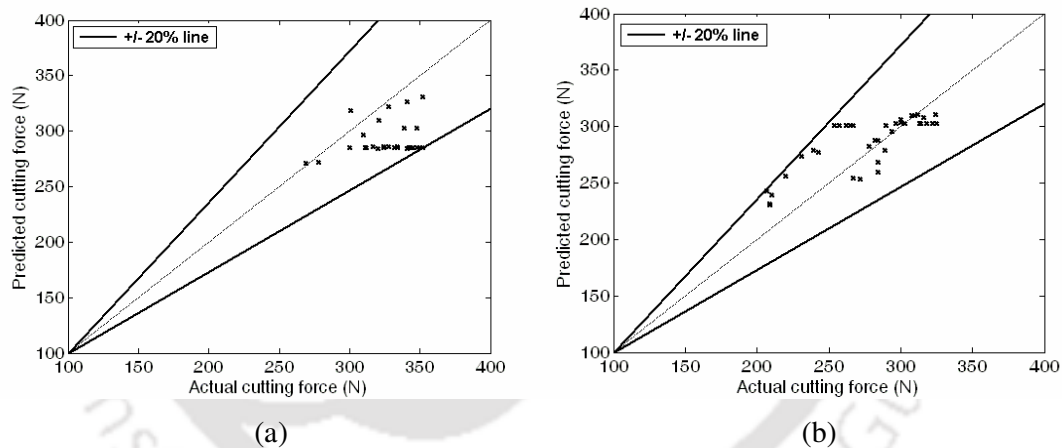


Figure 4.14. Predicted versus actual cutting force in turning of grey cast iron with ceramic tool: (a) dry turning and (b) air-cooled turning

Figure 4.14 gives the pictorial representation of the results of cutting force prediction for testing data. It is observed that in all the cases, the prediction error is less than 20%. Figure 4.15 shows the results of feed force prediction pictorially for testing data. It is observed that in the case of dry turning, prediction could be made within 20% accuracy in almost all the cases. In the case of air-cooled turning, in 4 cases, the error is more than 20%.

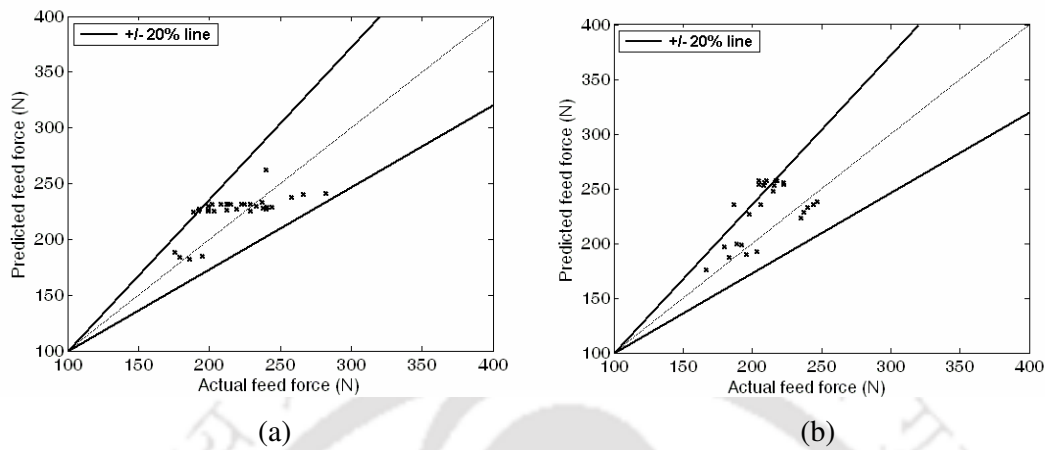


Figure 4.15. Predicted versus actual feed force in turning of grey cast iron with ceramic tool: (a) dry turning and (b) air-cooled turning

A parametric study was conducted based on the results of neural network predictions. This has been done to get an insight into the process as well to assess the qualitative prediction capability of the neural network. Figures 4.16 to 4.21 show the variation of feed and cutting forces with time for different cutting conditions. In all the cases, the forces are observed to increase with time due to tool wear and cutting force is always more than the feed force.

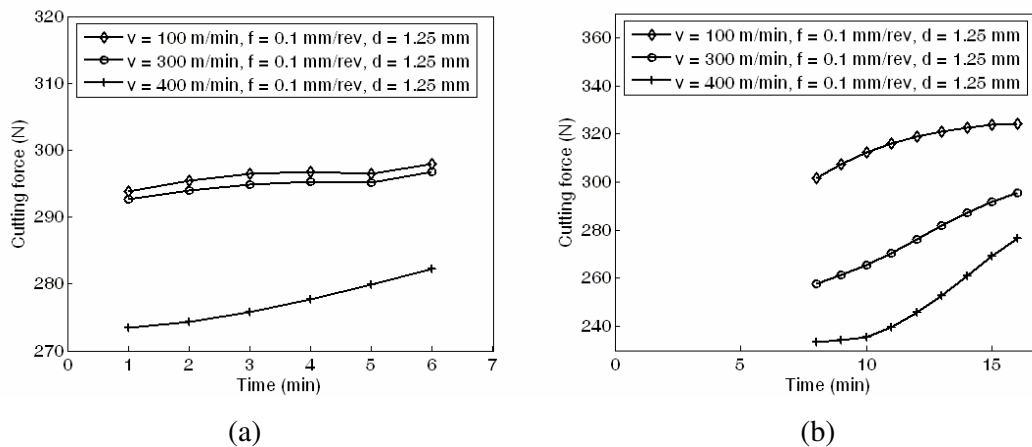


Figure 4.16. Effect of cutting speed on variation of cutting force with time in turning of grey cast iron with ceramic tool: (a) dry turning and (b) air-cooled turning

Figures 4.16 and 4.17 represent the effect of cutting speed in variation of cutting and feed force with respect to time. Figure 4.16 shows the cutting force decreases with increase in cutting speed for both the dry and air-cooled turning. There is a large variation in the cutting forces for the cutting speed of 100 m/min and 400 m/min. The corresponding variation for the feed force is not as high, as shown in Figure 4.17.

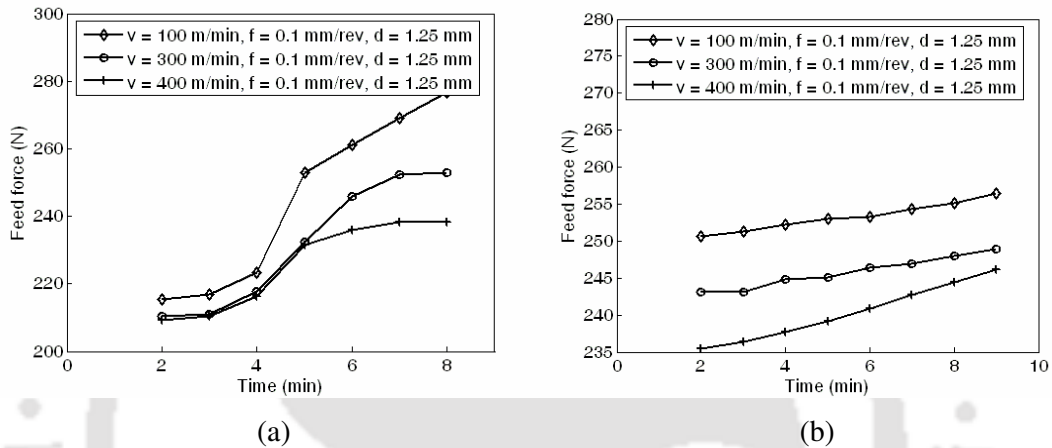


Figure 4.17. Effect of cutting speed on variation of feed force with time in turning of grey cast iron with ceramic tool: (a) dry turning and (b) air-cooled turning

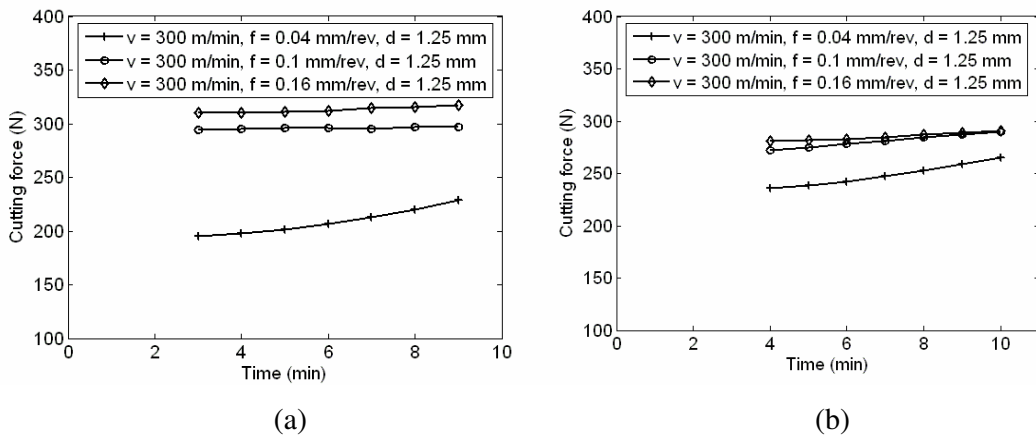


Figure 4.18. Effect of feed on variation of cutting force with time in turning of grey cast iron with ceramic tool: (a) dry turning and (b) air-cooled turning

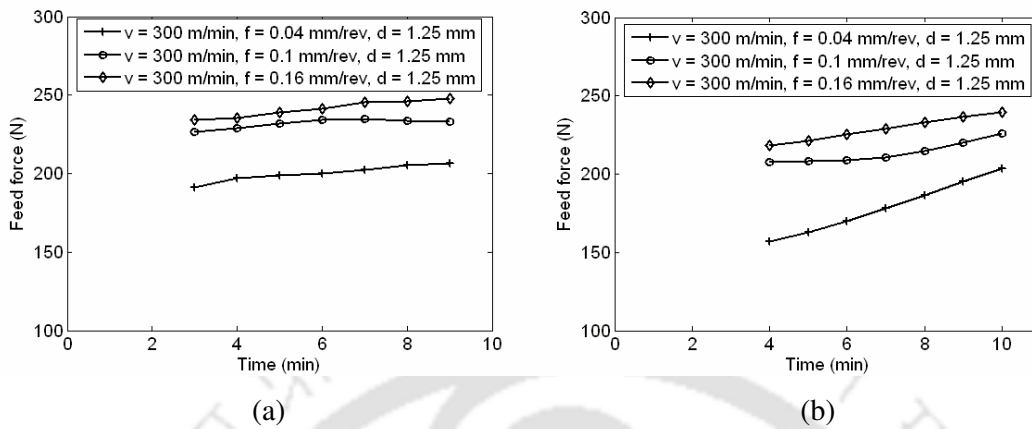


Figure 4.19. Effect of feed on variation of feed force with time in turning of grey cast iron with ceramic tool: (a) dry turning and (b) air-cooled turning

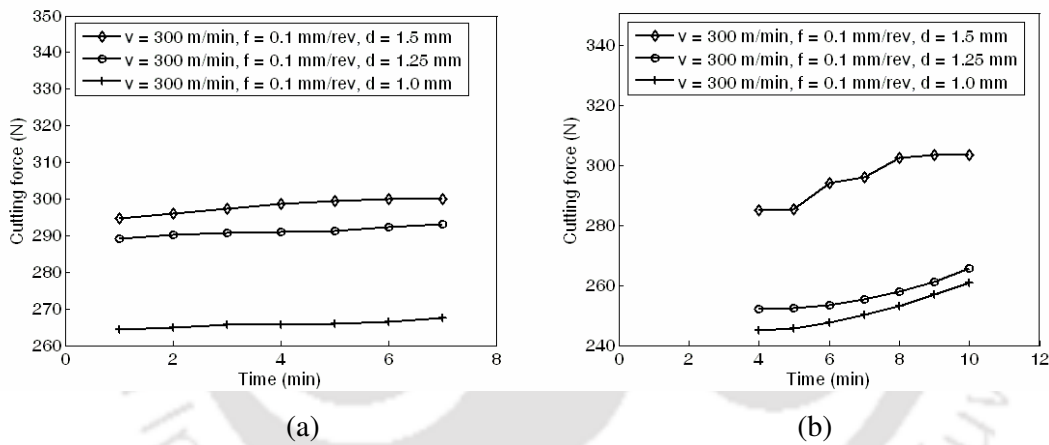


Figure 4.20. Effect of depth of cut on variation of cutting force with time in turning of grey cast iron with ceramic tool: (a) dry turning and (b) air-cooled turning

Figures 4.18 and 4.19 represent the effect of feed in variation of cutting and feed force with respect to time. Similarly, Figures 4.20 and 4.21 represent the effect of depth of cut in variation of cutting and feed force with respect to time. In all cases, the cutting as well as feed force increases with increase in feed and depth of cut, as expected.

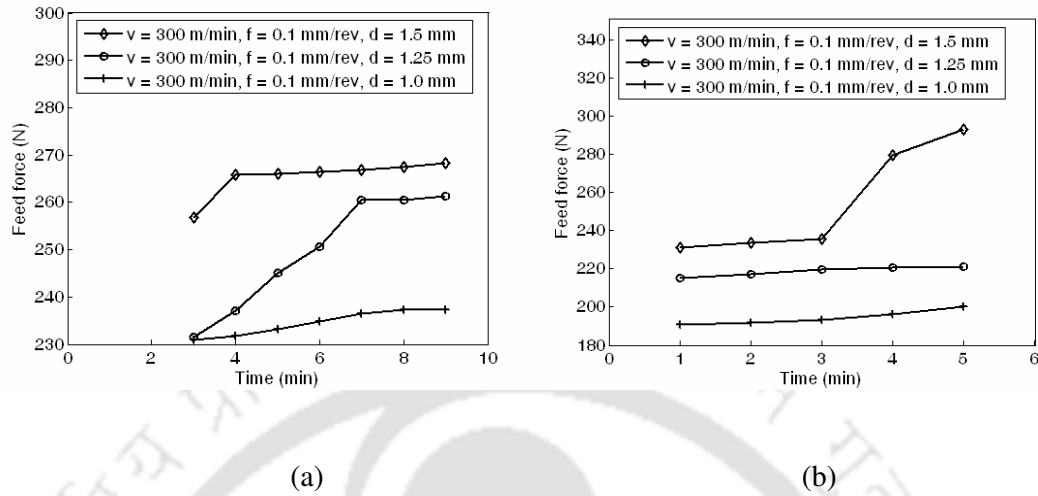


Figure 4.21. Effect of depth of cut on variation of feed force with time in turning of grey cast iron with ceramic tool: (a) dry turning and (b) air-cooled turning

4.5.3 Neural Network Modelling for Indirect Prediction of Tool Wear using Cutting Forces

For modelling of tool wear using cutting/feed force, it is essential to know the correlation between flank wear, cutting force and feed force. Initially, 8 experiments were conducted as per factorial design to study the correlation between the flank wear, cutting and feed forces. It is observed that, in general, the cutting force and feed force increases with increase in flank wear. Table 4.20 and Table 4.21 show that, in most of the cases, the coefficient of correlation is close to 1. However, in some cases, a low value of coefficient of correlation is observed. This is due to the presence of random factors in machining. It is also observed that at low feed the correlation is better than at high feed. This indicates that the force measurement can be used for wear estimation at low feed. It was also observed that the ratio of feed force to cutting force does not have a good correlation with the flank wear. This is in contrast to the results reported by some researchers for different tool-work piece material combinations [Choudhury and Kishore, 2000].

Table 4.20: Correlation of flank wear with cutting and feed forces in turning of grey cast iron with ceramic tool for different cutting conditions in dry turning

Cutting condition: v (m/min) - f (mm/rev) - d (mm)	Flank wear(mm) after each pass	Cutting force(N) after each pass	Feed force(N) after each pass	Coefficients of correlation	
				Flank wear and cutting force	Flank wear and feed force
119-0.04-1	0.06	165	114	0.85	0.90
	0.12	193	208		
	0.14	197	214		
	0.19	198	226		
	0.22	199	239		
100-0.04-1.5	0.11	315	246	0.74	0.97
	0.13	313	298		
	0.14	307	379		
	0.16	329	413		
	0.17	376	435		
106-0.16-1	0.02	287	155	0.01	0.70
	0.03	277	178		
	0.05	292	171		
	0.08	281	167		
	0.09	292	192		
	0.09	278	189		
113-0.16-1.5	0.02	421	195	0.61	0.76
	0.03	448	204		
	0.03	433	210		
	0.04	439	218		
	0.05	440	220		
	0.05	443	208		
393-0.04-1	0.09	117	96	0.90	0.97
	0.12	134	122		
	0.15	134	128		
	0.16	132	146		
	0.19	142	148		
	0.2	142	165		

433-0.04-1.5	0.1	149	143	0.99	0.96
	0.16	167	198		
	0.16	175	226		
	0.2	192	226		
	0.22	197	260		
	0.23	200	281		
417-0.16-1	0.07	243	130	0.70	0.82
	0.08	266	157		
	0.09	267	165		
	0.11	267	167		
400-0.16-1.5	0.1	309	208	0.97	0.94
	0.12	329	263		
	0.13	345	282		
	0.17	360	295		
	0.18	363	319		
	0.18	368	327		

Table 4.21: Correlation of flank wear with cutting and feed forces in turning of grey cast iron with ceramic tool for different cutting conditions in air-cooled turning

Cutting condition: v (m/min)- f (mm/rev)- d (mm)	Flank wear (mm) after each pass	Cutting force (N) after each pass	Feed force (N) after each pass	Coefficients of correlation	
				Flank wear and cutting force	Flank wear and feed force
96-0.04-1	0.09	156	168	0.75	0.84
	0.13	158	218		
	0.16	171	253		
	0.21	217	254		
	0.23	180	245		
106-0.04-1.5	0.13	246	226	0.79	0.91
	0.14	243	291		
	0.15	277	332		
	0.16	290	403		
	0.19	286	421		

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112-0.16-1	0.03	258	154	0.70	0.69
	0.04	260	173		
	0.06	261	165		
	0.09	286	171		
	0.09	336	220		
	0.1	285	193		
115-0.16-1.5	0.03	309	185	0.45	0.63
	0.04	231	198		
	0.04	305	200		
	0.05	318	212		
	0.06	327	197		
	0.06	320	207		
400-0.04-1	0.06	114	101	0.81	0.94
	0.1	119	111		
	0.11	121	124		
	0.12	124	139		
	0.13	125	146		
	0.14	143	160		
419-0.04-1.5	0.07	111	162	0.91	0.89
	0.11	111	171		
	0.15	117	177		
	0.15	123	186		
	0.17	126	204		
	0.18	126	219		
448-0.16-1	0.02	178	131	0.76	0.95
	0.03	179	141		
	0.04	178	145		
	0.06	180	151		
420-0.16-1.5	0.08	299	225	0.96	0.97
	0.09	314	248		
	0.1	318	256		
	0.11	323	264		
	0.11	333	269		
	0.12	336	273		

In order to develop a model for the estimation of flank wear by the measurement of forces, a total of 33 experiments were conducted for air-cooled turning and 29 experiments for dry turning. The ranges of the parameters were— cutting speed: 100–400 m/min, feed: 0.04–0.16 mm/rev and depth of cut: 1.0–1.5 mm. At each cutting condition, a number of machining passes were conducted and a line of the form $y=mx$ was fitted, y representing the flank wear and x the feed/cutting force. Initially, the dependency of m on process parameters was modelled using the MLP neural network. However, the network could not predict a satisfactory result, perhaps due to probabilistic nature of dependency of flank wear on the forces. Even no clear trend of the variation of m with process parameters emerged.

Smithey *et al.* [2000] observed analytically and experimentally that for a given tool and work-piece material, the incremental increase in the cutting force due to flank wear is solely a function of the amount and nature of the wear and is independent of cutting conditions. Thus, knowing the initial wear, the wear can be estimated as

$$w = w_i + (\text{rate of change of wear with respect to force}) \times (F - F_i) \quad (4.23)$$

where w denotes the maximum flank wear, F denotes the force (cutting or feed) and subscript i indicates the initial value. With this method, a rough estimation of the wear could be obtained by knowing the initial wear, when a representative value of rate of change of maximum flank wear with cutting/feed force is known. However, the estimation of the wear can be done only in a probabilistic manner.

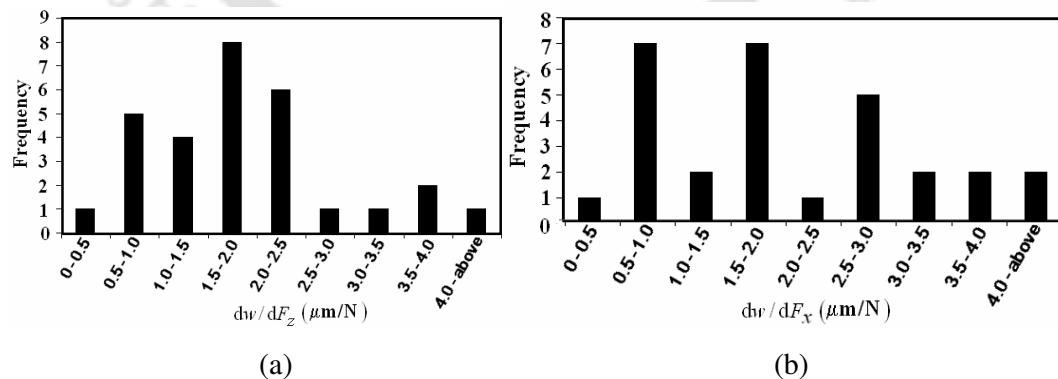


Figure 4.22. Bar chart showing the rate of change of wears (in dry turning) with respect to (a) cutting and (b) feed force in turning of grey cast iron with ceramic tool

Figure 4.22(a) shows a bar chart for the rate of change of flank wear with respect to cutting force (dw/dF_z) for dry turning. It is observed that, in most of the cases, the value of (dw/dF_z) is in the range of 0.5 to 2.0 $\mu\text{m}/\text{N}$. Thus, by the measurement of cutting force, the tool wear can be estimated within a range. Figure 4.22(b) shows the bar chart for the rate of change of flank wear with respect to feed force (dw/dF_x) for dry turning. In this case, in most of the cases, dw/dF_x lies in the range of 0.5 to 3.0 $\mu\text{m}/\text{N}$. Figure 4.23(a) shows the bar chart for the rate of change of flank wear with respect to cutting force (dw/dF_z) for air-cooled turning.

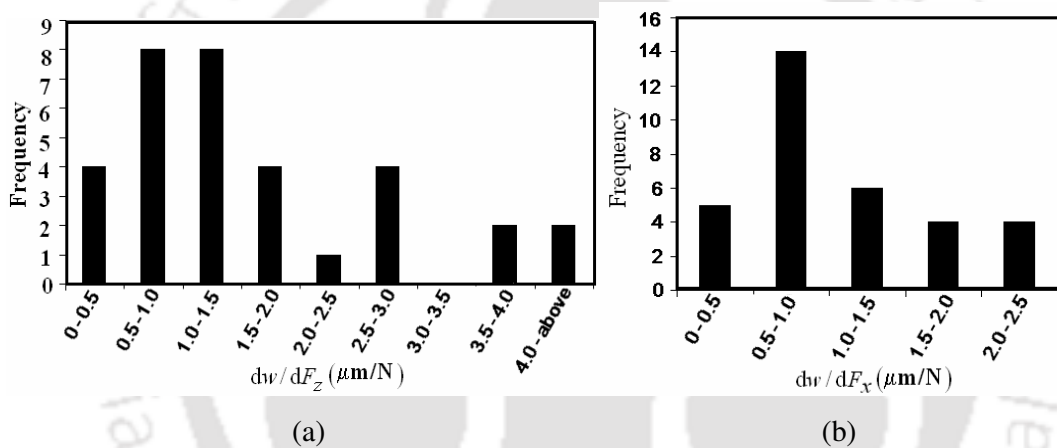


Figure 4.23. Bar chart showing the rate of change of wear (in air-cooled turning) with respect to (a) cutting force and (b) feed force in turning of grey cast iron with ceramic tool

A greater statistical variation is obtained in air-cooled turning compared to dry turning. However, the number of data points falling in the range of 0.5 to 1.5 $\mu\text{m}/\text{N}$ for dw/dF_z is more compared to the number of data points falling in other ranges. Figure 4.23(b) shows the bar chart for the rate of change of flank wear with respect to feed force (dw/dF_x) for air-cooled turning. In this case, the range of 0.5–1.0 $\mu\text{m}/\text{N}$ for dw/dF_x corresponds to the highest frequency. All this suggests that, based on the force measurement, the tool wear can be estimated statistically. Measuring the forces, we can estimate the likely frequency distribution of the wear based on the frequency distributions of Figures 4.22 and 4.23. Tables 4.22 and 4.23 show the

replicates for the rate of change of wear with cutting force and feed forces for air-cooled turning.

Table 4.22: Repeatability of the rate of change of wear (in air-cooled turning) with respect to cutting force for a typical cutting condition

Cutting condition: $v(\text{m/min})-f(\text{mm/rev})-d$ (mm)	dw/dF_z ($\mu\text{m/N}$)				
	Replicate 1	Replicate 2	Replicate 3	Replicate 4	Replicate 5
118-0.16-1.0	0.94	1.35	1.01	1.40	1.1
120-0.04-1.5	0.87	1.00	0.89	0.93	0.96
408-0.16-1.5	0.84	0.92	0.88	1.10	1.00
195-0.10-1.24	1.00	1.44	0.75	0.86	2.50

Table 4.23: Repeatability of the rate of change of wear (in air-cooled turning) with respect to feed force for a typical cutting condition

Cutting condition: $v(\text{m/min})-f(\text{mm/rev})-d$ (mm)	dw/dF_x ($\mu\text{m/N}$)				
	Replicate 1	Replicate 2	Replicate 3	Replicate 4	Replicate 5
118-0.16-1.0	1.50	0.85	0.72	1.25	1.24
120-0.04-1.5	0.76	0.64	0.56	0.70	0.24
408-0.16-1.5	0.72	0.84	0.86	0.68	0.73
195-0.10-1.24	0.83	0.78	1.04	0.90	1.57

A test of hypothesis using Student's t-test was carried out at 95% confidence level to have an assessment of the prediction accuracy of the rate of change of wear with respect to forces. It is observed that for dw/dF_x , the prediction accuracy is expected to be in the range of 36–44% and for dw/dF_z , it is expected to be in the range of 7–38%. It means that the definite prediction of tool flank wear may not be possible by force measurements. This viewpoint was expressed by Micheletti *et al.* [1968]. The results in this work show that although we may not be able to predict the tool wear with definiteness, a probabilistic estimation is still possible.

4.6 Summary

In this chapter, first, a study was carried out about the background of the neural networks for application in machining for modelling. Next, neural network modelling was carried out for prediction of surface roughness and tool life in turning of mild steel with coated carbide tool during dry and air-cooled turning. It is observed that air does not have much effect in improvement of surface finish at high cutting speed (about 300 m/min). However, air reduces the tool flank wear during high cutting speed. At low cutting speed (about 150 m/min), air-cooling has shown random effect in reduction of flank wear. Using neural network model, the prediction of surface roughness and tool life can be carried out for any general cutting condition within a particular range of process parameters. Also, the contour plots of surface roughness and tool life can be plotted.

The next phase of work was to explore the possibility of improving the cutting performance of mixed oxide ceramic tool in turning of grey cast iron by means of air-cooling. The major advantage of air-cooled turning seems to be reduction of tool wear at high cutting speed. However, air-cooled turning produced slightly higher surface roughness compared to dry turning. The replicate experiments conducted for different cutting conditions prove the consistency of the cutting performance indicators such as surface roughness, flank wear, cutting forces or vibrations.

The neural network model helps in prediction of surface finish and tool life in turning of grey cast iron with ceramic tool. However, due to limited and noisy experimental data for training and testing, the RMS errors were found to be more than 10% in training and 25% in testing. Hence, a novel procedure is employed using both MLP and RBF network which provides a good prediction with the RMS error less than 5% in training and 15% in testing. The results of the fitted neural network model were verified with the statistically calculated hypothesis testing. It was observed that, if appropriate operating conditions are employed, ceramic tool provides the best performance in finish turning. However, the economics of machining, number of pieces required to be manufactured and desired production rate, will decide the suitability of ceramic tool for this task. The experimental

database generated knowledge and conclusions drawn can be utilized in the expert system.

Another important work was the modelling of the cutting force and feed force using RBF network. The model was successful in prediction of feed force and cutting force. With the help of the trained neural network, predictions could be made within a root mean squared accuracy of 15%. A parametric study was carried out. The results of the parametric study match qualitatively with the expected trend.

One of the major challenges in this work was to model for indirect prediction of tool flank wear based on the cutting and feed force. Neural network was used but could not be employed successfully due to probabilistic nature of dependency of flank wear on the forces. It is observed that rate of change of wear with respect to forces varies statistically with distinct modes in the bar chart. Hence, it is concluded that tool wear can be predicted only in a probabilistic manner.

Optimization of Finish Turning Process

5.1 Introduction

Machining is one of the most important and widely investigated manufacturing processes. A number of researchers have presented different strategies for optimizing the process parameters in machining [Aggarwal and Singh, 2005, Mukherjee and Ray, 2006]. Efficient utilization of cutting tool is central to almost all of the optimization techniques, either explicitly or implicitly. This is why all optimization techniques are dependent on a tool life model, which may not be easily available on the shop floor. According to a CIRP working paper [Armarego *et al.*, 1996], a survey result of a major cutting tool manufacturer reports "... in USA, the correct cutting tool is selected 50% of the time, the tool is used at the rated cutting speed only 58% of the time and only 38% of the tools are used up to their full tool life capability...". This highlights the need to develop the strategies for proper utilization of cutting tools in machining.

The focus of the present work is to develop suitable strategies for the efficient utilization of cutting tools for finish turning process. The statistical nature of tool life in turning of mild steel with coated carbide tools is investigated for both dry and air-cooled turning. A strategy is developed that uses both air-cooled turning and dry turning in a sequence for effective utilization of cutting tool. The possibility of enhancing the usable life of cutting tool by changing the cutting conditions is explored. Finally, a heuristic optimization method has been proposed for finish turning that gathers the information about the tool life online.

5.2 Tool Life in Finish Turning

The tool life criterion may be based on the tool wear or surface roughness. Many a times, a criterion limiting the maximum flank wear to 0.6 mm is employed. However, the main concern in finish turning is to obtain a good surface roughness. Therefore, in this work a criterion based on the maximum centerline average (CLA) surface roughness of 2.5 μm was used. This surface roughness value is in between the ISO surface roughness grades N7 and N8 and can be considered a typical value for many finish turning processes. The following aspects are investigated experimentally:

- The statistical nature of tool life based on the maximum surface roughness criterion.
- The correlation between surface roughness and flank wear.
- The sensitivity of tool life to cutting speed and air-cooling.

The finish turning of rolled steel containing about 0.35% carbon was carried out by TiN coated carbide tool. The hardness of the work piece was 130 BHN, yield strength 290 MPa and ultimate tensile strength 477 MPa. It has been observed by a number of researchers that tool life is a stochastic phenomenon [Iakovou *et al*, 1996, Fenton and Joseph, 1979, Bonifacio *et al*, 1994]. In view of it, here 7 replicates were carried out at each cutting condition. The four cutting conditions used correspond to cutting speed of 300 m/min and 270 m/min in dry and air-cooled condition. The feed was kept at 0.1 mm/rev and depth of cut at 0.3 mm at each condition. The air velocity at the nozzle of 5 mm diameter was 150 m/s and air temperature was about 2°C less than the ambient temperature. The tool life was modelled using Weibull distribution. The following subsection provides the background of Weibull distribution.

5.2.1 Introduction to Weibull Distribution

The Weibull distribution is one of the most commonly used distributions in reliability engineering because of the many shapes it attains for various values of β

(slope parameter). Also, Weibull distribution is chosen for of its ability to model a great variety of life characteristics. A typical two-parameter Weibull probability density function (*pdf*) is defined as

$$f(T) = \frac{\beta}{\eta} \left(\frac{T}{\eta} \right)^{\beta-1} e^{-\left(\frac{T}{\eta} \right)^\beta}, \quad (5.1)$$

where η is a scale parameter, β is the shape parameter or slope of the Weibull distribution and T is the tool failure time in minute. The parameters of the Weibull distribution were estimated by the graphical probability plotting method combined with the principle of least squares [Murthy *et al.*, 2004]. Figure 5.1 shows a plot of Weibull *pdf*. Figure 5.1 (a) shows the effect of change in β on the shape of the Weibull *pdf*. For $\beta < 1$, the failure rate decreases with time and $f(T)$ decreases monotonically.

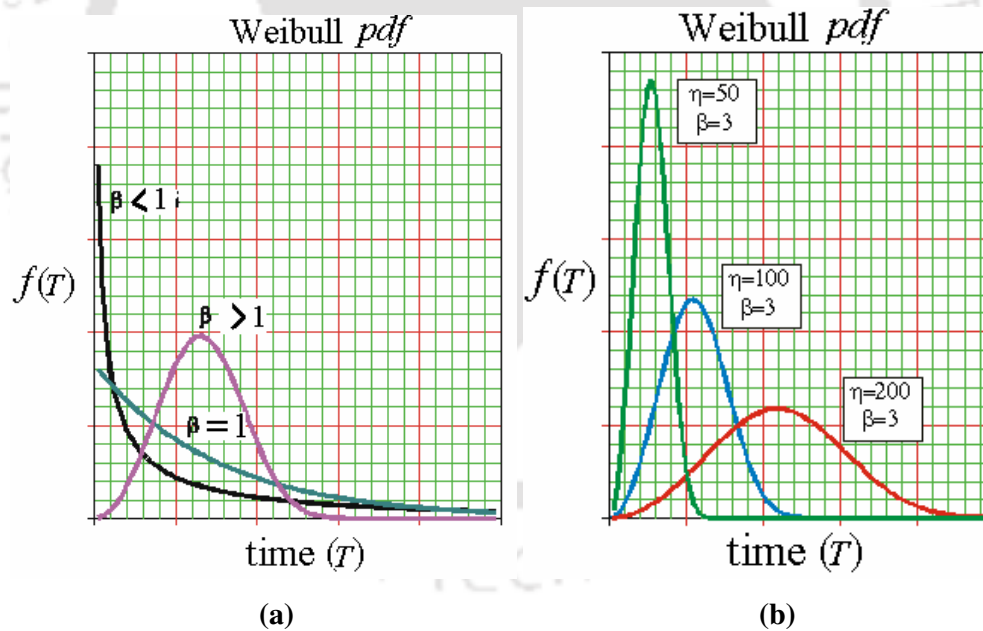


Figure 5.1. Weibull probability distribution plot

For $\beta = 1$, the failure rate decreases with time and $f(T)$ decreases exponentially. When the value of $\beta > 1$ the failure rate first increases with time and the shape becomes a normal *pdf*. However, for a value of $\beta < 2.6$ the Weibull *pdf* is positively skewed (has a right tail), for $2.6 < \beta < 3.7$ the skewness approaches zero (no tail)

and for $\beta > 3.7$ the Weibull *pdf* becomes negatively skewed (left tail). Figure 5.1(b) shows a change in the Weibull *pdf* as the scale parameter η changes its value. If η is increased, while β is kept the same, the distribution gets stretched out to the right and its height decreases, while maintaining its shape and location. If η is decreased, while β is kept the same, the distribution gets pushed in toward the left (*i.e.* toward its beginning or zero) and its height increases. The estimates of parameters of the Weibull distribution can be found with probability plotting paper or analytically, either using least squares analysis (regression analysis) or maximum likelihood method.

For least square analysis, following steps are to be followed for calculation of the value of η and β :

- (1) First make the array for times-to-failure (T_i) in ascending order
- (2) Make the rank of the times-to-failure in ascending order. Obtain their median rank. Median rank is given by

$$MR \approx \frac{i - 0.3}{N + 0.4}, \quad (5.2)$$

where i is the failure order number and N is the total sample size. This is considered as cumulative density function, $F(T_i)$.

- (3) Perform the rank regression on Y -axis using following equation:

$$x_i = \ln(T_i) \quad (5.3)$$

$$y_i = \ln\{-\ln[1 - F(T_i)]\} \quad (5.4)$$

For two-parameter, Weibull distribution the term $F(T_i)$ is called the cumulative density function (*cdf*), which is estimated from the median rank.

- (4) Calculate the value of $(\ln T_i)^2$, y_i^2 and $(\ln T_i) y_i$
- (5) For a linear equation, $y = a + bx$, the parameters a and b are given by

$$b = \frac{\sum_{i=1}^N x_i y_i - \frac{\sum_{i=1}^N x_i \sum_{i=1}^N y_i}{N}}{\sum_{i=1}^N x_i^2 - \frac{\left(\sum_{i=1}^N x_i\right)^2}{N}} \quad (5.5)$$

$$a = \frac{\sum_{i=1}^N y_i}{N} - b \frac{\sum_{i=1}^N x_i}{N}, \quad (5.6)$$

(6) From the value of a and b , the value of η and β can be calculated as

$$\beta = b, \quad (5.7)$$

and

$$\eta = e^{-\frac{a}{b}} \quad (5.8)$$

5.2.2 Application of Weibull Distribution for Calculation of Tool Life

Considering the experimental results of time of failure of cutting tool, Weibull distributions were fitted at each cutting condition to represent the probability density function of the tool life. Figure 5.2 shows the *pdfs* of the cutting tool life at different cutting conditions and Table 5.1 shows the corresponding Weibull probability density functions. The calculation for determination of the value of β and η is shown in Appendix C. Based on these parameters, Weibull distribution is constructed. It is observed that in all the cases, β values are more than 3.7 providing a normal *pdf* with left-tailed distribution. It is observed that the dispersion of the tool life in air-cooled turning is smaller than that in dry turning. Similarly, the dispersion in tool life is more at high cutting speed than at low cutting speed.

At each cutting condition, the mean tool life is calculated using the following formula:

$$\bar{T} = \eta \Gamma\left(\frac{1}{\beta} + 1\right), \quad (5.9)$$

where $\Gamma(1/\beta + 1)$ is the gamma function evaluated at the value of $(1/\beta + 1)$. Table 5.2 displays the mean tool lives along with averages and standard deviations of flank wear when the surface roughness reached $2.5 \mu\text{m}$ at different cutting conditions.

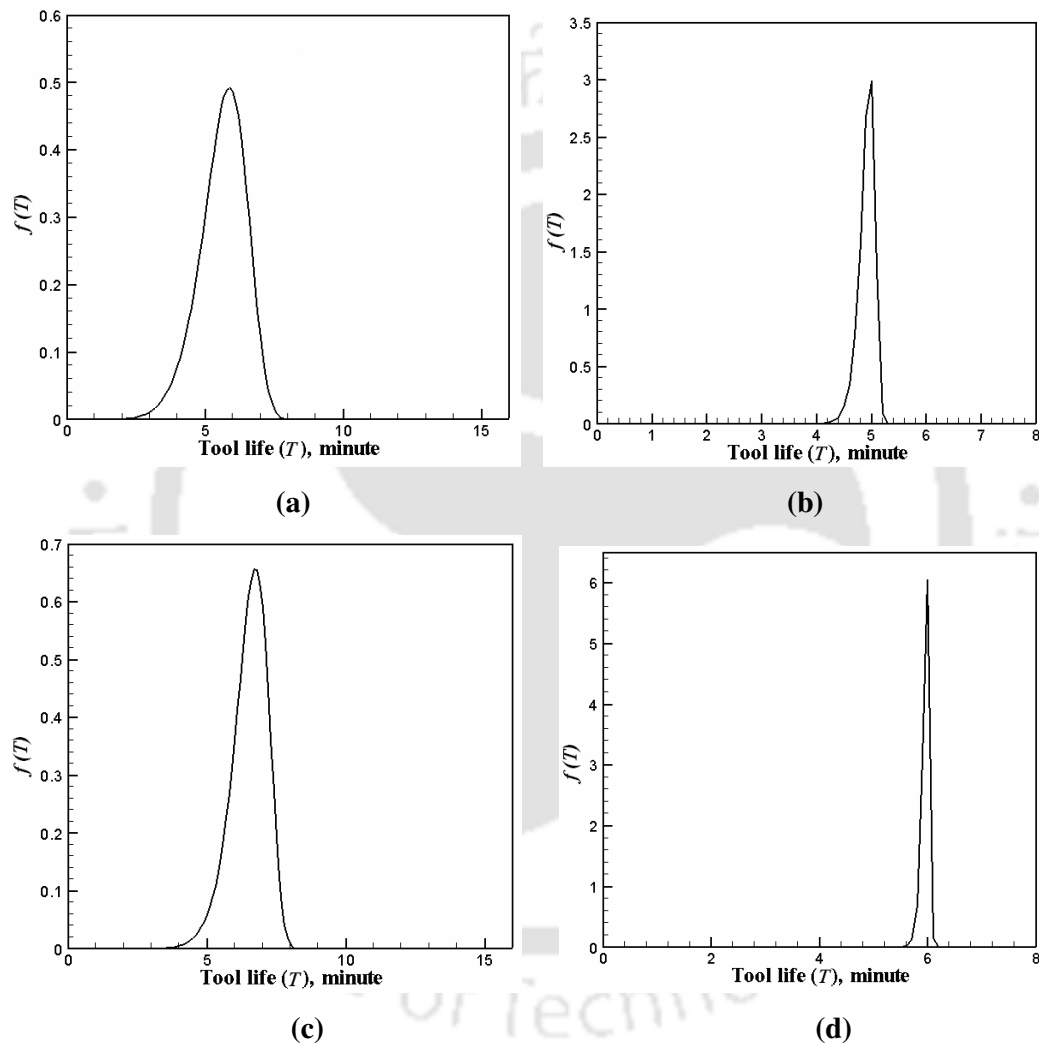


Figure 5.2. Probability distributions of tool life at various cutting conditions: (a) dry turning at cutting speed of 300 m/min (b) air-cooled turning at cutting speed of 300 m/min (c) dry turning at cutting speed of 270 m/min (d) air-cooled turning at cutting speed of 270 m/min

Table 5.1: Weibull probability density function for probability distribution of tool lives shown in Figure 5.2

Figure number	Weibull probability density function
Figure 5.2 (a)	$f(T) = \frac{7.94}{5.98} \left(\frac{T}{5.98} \right)^{6.94} e^{-\left(\frac{T}{5.98} \right)^{7.94}}$
Figure 5.2 (b)	$f(T) = \frac{41.69}{4.97} \left(\frac{T}{4.97} \right)^{40.69} e^{-\left(\frac{T}{4.97} \right)^{41.69}}$
Figure 5.2 (c)	$f(T) = \frac{12.12}{6.79} \left(\frac{T}{6.79} \right)^{11.12} e^{-\left(\frac{T}{6.79} \right)^{12.12}}$
Figure 5.2 (d)	$f(T) = \frac{101.27}{5.99} \left(\frac{T}{5.99} \right)^{100.27} e^{-\left(\frac{T}{5.99} \right)^{101.27}}$

Table 5.2: Mean tool lives and maximum flank wears at different cutting conditions

Type of turning	Cutting speed (m/min)	Mean tool life (minute)	Maximum flank wear (mm)	
			Average value	Standard deviation
Dry	300	5.63	0.15	0.0149
Dry	270	6.51	0.12	0.0095
Air-cooled	300	4.90	0.08	0.0078
Air-cooled	270	6.00	0.07	0.0069

It is observed that although the tool wear is less in air-cooled turning compared to dry turning, the tool life based on surface roughness is more in the case of dry turning. It is also observed that the maximum tool flank wear at the end of tool life is dependent on the cutting conditions. Thus, the flank wear is not the only parameter affecting the surface roughness. At dry cutting conditions, the temperature generated at the tool-job interface softens the job-material and helps in proper cutting, thus

providing better surface finish. Lowering the cutting speed from 300 m/min to 270 m/min improves tool life in both dry and air-cooled turning.

5.3 Enhancing the Tool Life with Air-cooling

It is observed that although the tool life based on surface roughness is lower for air-cooled turning, the flank wear is reduced. After getting failed in air-cooled turning, the tools can be reused in dry turning till they fail in dry turning too. To assess this strategy, seven experiments at each of the cutting speed of 300 m/min and 270 m/min were carried out. Each tool was first used in air-cooled turning. When surface roughness of machined components exceeded the prescribed limit of $2.5 \mu\text{m}$, airflow was stopped and dry turning was carried out. The dry turning continued till the surface roughness value exceeded $2.5 \mu\text{m}$.

The probability density function of the tool life is plotted in Figure 5.3. Figure 5.3(a) corresponding to cutting speed of 300 m/min and Figure 5.3(b) corresponding to tool life of 270 m/min. Table 5.3 shows the Weibull probability density function of Figure 5.3(a) and Figure 5.3(b).

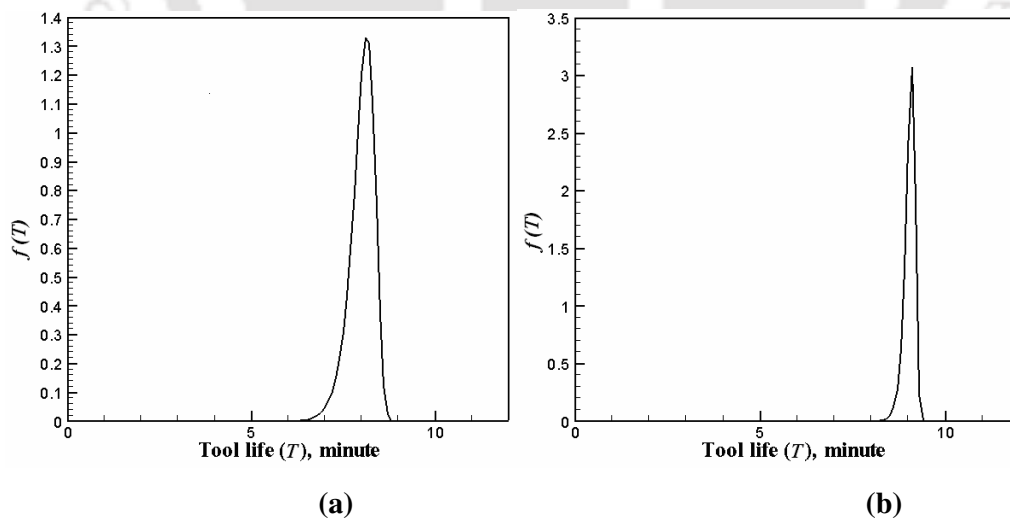


Figure 5.3. Probability distributions of tool life when dry turning followed air-cooled turning: (a) Cutting speed of 300 m/min (b) Cutting speed of 270 m/min

Table 5.3: Weibull probability density function for probability distribution of tool lives shown in Figure 5.3

Figure no	Weibull probability density function
Figure 5.3 (a)	$f(T) = \frac{29.69}{8.15} \left(\frac{T}{8.15}\right)^{28.69} e^{-\left(\frac{T}{8.15}\right)^{29.69}}$
Figure 5.3 (b)	$f(T) = \frac{75.81}{9.10} \left(\frac{T}{9.10}\right)^{74.81} e^{-\left(\frac{T}{9.10}\right)^{75.81}}$

Table 5.4 shows the mean tool life and corresponding maximum flank wear. A comparison with Table 5.2 reveals that the turning carried out with this strategy enhances the tool life. In the present case, tool life got increased by 42% at cutting speed of 300 m/min and 38% at cutting speed of 270 m/min.

Table 5.4: Mean tool lives and maximum flank wears when dry turning followed the air-cooled turning

Cutting speed (m/min)	Mean tool life (minute)	Maximum flank wear (mm)	
		Average value	Standard deviation
300	8.00	0.13	0.0078
270	9.03	0.11	0.0115

An explanation for the success of the present strategy is as follows. Initially, the rate of wear is high and air-cooling is quite effective in reducing the flank wear. Till some time, cutting edge remains sharp and provides a good surface finish. After some time, the change in cutting edge and tool geometry due to wear deteriorates the surface roughness. At this stage, dry turning is carried out, in which the material softening due to temperature compensates for the deterioration of surface roughness due to tool wear.

Although the strategy is quite effective, it introduces the additional cost of compressed air. If the increase of tool life due to air cooling is significant, then the

use of air would come out to be economical. A simplified mathematical analysis to assess the economic benefit is as follows.

Let the tool edge cost be C_t and total tool life in dry turning be denoted as T_1 . Then, the cost of tool edge per unit time in dry turning is equal to C_t/T_1 . Assume the total tool life for both air-cooled and dry turning is T_2 . If C_a is the cost of compressed air per minute, the total cost of compressed air is $C_a T_3$, where T_3 is the tool life in air-cooled turning. The total cost of the tool and air is $(C_t + C_a T_3)$. Therefore,

$$\text{Cost of tool edge and air per unit time} = \frac{C_t + C_a T_3}{T_2}. \quad (5.10)$$

The machining will be economical as long as the cost of tool edge and air per unit time is less than the tool edge cost per unit time in dry turning. Thus, the required condition for economical machining is

$$\frac{C_t + C_a T_3}{T_2} < \frac{C_t}{T_1}, \quad (5.11)$$

or

$$\frac{C_a T_3}{T_2} < \left(\frac{C_t}{T_1} - \frac{C_t}{T_2} \right), \quad (5.12)$$

From the above equation, the critical value of cost of compressed air per minute is obtained as

$$(C_a)_{\text{crit}} = \frac{C_t (T_2 - T_1)}{T_1 T_3} \quad (5.13)$$

If the actual cost of compressed air per minute is less than the critical value calculated from Equation 5.13, then the proposed strategy of air-cooled turning followed by dry turning will be economical.

In the workshop at Indian Institute of Technology Guwahati, the compressed air cost was about \$ 0.01 (approx. Rs. 0.50) per minute [Appendix D]. One edge of the cutting tool costed \$ 2 (approx. Rs 100.00) [Appendix D]. The critical cost $(C_a)_{\text{crit}}$

of air per minute can be determined from Equation 5.13 and using the mean tool life data of Table 5.2. For cutting speed of 300 m/min, the critical cost of air is about \$ 0.17/minute (approx. Rs. 8.59 per minute) and for cutting speed of 270 m/min, it is about \$ 0.13/minute (approx. Rs. 6.45 per minute) [Appendix D]. The actual compressed air cost is Rs. 0.50 per minute. Hence, employing the air results in saving of the tool cost in addition to reduces the problem of worn tool disposal.

5.4 Enhancing the Utilization of Cutting Tool by Changing Cutting Conditions

A cutting tool should be used at the optimum cutting conditions till failure. If the tool failure is based on the maximum flank wear, the tool cannot be reused. However, if it is based on the maximum surface roughness, there is a possibility to reuse it by changing the cutting conditions. In finish turning, if the feed is reduced, the surface roughness reduces. However, too much reduction in the feed will be counter productive, as it reduces the production rate.

A simple way to assess whether reusing the tool at the reduced feed is economical is as follows. For optimization of different parameters during finish turning, mainly two objectives are considered. The first one is the minimization of the production time and the other is the minimization of cost. In finish turning, the time for producing a work piece is expressed as [Lal, 2003].

$$T_p = \frac{\pi LD}{fv} \left(1 + \frac{t_c}{T} \right), \quad (5.14)$$

where L is the machining length, D is the diameter of job, v is the cutting speed, f is the feed, t_c is the tool change time and T is the tool life. The second objective, cost of turning of a job is defined as

$$C = C_0 \frac{\pi LD}{fv} \left(1 + \frac{t_c}{T} \right) + C_t \frac{\pi LD}{fvT}, \quad (5.15)$$

where C_0 is the operating cost per minute and C_t is the tool cost per edge. Equation 5.15 can be rearranged as

$$C = C_0 \frac{\pi LD}{fv} \left[\left(1 + \frac{t_c}{T} \right) + \frac{C_t}{C_0 T} \right], \quad (5.16)$$

or

$$C = C_0 \frac{\pi LD}{fv} \left[1 + \frac{t_c + C_t / C_0}{T} \right], \quad (5.17)$$

If $t_c + C_t / C_0$ is denoted by t_c^* , then Equation 5.17 can be written as

$$C = C_0 \frac{\pi LD}{fv} \left[1 + \frac{t_c^*}{T} \right], \quad (5.18)$$

where

$$t_c^* = \begin{cases} t_c & \text{for minimum production time} \\ t_c + C_t / C_0 & \text{for minimum cost of machining} \end{cases}. \quad (5.19)$$

Assume that f_1 is the optimum feed and f_2 is the reduced feed after the tool failed based on the maximum surface roughness at feed f_1 . Thus, the cost of turning the job at feed f_1 can be expressed as

$$C_1 = C_0 \frac{\pi LD}{f_1 v} \left[1 + \frac{t_c + C_t / C_0}{T_1} \right], \quad (5.20)$$

and the cost of turning the job at feed f_2 is

$$C_2 = C_0 \frac{\pi LD}{f_2 v} \left[1 + \frac{t_c}{T_2} \right]. \quad (5.21)$$

Note that in the expression for C_2 , the tool cost is taken as zero. Reusing the tool at the reduced feed will be economical as long as C_2 is less than C_1 . The required condition for economical machining is

$$C_0 \frac{\pi LD}{f_2 v} \left[1 + \frac{t_c}{T_2} \right] < C_0 \frac{\pi LD}{f_1 v} \left[1 + \frac{t_c + C_t / C_0}{T_1} \right] \quad (5.22)$$

or

$$f_2 > \frac{f_1 \left[1 + \frac{t_c}{T_2} \right]}{\left[1 + \frac{t_c + C_t / C_0}{T_1} \right]}. \quad (5.23)$$

If the tool change time is a very small fraction of time to failure of tool, then a simplified relation is

$$f_2 > \frac{f_1}{\left[1 + \frac{C_t / C_0}{T_1}\right]} \quad (5.24)$$

Taking $C_0 = \$0.06/\text{min}$ (approximately Rs. 3.00), [Appendix D], $C_t = \$2/\text{min}$ (approx. Rs 100.00), $T_1 = 5.63$ minute and $f_1 = 0.1$ mm/rev, the following condition is obtained: $f_2 > 0.014$ mm/rev.

For experimental verification of this strategy, after the tool failed at a feed of 0.1 mm/rev in dry turning, it was operated at the feed of 0.07 mm/rev. Table 5.6 (when compared with Table 5.2) shows that in this manner the time to failure of tool got enhanced by 68% at 270 m/min and by 92% at 300 m/min. Table 5.6 also shows that although the flank wear keeps increasing, it was still less than 0.6 mm when the tool failed based on the surface roughness at a feed of 0.07 mm/rev. Figure 5.4 shows the probability distribution of the total time to failure of tool at dry turning conditions. Table 5.5 shows the Weibull probability density function of Figure 5.4(a) and Figure 5.4(b).

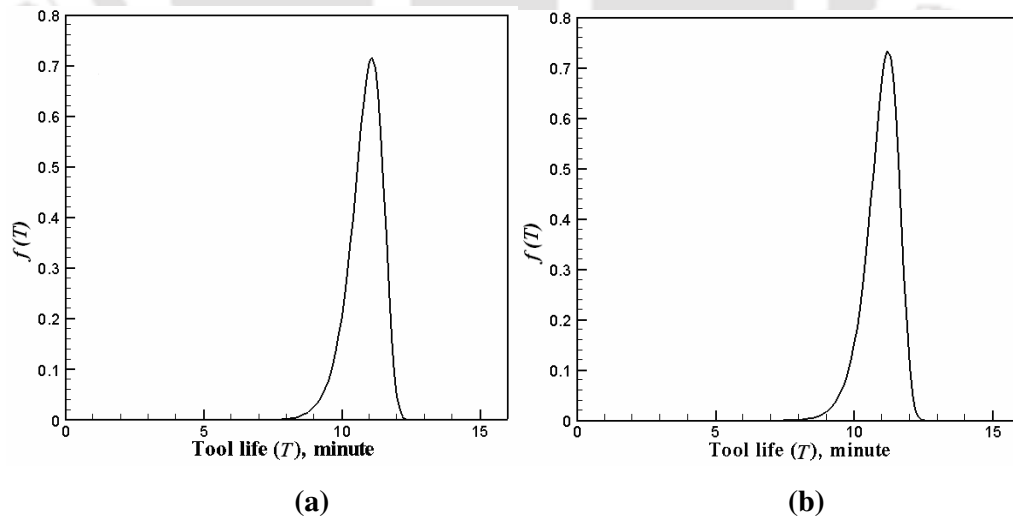


Figure 5.4. Probability distributions of time to failure of tool when tool was initially used at 0.1 mm/rev feed and after failure at this feed, the feed was reduced to 0.07 mm/rev (a) Cutting speed of 300 m/min (b) Cutting speed of 270 m/min

Table 5.5: Weibull probability density function for probability distribution of total time to failure of tool shown in Figure 5.4

Figure number	Weibull probability density function
Figure 5.4 (a)	$f(T) = \frac{21.55}{11.10} \left(\frac{T}{11.10} \right)^{20.55} e^{-\left(\frac{T}{11.10} \right)^{21.55}}$
Figure 5.4 (b)	$f(T) = \frac{22.39}{11.24} \left(\frac{T}{11.24} \right)^{21.39} e^{-\left(\frac{T}{11.24} \right)^{22.39}}$

Table 5.6: Total time to failure of tool and maximum flank wears when tool was first operated at 0.1 mm/rev and then at 0.07 mm/rev in dry turning

Cutting speed (m/min)	Mean tool life (minute)	Maximum flank wear (mm)	
		Average value	Standard deviation
300	10.82	0.17	0.023
270	10.97	0.14	0.012

5.5 A Heuristic Method for Optimizing the Finish Turning Process

Nowadays a number of tool-work combinations are used for turning in industries. A number of techniques have been proposed for optimizing the process parameters [Mukherjee and Ray, 2006]. However, almost all of them require knowledge of tool life as a function of cutting parameters. It is not economical to conduct tool life tests for each combination. In view of it, in this section, a heuristic based method is proposed for optimizing the machining process. The method does not require *a priori* information of tool life.

The objective function to be minimized in finish turning process is [Kilic, 1987]

$$\text{Minimize } F = \frac{1}{fv} \left(1 + \frac{t_c^*}{T} \right), \quad (5.25)$$

where t_c^* is given by Equation 5.19. Equation 5.25 contains the addition of two terms $\frac{1}{(fv)}$ and $\frac{t_c^*}{(fvT)}$. In both the terms, increasing fv reduces the objective function value. However, increase of fv generally reduces the tool life. For a particular value of fv , tool life is dependent on the value of f or v . In general, increase in fv reduces the maximum possible tool life T at that fv . Thus, with increase in fv the term fvT may decrease. If with the increase in fv , the term fvT does not increase, then the objective function will decrease irrespective of the value of t_c^* . However, if an increase in fv decreases the fvT , then the objective function may increase or decrease depending on the value of t_c^* .

Let the highest possible fv be denoted by x_1 and the corresponding maximum possible tool life be denoted by T_1 . If any other fv is denoted by x_2 and the corresponding maximum possible tool life be denoted by T_2 , then the following condition will yield a smaller value of the objective function (F) compared to the highest possible fv :

$$\frac{1}{x_2} \left(1 + \frac{t_c^*}{T_2} \right) < \frac{1}{x_1} \left(1 + \frac{t_c^*}{T_1} \right) \quad (5.26)$$

This gives,

$$t_c^* > \frac{T_1 T_2 (x_1 - x_2)}{T_2 x_2 - T_1 x_1}. \quad (5.27)$$

As long as the above condition is satisfied, operating at the conditions corresponding to tool life T_2 will be beneficial.

Based on this fact, the following heuristic algorithm is developed:

Step 1. Select the maximum possible feed based on the surface roughness consideration. Then, select the maximum possible speed based on the maximum power available in machine tool and any other bound on the cutting speed. Carry out the machining till the tool fails. Record the tool life T_1 .

Step 2. Reduce the speed by 10% and carry out the machining till tool failure. Record the tool life T_2 .

Step 3. For a small range, the tool life may be considered to vary in a linear manner. Assume that there is a linear relationship between T and x , *i.e.*,

$$T = a + bx \quad (5.28)$$

Note that x is fv , the product of cutting speed and feed.

For $x=x_1$,

$$T_1 = a + bx_1. \quad (5.29)$$

For $x=x_2$,

$$T_2 = a + bx_2 \quad (5.30)$$

When the cutting speed v is reduced by 10%, then x_2 becomes $0.9x_1$. Therefore,

$$T_2 = a + 0.9bx_1 \quad (5.31)$$

Equations 5.29 and 5.31 give

$$b = \frac{T_1 - T_2}{0.1x_1}.$$

Putting the value of b in Equation 5.29,

$$a = T_1 - \frac{(T_1 - T_2)}{0.1},$$

or

$$a = 10T_2 - 9T_1.$$

Now, if fv is reduced by a factor of $(1-c)$ from the maximum possible value; then the tool life T_c can be expressed using Equation 5.28 as follows:

$$T_c = a + b(1-c)x_1. \quad (5.32)$$

Putting the value of a and b in Equation 5.32:

$$\begin{aligned} T_c &= 10T_2 - 9T_1 + \frac{(T_1 - T_2)}{0.1}(1-c) \\ &= 10T_2 - 9T_1 + 10(1-c)T_1 - 10(1-c)T_2. \end{aligned}$$

Thus,

$$T_c = (1-10c)T_1 + 10cT_2 \quad (5.33)$$

It is clearly seen from the above equation that for c equal to zero, T_c becomes equal to T_1 . When the value of c is equal to 0.1 (corresponding to 10% reduction in f_v from the highest possible value), then T_c becomes equal to T_2 . Once we know the tool changing time t_c^* , the optimum value of c can be evaluated by converting the inequality of Equation 5.27 to equality, *i.e.*,

$$t_c^* = \frac{T_1 T_c ((x_1 - (1-c)x_1))}{(T_c(1-c)x_1 - T_1 x_1)}, \quad (5.34)$$

or

$$t_c^* = \frac{c T_1 T_c}{(T_c(1-c) - T_1)} \quad (5.35)$$

The optimum value of c can be obtained by solving Equation 5.35.

Step 4. Once the optimum value of c is obtained, the machining is carried out at a cutting speed of $(1-c)$ times the maximum speed. Note that Equation 5.35 is the estimated value of T_c from Equation 5.33. Now, the actual value of T_c can be recorded after the tool fails.

Step 5. If the actual T_c is the same as that estimated by Equation 5.33, the optimum is reached. If actual T_c is different from that obtained by Equation 5.33, a new tool life relation is developed with obtained data and the procedure can be repeated.

As an example, initially dry turning was carried out at 300 m/min. The mean tool life T_1 corresponding to that speed is 5.63 minute. When the cutting speed was reduced by 10% making it 270 m/min, the mean tool life became 6.51 minute. Assuming t_c^* as 6 minute, the value of c in this case is 0.12. [Appendix E]. Thus, the optimum speed is $(1-0.12) \times 300 = 264$ m/min. This is close to 270 m/min. Hence, the machining may be carried out at this speed itself.

As more number of pieces are machined, information about tool life gets updated. With revised information, the optimization procedure may be revisited. Thus, in the presence of statistical variations, the optimization is a dynamic process initially. When sufficient numbers of data are available in the vicinity of expected optimum solution, the optimum solution may be frozen. In this work, however, due to constraints on the number of experiments, this procedure is not demonstrated.

5.6 Summary

In this work, some experiments were conducted on dry and air-cooled turning of mild steel with TiN coated carbide tool. The probability density function of tool life is represented by Weibull distribution and the mean tool life is obtained. It is observed that tool life (based on surface roughness) in dry turning is more than that in air-cooled turning. Thus, the tool which failed in air-cooled turning may be utilized in dry turning. This procedure enhances the effective tool life. The failed tool can be further utilized by reducing the feed. It is imperative that tools should be operated at optimum cutting conditions. Often, the dependency of tool life on cutting conditions is not known. With this viewpoint, a heuristic method for optimization of cutting conditions is proposed and tested on shop floor.

Conclusions and Scope for Future Work

6.1 Conclusions

The objectives of the present thesis are to study the cutting performance, modelling of the performance parameters and optimization of cutting conditions in an environment-friendly air-cooled and dry turning processes. During dry and air-cooled turning, cutting fluid is not used, thus reducing pollution on the shop floor. To study the effect of air-cooling on cutting performance, several experiments were conducted with different tool-workpiece combinations in dry and air-cooled condition. The comparative study was carried out mainly on the results of surface finish of machined workpiece, tool wear, machining forces and vibrations. It is observed that air-cooling has a great influence in reducing the tool wear, but does not have much effect in improving the surface finish and reducing the cutting forces. Neural networks have been used successfully for prediction of surface finish, tool life and machining forces. A novel neural network modelling procedure has been developed in this thesis for the prediction of surface finish and tool life considering limited and noisy experimental data. The method utilizes both MLP and RBF networks. However, neural networks could not be employed successfully for predicting the tool wear based on the machining force measurement. A simple method has been developed for the indirect estimation of tool wear in a probabilistic manner using the rate of change of wear with respect to cutting/feed force. In the present thesis, a few strategies have been developed for efficient utilization of cutting tools in finish turning operation in both dry and air-cooled condition. Finally, a simple heuristic method for the optimization of cutting conditions that does not require *a priori* information of tool life has been developed for finish turning operation.

The conclusions of the thesis can be summarized as follows:

- From the experiment, it has been observed that HSS tool is not suitable for finish turning (corresponding to N7 surface roughness) of grey cast iron. However, non-coated carbide and ceramic tool can be employed for finish turning operation of grey cast iron. It is observed that ceramic tool is capable of providing a much lower surface finish compared to carbide tool.
- It is observed that during dry turning of grey cast iron with a ceramic tool at a cutting speed of more than 480 m/min, rapid flank wear occurred and the surface roughness of the machined workpiece increased. At a combination of high speed and high feed, the crater wear was observed along with the flank wear. The crater wear was not seen when the cutting speed was less than 400 m/min.
- It has been observed that the air-cooling has a great influence in reducing the tool wear and increasing the tool life compared to dry turning for various tool-workpiece combinations studied in this thesis. However, the air-cooling does not help in improving the surface finish. In some cases, the air-cooled turning produced slightly higher surface roughness compared to dry turning. It is also observed that air-cooling does not help in reducing the cutting and feed forces.
- It is observed that air-cooling is highly useful in hard turning (workpiece hardness more than 45 HRC) of H13 steel with CBN tool. Air-cooling reduces the tool flank wear, crater wear and the built-up edge during hard turning.
- During the turning of grey cast iron with ceramic tool, it was observed that acceleration of vibrations did not provide any correlation with surface roughness or flank wear.
- It has been observed that the neural network modelling helps in the prediction of surface finish, tool life and cutting forces during turning. The MLP network used for the prediction of surface finish

and tool life in the machining of mild steel with coated carbide tool gives a good prediction with RMS error within 15%. For the prediction of the cutting force in turning of grey cast iron with ceramic tool, an RBF network was used. The prediction accuracy of the model was found within an RMS error of 15%. However, in the case of the prediction of surface roughness and tool life in turning of grey cast iron with ceramic tool, the RMS prediction error was found to be around 27% due to limited and noisy data. Therefore, a novel neural network modelling was developed to suppress the noisy data generated during machining. This improved the accuracy of modelling to an RMS error less than 15%.

- The different neural network models that have been developed in the thesis require lesser number of learning data compared to traditional neural network models. This is because factorial design and effect of factors have been used to produce the learning data in a systematic way. For eliminating the spurious data, a novel methodology has been developed which is found effective in improving the prediction accuracy. Also, a test of hypothesis using Student's *t*-test was carried for the analysis of statistical variations of experimental data to assess the results of fitted neural network models.
- It has been observed that neural networks could not be used successfully for the prediction of the tool flank wear based on the measurement of machining forces. However, a simplified procedure that has been proposed for the indirect estimation of tool wear, using the rate of change of wear with respect to cutting/feed forces, can estimate the tool wear in a probabilistic manner.
- In the thesis, some simple strategies have been proposed for the efficient utilization of a cutting tool. It is observed that tool life based on surface roughness in dry turning is more than that in air-cooled turning. Thus, the tool failed in air-cooled turning may be utilized in dry turning. Also, the failed tool can be further utilized by

reducing the feed. The strategies presented in this thesis enhance the effective tool life of a cutting tool.

- In the present thesis, a heuristic method has been developed for the optimization of cutting conditions in a finish turning operation. The advantage of this method is that it does not require *a priori* information of tool life, which is mostly required in conventional optimization strategies.

6.2 Scope for Future Work

- In the present work, a comparative study was carried out for surface roughness, tool wear, cutting force and vibration for a few tool-workpiece combinations during dry and air-cooled turning. The work can be extended to other tool-workpiece combinations and to other cutting performance parameters like dimensional deviation, temperature, residual stress *etc.*
- It was noticed that the ceramic tool has the capability to do high speed turning provided some precautions could be taken for minimizing the crater wear and flank wear. In the present work, air-cooling has great influence in reducing the tool wear compared to the dry turning during high speed turning. However, for some combinations of high speed and high feed, air-cooling could not reduce the crater wear. Future work can be carried out with high a velocity jet of air in tool-workpiece cutting zone for more effective cooling.
- During performance study of CBN tool, it was observed that the air-cooling has a great influence in reducing the tool wear and increasing the tool life. Future study may be carried out on white layer formation during hard turning and optimization of cutting parameters for minimizing the depth of white layer.
- In the present work, temperature was not considered as a parameter to study the performance of dry and air-cooled turning due to various reasons. The

future work may be carried out considering temperature as a parameter for comparative study of performance of dry and air-cooled turning.

- In the present work, neural network modelling has been developed using cutting speed, feed and depth of cut as input parameters for the prediction of surface finish and tool life. Cutting time was considered as the additional parameter in the prediction of cutting forces. Future study may be carried out considering time as another input parameter for the prediction of surface finish, as the surface roughness changes with cutting time during machining.
- The neural network requires a lot of data for learning. Future work can develop a soft computing based methodology to have the capability to learn from limited, imprecise and missing data. Moreover, a robust data filtration algorithm can be developed in future to deal with the outliers in the data. Compatible hardware systems like sensors, actuators *etc* should also be developed to take the maximum advantage of the soft computing methods for adaptive control of the process.
- In the present work, neural network is trained in an offline manner for prediction of surface finish and tool life with the data generated from the experiment. Future work may be carried out on dynamic training of neural network models for monitoring tool heath and part quality.
- In the present work, the optimization of process parameters has been carried out for finish turning operation on a single pass turning. The work may be extended for rough turning operation with multiple passes. Moreover, a scheme can be developed for the optimization with online learning.
- The recent developments in internet technologies can be utilized as a platform to do research for internet-based machining. The strategies developed in the present work for the efficient utilization of cutting tool and the optimization of cutting conditions can be integrated with internet and other web-based systems to enable the exchange of data from one factory to the other factory.



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Appendix

Appendix A

Hypothesis Testing using Student's *t*-test

1. Hypothesis test for the prediction of surface roughness and tool life in turning of mild steel with coated carbide tool

When the test sample size is *small*, then the test of significance is carried out based on Student's *t*-test. The test is carried out to see whether for a given sample of size *n*, the difference between sample mean (\bar{x}) and population mean (μ) is significant or not. For this, first we compute the mean \bar{x} of the sample and the standard deviation σ of the distribution. Then the *t*-statistic is calculated as

$$t = \frac{|\bar{x} - \mu|}{\frac{\sigma}{\sqrt{n}}} \quad (A1)$$

For surface roughness and tool life (considering the maximum flank wear value), several experiments with replicates were carried out for both dry and air-cooled turning. The cutting conditions for the experiments were as follows:

Cutting condition 1: speed 150 m/min, feed 0.10 mm/rev, depth of cut 1 mm

Cutting condition 2: speed 300 m/min, feed 0.32 mm/rev, depth of cut 3 mm

Cutting condition 3: speed 270 m/min, feed 0.24 mm/rev, depth of cut 1.5 mm

Cutting condition 4: speed 200 m/min, feed 0.20 mm/rev, depth of cut 2.4 mm

Table A-1 and Table A-2 shows the average surface roughness values/flank wear values, sample size (n), sample mean (\bar{x}) and standard deviation (σ) during dry turning. Similarly, Table A-3 and Table A-4 show the average surface roughness values/flank wear values, sample size (n), sample mean (\bar{x}) and standard deviation (σ) during air-cooled turning.

Table A-1: Replicated experiments for measurement of average surface roughness during dry turning.

Cutting condition	Average surface roughness value (μm)				Sample size (n)	Sample mean (\bar{x}) (μm)	Standard deviation (σ) (μm)
	Replicate 1	Replicate 2	Replicate 3	Replicate 4			
Cutting condition 1	3.63	3.37	3.31	3.44	4	3.437	0.138
Cutting condition 2	4.02	3.70	3.48	3.39	4	3.647	0.280
Cutting condition 3	3.16	3.31	3.19	3.08	4	3.185	0.095
Cutting condition 4	3.73	3.56	3.33	3.41	4	3.507	0.176

For each cutting condition shown in the Table A-1, Based on the data provided in Table A-1, an assessment of the accuracy that should be expected by any prediction model is made. This is done based on the Student's t -test using 95% confidence level. In each case, let μ be the exact population mean of surface roughness. The null hypothesis in each case is

$$H_0: \text{The mean surface roughness is } \mu.$$

It is intended to find out the critical value of μ for which the hypothesis will not be rejected based on the experimental result. The difference between \bar{x} and critical μ can be considered as the error that any prediction model can make without rejecting the hypothesis. Thus, the percentage prediction accuracy that should be expected from the model can be calculated. For each cutting condition, the calculations are shown below.

Cutting condition 1: Using Equation A1

$$t = \frac{|3.437 - \mu|}{\frac{0.138}{\sqrt{4}}} = \frac{|3.437 - \mu|}{0.069}$$

At 95% confidence level, for 2-tailed and 3 degree of freedom the critical value of t is 3.18. Substituting this value in the above equation:

$$3.18 = \frac{|3.437 - \mu|}{0.069}$$

or

$$|3.437 - \mu| = 0.2194$$

Thus, the sample mean may differ from population mean by 0.2194 μm .

Thus, the maximum possible prediction accuracy (in percentage) = $\frac{0.2194}{3.437} \times 100 = 6.38\%$. In other words 6.38% deviation from the experimental results cannot be considered significant.

Cutting condition 2: Using Equation A1

$$t = \frac{|3.647 - \mu|}{\frac{0.28}{\sqrt{4}}} = \frac{|3.647 - \mu|}{0.14}$$

At 95% confidence level, for 2-tailed and 3 degree of freedom the critical value of t is 3.18. Substituting this value in the above equation:

$$3.18 = \frac{|3.647 - \mu|}{0.14}$$

or

$$|3.647 - \mu| = 0.4452$$

Thus, the sample mean may differ from population mean by 0.4452 μm .

Thus, the maximum possible prediction accuracy (in percentage) = $\frac{0.4452}{3.647} \times 100 = 12.2\%$.

Cutting condition 3: Using Equation A1

$$t = \frac{|3.185 - \mu|}{\frac{0.095}{\sqrt{4}}} = \frac{|3.185 - \mu|}{0.0475}$$

At 95% confidence level, for 2-tailed and 3 degree of freedom the critical value of t is 3.18. Substituting this value in the above equation:

$$3.18 = \frac{|3.185 - \mu|}{0.0475}$$

or

$$|3.185 - \mu| = 0.1510$$

Thus, the sample mean may differ from population mean by 0.1510 μm .

Thus, the maximum possible prediction accuracy (in percentage) = $\frac{0.151}{3.185} \times 100 = 4.74\%$

Cutting condition 4: Using Equation A1

$$t = \frac{|3.507 - \mu|}{\frac{0.176}{\sqrt{4}}} = \frac{|3.507 - \mu|}{0.088}$$

At 95% confidence level, for 2-tailed and 3 degree of freedom the critical value of t is 3.18. Substituting this value in the above equation:

$$3.18 = \frac{|3.507 - \mu|}{0.088}$$

or

$$|3.507 - \mu| = 0.2798$$

Thus, the sample mean may differ from population mean by 0.2798 μm .

Thus, the maximum possible prediction accuracy (in percentage) = $\frac{0.2798}{3.507} \times 100 = 7.97\%$

To summarize, the maximum possible prediction accuracies for four cutting conditions are 6.38%, 12.2%, 4.74% and 7.97% respectively. Hence, a neural network model providing about 15% error may be considered satisfactory.

Table A-2: Replicate experiment for measurement of average flank wear during dry turning.

Cutting condition	Average flank wear value (mm)				Sample size (<i>n</i>)	Sample mean (\bar{x}) (mm)	Standard deviation (σ) (mm)
	Replicate 1	Replicate 2	Replicate 3	Replicate 4			
Cutting condition 1	0.09	0.09	0.11	0.09	4	0.095	0.01
Cutting condition 2	0.12	0.13	0.11	0.11	4	0.117	0.0095
Cutting condition 3	0.118	0.11	0.10	0.11	4	0.109	0.0073
Cutting condition 4	0.188	0.15	0.15	0.16	4	0.162	0.0179

The same procedure is carried out for the maximum flank wear. Here, the null hypothesis is

H_0 : The mean value of maximum flank wear is μ .

The percentage prediction accuracy that should be expected from the model can be calculated. For each cutting condition, the calculations are shown below.

Cutting condition 1: Using Equation A1

$$t = \frac{|0.095 - \mu|}{\frac{0.01}{\sqrt{4}}} = \frac{|0.095 - \mu|}{0.005}$$

At 95% confidence level, for 2-tailed and 3 degree of freedom the critical value of t is 3.18. Substituting this value in the above equation:

$$3.18 = \frac{|0.095 - \mu|}{0.005}$$

or

$$|0.095 - \mu| = 0.0159$$

Thus, the sample mean may differ from population mean by 0.0159 mm.

Thus, the maximum possible prediction accuracy (in percentage) = $\frac{0.0159}{0.095} \times 100 =$

16.7%

Cutting condition 2: Using Equation A1

$$t = \frac{|0.117 - \mu|}{\frac{0.0095}{\sqrt{4}}} = \frac{|0.117 - \mu|}{0.00475}$$

At 95% confidence level, for 2-tailed and 3 degree of freedom the critical value of t is 3.18. Substituting this value in the above equation:

$$3.18 = \frac{|0.1171 - \mu|}{0.00475}$$

or

$$|0.117 - \mu| = 0.0151$$

Thus, the sample mean may differ from population mean by 0.0151 mm.

Thus, the maximum possible prediction accuracy (in percentage) = $\frac{0.0151}{0.117} \times 100 =$

12.9%

Cutting condition 3: Using Equation A1

$$t = \frac{|0.109 - \mu|}{\frac{0.0073}{\sqrt{4}}} = \frac{|0.109 - \mu|}{0.00365}$$

At 95% confidence level, for 2-tailed and 3 degree of freedom the critical value of t is 3.18. Substituting this value in the above equation:

$$3.18 = \frac{|0.109 - \mu|}{0.00365}$$

or

$$|0.109 - \mu| = 0.0116$$

Thus, the sample mean may differ from population mean by 0.0116 mm.

$$\text{Thus, the maximum possible prediction accuracy (in percentage)} = \frac{0.0116}{0.109} \times 100 =$$

10.65%

Cutting condition 4: Using Equation A1

$$t = \frac{|0.162 - \mu|}{\frac{0.0179}{\sqrt{4}}} = \frac{|0.162 - \mu|}{0.00895}$$

At 95% confidence level, for 2-tailed and 3 degree of freedom the critical value of t is 3.18. Substituting this value in the above equation:

$$3.18 = \frac{|0.162 - \mu|}{0.00895}$$

or

$$|0.162 - \mu| = 0.0284$$

Thus, the sample mean may differ from population mean by 0.0284 mm.

$$\text{Thus, the maximum possible prediction accuracy (in percentage)} = \frac{0.0284}{0.162} \times 100 =$$

17.56%

To summarize, the maximum possible prediction accuracies for four cutting conditions are 16.7%, 12.9%, 10.65% and 17.56% respectively. Hence, a neural network model providing about 18% error may be considered satisfactory.

Table A-3 and Table A-4 respectively show the average surface roughness value and maximum flank wear value in turning of mild steel with coated carbide tool during air-cooled condition. The procedure employed in dry turning for calculation of maximum possible prediction (in percentage) has been employed here too. The details of calculation are not shown.

To summarize, the maximum possible prediction accuracy for surface roughness and flank wear are as follows.

For surface roughness, the maximum possible prediction accuracy for four cutting condition are 2.17%, 3.92%, 13.33% and 5.72%. Hence, a neural network model providing about 15% error may be considered satisfactory.

For flank wear, the maximum possible prediction accuracy for four cutting condition are 21.2%, 17.75%,15.81% and 7.88%. Hence, a neural network model providing about 21% error may be considered satisfactory.

Table A-3: Replicate experiment for measurement of average surface roughness value during air-cooled turning.

Cutting condition	Average surface roughness value (μm)				Sample size (n)	Sample mean (\bar{x}) (μm)	Standard deviation (σ) (μm)
	Replicate 1	Replicate 2	Replicate 3	Replicate 4			
Cutting condition 1	2.17	2.21	2.19	2.14	4	2.177	0.0298
Cutting condition 2	4.26	4.16	4.09	4.02	4	4.132	0.102
Cutting condition 3	2.86	2.78	2.59	2.36	4	2.647	0.222
Cutting condition 4	4.49	4.26	4.35	4.12	4	4.305	0.155

Table A-4: Replicate experiment for measurement of average flank wear during air-cooled turning.

Cutting condition	Average flank wear value (mm)				Sample size (n)	Sample mean (\bar{x}) (mm)	Standard deviation (σ) (mm)
	Replicate 1	Replicate 2	Replicate 3	Replicate 4			
Cutting condition 1	0.05	0.06	0.07	0.06	4	0.06	0.008
Cutting condition 2	0.10	0.11	0.11	0.13	4	0.112	0.0125
Cutting condition 3	0.12	0.10	0.10	0.12	4	0.11	0.011
Cutting condition 4	0.11	0.12	0.11	0.12	4	0.115	0.0057

2. Hypothesis test for prediction of surface roughness and tool life in turning of grey cast iron with ceramic tool

For prediction of surface roughness and tool life (considering the maximum flank wear value) in turning of grey cast iron with ceramic tool, several replicate experiments were carried out in air-cooled turning. The cutting condition for conducting replicate experiments were as follows:

Cutting condition 1: speed 106 m/min, feed 0.04 mm/rev, depth of cut 1.5 mm

Cutting condition 2: speed 448 m/min, feed 0.16 mm/rev, depth of cut 1.0 mm

Cutting condition 3: speed 115 m/min, feed 0.16 mm/rev, depth of cut 1.0 mm

Cutting condition 4: speed 420 m/min, feed 0.16 mm/rev, depth of cut 1.5 mm

Table A-5 and Table A-6 show the average surface roughness value and maximum flank wear value respectively in turning of grey cast iron with ceramic tool during air-cooled condition. The procedure for calculation of maximum possible prediction

(in percentage) in turning of mild steel with coated carbide tool has been employed here too. However, in this case the sample size was 5 and at 95% confidence level, for 2-tailed and 4 degree of freedom the *t*-distribution value was 2.78. The details of calculation are not shown. To summarize, the maximum possible prediction accuracy for surface roughness and flank wear are as follows.

For surface roughness, the maximum possible prediction accuracy for four cutting condition are 19.78%, 19.87%, 16.90% and 18,60%. Hence, a neural network model providing about 20% error may be considered satisfactory.

For flank wear, the maximum possible prediction accuracy for four cutting condition are 16.33%, 25.17%,16.50% and 15.74%. Hence, a neural network model providing about 25% error may be considered satisfactory.

Table A-5: Replicate experiment for measurement of average surface roughness during air-cooled turning.

Cutting condition	Average surface roughness value (μm)					Sample size (<i>n</i>)	Sample mean (\bar{x}) (μm)	Standard deviation (σ) (μm)
	Repliate 1	Repliate 2	Repliate 3	Repliate 4	Repliate 5			
Cutting condition 1	1.93	1.70	1.33	1.44	1.42	5	1.564	0.2466
Cutting condition 2	1.79	1.89	2.12	1.47	1.47	5	1.748	0.280
Cutting condition 3	2.30	2.18	1.79	1.78	1.74	5	1.958	0.2615
Cutting condition 4	2.26	1.70	1.69	1.57	1.72	5	1.788	0.270

Table A-6: Replicate experiment for measurement of average flank wear during air-cooled turning.

Cutting condition	Average flank wear value (mm)					Sample size (n)	Sample mean (\bar{x}) (mm)	Standard deviation (σ) (mm)
	Repliate 1	Repliate 2	Repliate 3	Repliate 4	Repliate 5			
Cutting condition 1	0.18	0.14	0.12	0.16	0.14	5	0.16	0.021
Cutting condition 2	0.037	0.040	0.060	0.047	0.057	5	0.048	0.102
Cutting condition 3	0.033	0.030	0.024	0.027	0.025	5	0.028	0.0037
Cutting condition 4	0.039	0.037	0.050	0.042	0.047	5	0.043	0.0055

3. Hypothesis test for prediction of feed force and cutting force in turning of grey cast iron with ceramic tool

For prediction of feed force and cutting force in turning of grey cast iron with ceramic tool, several replicate experiments were carried out in both dry and air-cooled turning. Here, we have shown the replicate experiment for the air-cooled turning. The cutting conditions for replicate experiments were as follows:

Cutting condition 1: speed 118 m/min, feed 0.16 mm/rev, depth of cut 1.0 mm

Cutting condition 2: speed 120 m/min, feed 0.04 mm/rev, depth of cut 1.5 mm

Cutting condition 3: speed 448 m/min, feed 0.16 mm/rev, depth of cut 1.0 mm

Cutting condition 4: speed 408 m/min, feed 0.16 mm/rev, depth of cut 1.5 mm

Cutting condition 5: speed 195 m/min, feed 0.10 mm/rev, depth of cut 1.24 mm

Table A-7 and Table A-8 show the feed force and cutting force respectively during air-cooled turning. Same procedure has been adopted for calculation of maximum

possible prediction (in percentage) that was carried out in turning of mild steel with coated carbide tool. In this work, the sample size was considered 4 or 5 depending upon the number of replicate experiment. The details of calculation are not shown here. To summarize, the maximum possible prediction accuracy for feed force and cutting force are as follows.

For feed force, the maximum possible prediction accuracy for five cutting condition are 6.6%, 21.5%, 30.0%, 6.26% and 6.22%. Hence, a neural network model providing about 30% error may be considered satisfactory.

For cutting force, the maximum possible prediction accuracy for five cutting condition are 6.39%, 12.9%, 26%, 13.3% and 6.7%. Hence, a neural network model providing about 26% error may be considered satisfactory.

Table A-7: Replicate experiment for measurement of feed force during air-cooled turning.

Cutting condition	Feed force (N)					Sample size (n)	Sample mean (\bar{x}) (N)	Standard deviation (σ) (N)
	Repliate 1	Repliate 2	Repliate 3	Repliate 4	Repliate 5			
Cutting condition 1	179	167	176	162	158	5	168	8.96
Cutting condition 2	260	280	207	227	-----	4	244	33.00
Cutting condition 3	142	210	152	152	-----	4	164	31.00
Cutting condition 4	256	229	229	231	247	5	238	12.00
Cutting condition 5	188	179	164	183	180	5	179	8.98

Table A-8: Replicate experiment for measurement of cutting force during air-cooled turning.

Cutting condition	Cutting force (N)					Sample size (<i>n</i>)	Sample mean (\bar{x}) (N)	Standard deviation (σ) (N)
	Repliate 1	Repliate 2	Repliate 3	Repliate 4	Repliate 5			
Cutting condition 1	281	303	320	316	315	5	307	15.8
Cutting condition 2	267	285	235	253	-----	4	260	21.19
Cutting condition 3	179	307	296	249	-----	4	257	58.2
Cutting condition 4	321	387	416	428	406	5	392	42.2
Cutting condition 5	280	289	266	295	284	5	283	10.9

Appendix B

Training and Tesing Data Set for Prediction of Feed Force and Cutting Force in RBF Network

Table B-1: Training data for prediction of feed force and cutting force during air-cooled turning

Sl. no	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Cutting time (min)	Feed Force (Fx) (N)	Cutting Force (Fz) (N)
1	96	0.04	1	4.53	168	156
2	96	0.04	1	9.06	218	158
3	96	0.04	1	13.59	253	171
4	96	0.04	1	18.12	254	217
5	96	0.04	1	22.65	245	180
6	106	0.04	1.5	5.95	226	246
7	106	0.04	1.5	11.9	291	243
8	106	0.04	1.5	17.85	332	277
9	106	0.04	1.5	23.8	403	290
10	106	0.04	1.5	29.75	421	286
11	112	0.16	1	1.13	154	258
12	112	0.16	1	2.26	173	220
13	112	0.16	1	3.39	165	261
14	112	0.16	1	4.52	171	286
15	112	0.16	1	5.65	220	336
16	112	0.16	1	6.78	193	285
17	115	0.16	1.5	1.01	185	309
18	115	0.16	1.5	2.02	198	231
19	115	0.16	1.5	3.03	200	305

20	115	0.16	1.5	4.04	212	318
21	115	0.16	1.5	5.05	197	327
22	115	0.16	1.5	6.06	207	320
23	400	0.04	1	1.23	101	114
24	400	0.04	1	2.46	111	119
25	400	0.04	1	3.69	124	121
26	400	0.04	1	4.92	139	124
27	400	0.04	1	6.15	146	125
28	400	0.04	1	7.38	160	143
29	419	0.04	1.5	1.1	162	111
30	419	0.04	1.5	2.2	171	111
31	419	0.04	1.5	3.3	177	117
32	419	0.04	1.5	4.4	186	123
33	419	0.04	1.5	5.5	204	126
34	419	0.04	1.5	6.6	219	126
35	448	0.16	1	0.3	131	178
36	448	0.16	1	0.6	141	179
37	448	0.16	1	0.9	145	178
38	448	0.16	1	1.2	151	180
39	420	0.16	1.5	0.4	225	299
40	420	0.16	1.5	0.8	248	314
41	420	0.16	1.5	1.2	256	318
42	420	0.16	1.5	1.6	264	323
43	420	0.16	1.5	2	269	333
44	420	0.16	1.5	2.4	273	336
45	209	0.06	1.1	1.8	144	172
46	209	0.06	1.1	3.6	138	182
47	209	0.06	1.1	5.4	140	182
48	209	0.06	1.1	7.2	158	192
49	209	0.06	1.1	9	160	193

50	209	0.06	1.1	10.8	160	198
51	361	0.08	1.4	0.61	188	282
52	361	0.08	1.4	1.22	212	280
53	361	0.08	1.4	1.83	200	282
54	361	0.08	1.4	2.44	212	290
55	361	0.08	1.4	3.05	222	292
56	361	0.08	1.4	3.66	210	296
57	234	0.1	1.2	0.63	165	204
58	234	0.1	1.2	1.26	159	207
59	234	0.1	1.2	1.89	164	225
60	234	0.1	1.2	2.52	174	225
61	234	0.1	1.2	3.15	180	235
62	234	0.1	1.2	3.78	181	227
63	140	0.12	1.3	1.28	183	214
64	140	0.12	1.3	2.56	176	230
65	140	0.12	1.3	3.84	198	225
66	140	0.12	1.3	5.12	196	222
67	140	0.12	1.3	6.4	194	248
68	140	0.12	1.3	7.68	196	251
69	297	0.14	1.2	0.58	197	258
70	297	0.14	1.2	1.16	196	269
71	297	0.14	1.2	1.74	179	270
72	297	0.14	1.2	2.32	205	255
73	297	0.14	1.2	2.9	208	261
74	297	0.14	1.2	3.48	219	259
75	126	0.08	1.3	2.98	115	301
76	126	0.08	1.3	5.96	210	345
77	126	0.08	1.3	8.94	234	352
78	126	0.08	1.3	11.92	252	366

79	126	0.08	1.3	14.9	247	367
80	126	0.08	1.3	17.88	267	372
81	316	0.12	1.5	0.68	245	380
82	316	0.12	1.5	1.36	300	442
83	316	0.12	1.5	2.04	307	456
84	316	0.12	1.5	2.72	317	457
85	316	0.12	1.5	3.4	321	502
86	316	0.12	1.5	4.08	322	492
87	292	0.05	1.46	1.65	257	249
88	292	0.05	1.46	3.3	196	205
89	292	0.05	1.46	4.95	231	231
90	292	0.05	1.46	6.6	354	289
91	292	0.05	1.46	8.25	406	272
92	330	0.06	1.34	0.78	143	192
93	330	0.06	1.34	1.56	157	203
94	330	0.06	1.34	2.34	171	215
95	330	0.06	1.34	3.12	179	214
96	330	0.06	1.34	3.9	184	207
97	330	0.06	1.34	4.68	189	206
98	141	0.07	1.14	2.6	161	224
99	141	0.07	1.14	5.2	192	266
100	141	0.07	1.14	7.8	197	288
101	141	0.07	1.14	10.4	193	226
102	141	0.07	1.14	13	228	238
103	154	0.1	1.22	1.4	154	261
104	154	0.1	1.22	2.8	179	268
105	154	0.1	1.22	4.2	190	271
106	154	0.1	1.22	5.6	201	266
107	154	0.1	1.22	7	215	299
108	154	0.1	1.22	8.4	247	295

Table B-2: Training data set for prediction of feed force and cutting force during dry turning

Sl. no	Speed	Feed	Depth of cut	Cutting time	Feed Force (Fx)	Cutting Force (Fz)
	(m/min)	(mm/rev)	(mm)	(min)	(N)	(N)
1	119	0.04	1	4.53	114	165
2	119	0.04	1	9.06	208	193
3	119	0.04	1	13.59	214	197
4	119	0.04	1	18.12	226	198
5	119	0.04	1	22.65	239	199
6	100	0.04	1.5	5.95	246	315
7	100	0.04	1.5	11.9	298	313
8	100	0.04	1.5	17.85	379	307
9	100	0.04	1.5	23.8	413	329
10	100	0.04	1.5	29.75	435	376
11	106	0.16	1	1.13	155	287
12	106	0.16	1	2.26	178	277
13	106	0.16	1	3.39	171	292
14	106	0.16	1	4.52	167	281
15	106	0.16	1	5.65	192	292
16	106	0.16	1	6.78	189	278
17	113	0.16	1.5	0.86	195	421
18	113	0.16	1.5	1.72	204	448
19	113	0.16	1.5	2.58	210	433
20	113	0.16	1.5	3.44	218	439
21	113	0.16	1.5	4.3	220	440
22	113	0.16	1.5	5.16	208	443
23	393	0.04	1	1.23	96	117

24	393	0.04	1	2.46	122	134
25	393	0.04	1	3.69	128	134
26	393	0.04	1	4.92	146	132
27	393	0.04	1	6.15	148	142
28	393	0.04	1	7.38	165	142
29	433	0.04	1.5	1.23	143	149
30	433	0.04	1.5	2.46	198	167
31	433	0.04	1.5	3.69	226	175
32	433	0.04	1.5	4.92	226	192
33	433	0.04	1.5	6.15	260	197
34	433	0.04	1.5	7.38	281	200
35	417	0.16	1	0.4	130	243
36	417	0.16	1	0.8	158	266
37	417	0.16	1	1.2	165	267
38	417	0.16	1	1.6	167	267
39	417	0.16	1	2	170	249
40	400	0.16	1.5	0.4	208	309
41	400	0.16	1.5	0.8	263	329
42	400	0.16	1.5	1.2	282	345
43	400	0.16	1.5	1.6	295	360
44	400	0.16	1.5	2	319	363
45	400	0.16	1.5	2.4	327	368
46	333	0.05	1.2	1.48	141	130
47	333	0.05	1.2	2.96	184	134
48	333	0.05	1.2	4.44	185	154
49	333	0.05	1.2	5.92	191	150
50	333	0.05	1.2	7.4	193	177
51	333	0.05	1.2	8.88	205	187
52	184	0.12	1.5	0.8	221	339
53	184	0.12	1.5	1.6	239	356

54	184	0.12	1.5	2.4	247	348
55	184	0.12	1.5	3.2	238	380
56	184	0.12	1.5	4	231	369
57	184	0.12	1.5	4.8	254	406
58	210	0.04	1.5	2.06	264	324
59	210	0.04	1.5	4.12	299	321
60	210	0.04	1.5	6.18	364	344
61	210	0.04	1.5	8.24	366	357
62	210	0.04	1.5	10.3	384	364
63	332	0.14	1.2	0.32	230	400
64	332	0.14	1.2	0.64	237	393
65	332	0.14	1.2	0.96	273	420
66	332	0.14	1.2	1.28	229	433
67	332	0.14	1.2	1.6	275	441
68	332	0.14	1.2	1.92	287	458
69	213	0.04	1.4	1.86	102	136
70	213	0.04	1.4	3.72	108	147
71	213	0.04	1.4	5.58	112	154
72	213	0.04	1.4	7.44	140	151
73	213	0.04	1.4	9.3	120	164
74	213	0.04	1.4	11.16	115	169
75	149	0.06	1.5	2.72	133	167
76	149	0.06	1.5	5.44	152	169
77	149	0.06	1.5	8.16	142	190
78	149	0.06	1.5	10.88	152	205
79	149	0.06	1.5	13.6	161	219
80	149	0.06	1.5	16.32	165	228
81	100	0.08	1.3	2.045	156	254
82	100	0.08	1.3	4.09	172	280

83	100	0.08	1.3	6.135	170	287
84	100	0.08	1.3	8.18	184	291
85	100	0.08	1.3	10.225	190	297
86	100	0.08	1.3	12.27	193	304

Table B-3: Testing data set for prediction of feed force during air-cooled turning

Sl. no	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Cutting time (min)	Feed Force (Fx) (N)
1	295	0.12	1.38	0.5	205
2	295	0.12	1.38	1	209
3	295	0.12	1.38	1.5	205
4	295	0.12	1.38	2	210
5	295	0.12	1.38	2.5	217
6	295	0.12	1.38	3	218
7	259	0.08	1.42	3.09	208
8	259	0.08	1.42	4.12	216
9	259	0.08	1.42	5.15	223
10	259	0.08	1.42	6.18	223
11	255	0.10	1.28	7.2	198
12	255	0.10	1.28	9.0	206
13	255	0.10	1.28	10.8	215
14	303	0.05	1.44	3.78	180
15	303	0.05	1.44	5.04	187
16	194	0.10	1.24	1.08	167
17	194	0.10	1.24	2.16	183
18	194	0.10	1.24	3.24	192
19	194	0.10	1.24	4.32	189
20	194	0.10	1.24	5.4	203
21	194	0.10	1.24	6.48	196

22	386	0.06	1.36	1.05	235
23	386	0.06	1.36	2.1	237
24	386	0.06	1.36	3.15	240
25	386	0.06	1.36	4.2	244
26	386	0.06	1.36	5.25	247

Table B-4: Testing data set for prediction of cutting force during air-cooled turning

Sl. no	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Cutting time (min)	Cutting Force (Fz) (N)
1	303	0.05	1.44	1.26	207
2	303	0.05	1.44	2.52	209
3	303	0.05	1.44	3.78	209
4	303	0.05	1.44	5.04	210
5	303	0.05	1.44	6.3	220
6	303	0.05	1.44	7.56	231
7	195	0.14	1.18	0.58	303
8	195	0.14	1.18	1.16	313
9	195	0.14	1.18	1.74	314
10	195	0.14	1.18	2.32	325
11	195	0.14	1.18	2.9	318
12	195	0.14	1.18	3.48	322
13	255	0.1	1.28	1.8	278
14	255	0.1	1.28	3.6	284
15	255	0.1	1.28	5.4	294
16	255	0.1	1.28	7.2	290
17	255	0.1	1.28	9	297
18	255	0.1	1.28	10.8	300
19	386	0.06	1.36	4.2	239

20	386	0.06	1.36	5.25	243
21	194	0.1	1.24	1.08	267
22	194	0.1	1.24	2.16	272
23	194	0.1	1.24	3.24	284
24	194	0.1	1.24	4.32	284
25	194	0.1	1.24	5.4	289
26	194	0.1	1.24	6.48	282
27	259	0.08	1.42	1.03	254
28	259	0.08	1.42	2.06	257
29	259	0.08	1.42	3.09	267
30	259	0.08	1.42	4.12	265
31	259	0.08	1.42	5.15	262
32	259	0.08	1.42	6.18	257
33	295	0.12	1.38	0.5	300
34	295	0.12	1.38	1	316
35	295	0.12	1.38	1.5	308
36	295	0.12	1.38	2	312
37	295	0.12	1.38	2.5	310
38	295	0.12	1.38	3	324

Table B-5: Testing data set for prediction of feed force during dry turning

Sl. no	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Cutting time (min)	Cutting Force (Fz) (N)
1	260	0.1	1.4	0.74	199
2	260	0.1	1.4	1.48	202
3	260	0.1	1.4	2.22	213
4	260	0.1	1.4	2.96	215
5	260	0.1	1.4	3.7	223
6	260	0.1	1.4	4.44	237

7	233	0.16	1	0.357	229
8	233	0.16	1	0.714	240
9	233	0.16	1	1.071	238
10	233	0.16	1	1.428	244
11	233	0.16	1	1.785	241
12	233	0.16	1	2.142	233
13	113	0.04	1.5	4.55	225
14	113	0.04	1.5	9.1	240
15	156	0.08	1.4	1.34	176
16	156	0.08	1.4	2.68	179
17	156	0.08	1.4	4.02	186
18	156	0.08	1.4	5.36	195
19	246	0.1	1.1	0.49	208
20	246	0.1	1.1	0.98	212
21	246	0.1	1.1	1.47	223
22	246	0.1	1.1	1.96	229
23	107	0.12	1	1.16	189
24	107	0.12	1	2.32	193
25	107	0.12	1	3.48	192
26	107	0.12	1	4.64	199
27	354	0.16	1.2	0.62	258
28	354	0.16	1.2	0.93	266
29	354	0.16	1.2	1.24	282
30	100	0.12	1.3	1.54	199
31	100	0.12	1.3	3.08	203
32	100	0.12	1.3	4.62	212
33	100	0.12	1.3	6.16	219

Table B-6: Testing data set for prediction of cutting force during dry turning

Sl. no	Speed	Feed	Depth of cut	Cutting time	Cutting Force (Fz)
	(m/min)	(mm/rev)	(mm)	(min)	(N)
1	260	0.1	1.4	0.74	317
2	260	0.1	1.4	1.48	328
3	260	0.1	1.4	2.22	328
4	260	0.1	1.4	2.96	324
5	260	0.1	1.4	3.7	334
6	260	0.1	1.4	4.44	324
7	233	0.16	1	0.357	350
8	233	0.16	1	0.714	345
9	113	0.04	1.5	4.55	310
10	113	0.04	1.5	9.1	321
11	113	0.04	1.5	13.65	339
12	113	0.04	1.5	18.2	348
13	156	0.08	1.4	1.34	278
14	156	0.08	1.4	2.68	269
15	246	0.1	1.1	0.49	334
16	246	0.1	1.1	0.98	342
17	246	0.1	1.1	1.47	352
18	246	0.1	1.1	1.96	348
19	107	0.12	1	1.16	300
20	107	0.12	1	2.32	311
21	107	0.12	1	3.48	312
22	107	0.12	1	4.64	324
23	354	0.16	1.2	0.31	301
24	354	0.16	1.2	0.62	328
25	354	0.16	1.2	0.93	341

26	354	0.16	1.2	1.24	352
27	100	0.12	1.3	1.54	320
28	100	0.12	1.3	3.08	341
29	100	0.12	1.3	4.62	332
30	100	0.12	1.3	6.16	344



Appendix C

Determination of β and η value for Weibull Probability Distribution

(1) Calculation of β and η value for probability distribution of tool life during dry turning at cutting speed (a) 300 m/min and (b) 270 m/min

(a)

Time Failure (T_i)	order	MR	$\ln(T_i)$	$f(T_i)$	y_i	$(\ln T_i)^2$	$(y_i)^2$	$\ln(T_i)y_i$
4.5	1	9.459459	1.504077	0.094595	-2.30888	2.262249	5.330927	-3.47273
5	2	22.97297	1.609438	0.22973	-1.34318	2.59029	1.804138	-2.16177
6	3	36.48649	1.791759	0.364865	-0.78984	3.210402	0.623847	-1.4152
6	4	50	1.791759	0.5	-0.36651	3.210402	0.134332	-0.6567
6	5	63.51351	1.791759	0.635135	0.008195	3.210402	6.72E-05	0.014683
6	6	77.02703	1.791759	0.77027	0.385842	3.210402	0.148874	0.691335
6	7	90.54054	1.791759	0.905405	0.85788	3.210402	0.735957	1.537114
Column sum			12.07231		-3.5565	20.90455	8.778142	-5.46328

β	a	η
7.938	-14.198	5.981

(b)

Time Failure (T_i)	order	MR	$\ln(T_i)$	$f(T_i)$	y_i	$(\ln T_i)^2$	$(y_i)^2$	$\ln(T_i)y_i$
6	1	9.459459	1.791759	0.094595	-2.30888	3.210402	5.330927	-4.13696
6	2	22.97297	1.791759	0.22973	-1.34318	3.210402	1.804138	-2.40666
6	3	36.48649	1.791759	0.364865	-0.78984	3.210402	0.623847	-1.4152
6.7	4	50	1.902108	0.5	-0.36651	3.618013	0.134332	-0.69715
7	5	63.51351	1.94591	0.635135	0.008195	3.786566	6.72E-05	0.015946
7	6	77.02703	1.94591	0.77027	0.385842	3.786566	0.148874	0.750813
7	7	90.54054	1.94591	0.905405	0.85788	3.786566	0.735957	1.669356
Column sum			13.11512		-3.5565	24.60892	8.778142	-6.21985

β	a	η
12.122	-23.219	6.790

(2) Calculation of β and η value for probability distribution of tool life during air-cooled turning at cutting speed (a) 300 m/min and (b) 270 m/min

(a)

Time	Failure							
(T_i)	order	MR	$\ln(T_i)$	$f(T_i)$	y_i	$(\ln T_i)^2$	$(y_i)^2$	$\ln(T_i)y_i$
4.8	1	9.459459	1.568616	0.094595	-2.30888	2.460556	5.330927	-3.62175
4.8	2	22.97297	1.568616	0.22973	-1.34318	2.460556	1.804138	-2.10694
4.8	3	36.48649	1.568616	0.364865	-0.78984	2.460556	0.623847	-1.23896
5	4	50	1.609438	0.5	-0.36651	2.59029	0.134332	-0.58988
5	5	63.51351	1.609438	0.635135	0.008195	2.59029	6.72E-05	0.013189
5	6	77.02703	1.609438	0.77027	0.385842	2.59029	0.148874	0.620988
5	7	90.54054	1.609438	0.905405	0.85788	2.59029	0.735957	1.380704
Column sum			11.1436		-3.5565	17.74283	8.778142	-5.54264

β a η
41.693 -66.880 4.974

(b)

Time	Failure							
(T_i)	order	MR	$\ln(T_i)$	$f(T_i)$	y_i	$(\ln T_i)^2$	$(y_i)^2$	$\ln(T_i)y_i$
5.9	1	9.459459	1.774952	0.094595	-2.30888	3.150456	5.330927	-4.09815
5.9	2	22.97297	1.774952	0.22973	-1.34318	3.150456	1.804138	-2.38408
5.9	3	36.48649	1.774952	0.364865	-0.78984	3.150456	0.623847	-1.40193
6	4	50	1.791759	0.5	-0.36651	3.210402	0.134332	-0.6567
6	5	63.51351	1.791759	0.635135	0.008195	3.210402	6.72E-05	0.014683
6	6	77.02703	1.791759	0.77027	0.385842	3.210402	0.148874	0.691335
6	7	90.54054	1.791759	0.905405	0.85788	3.210402	0.735957	1.537114
Column sum			12.49189		-3.5565	22.29298	8.778142	-6.29774

β a η
101.266 -181.222 5.989

(3) Calculation of β and η for probability distribution of tool life when dry turning followed air-cooled turning at cutting speed (a) 300 m/min and (b) 270 m/min

(a)

Time	Failure							
(T_i)	order	MR	$\ln(T_i)$	$f(T_i)$	y_i	$(\ln T_i)^2$	$(y_i)^2$	$\ln(T_i)y_i$
7.73	1	9.459459	2.045109	0.094595	-2.30888	4.182475	5.330927	-4.72191
7.6	2	22.97297	2.028148	0.22973	-1.34318	4.113385	1.804138	-2.72417
8.03	3	36.48649	2.083185	0.364865	-0.78984	4.339658	0.623847	-1.64538
8.06	4	50	2.086914	0.5	-0.36651	4.355208	0.134332	-0.76488
8.15	5	63.51351	2.098018	0.635135	0.008195	4.401679	6.72E-05	0.017192
8.26	6	77.02703	2.111425	0.77027	0.385842	4.458114	0.148874	0.814676
8.27	7	90.54054	2.112635	0.905405	0.85788	4.463225	0.735957	1.812386
Column sum			14.56543		-3.5565	30.31374	8.778142	-7.21209
		β	a	η				
		29.697	-62.300	8.149				

(b)

Time	Failure							
(T_i)	order	MR	$\ln(T_i)$	$f(T_i)$	y_i	$(\ln T_i)^2$	$(y_i)^2$	$\ln(T_i)y_i$
8.92	1	9.459459	2.188296	0.094595	-2.30888	4.788639	5.330927	-5.05251
8.92	2	22.97297	2.188296	0.22973	-1.34318	4.788639	1.804138	-2.93928
9	3	36.48649	2.197225	0.364865	-0.78984	4.827796	0.623847	-1.73546
9.03	4	50	2.200552	0.5	-0.36651	4.842431	0.134332	-0.80653
9.03	5	63.51351	2.200552	0.635135	0.008195	4.842431	6.72E-05	0.018033
9.2	6	77.02703	2.219203	0.77027	0.385842	4.924864	0.148874	0.856261
9.2	7	90.54054	2.219203	0.905405	0.85788	4.924864	0.735957	1.903809
Column sum			15.41333		-3.5565	33.93966	8.778142	-7.75568
		β	a	η				
		75.814	-167.443	9.103				

(4) Calculation of β and η for probability distribution of tool life when tool was initially used at 0.1 mm/rev feed and after failure at this feed the feed was reduced to 0.07 mm/rev during dry turning at cutting speed (a) 300 m/min and (b) 270 m/min

(a)

Time	Failure							
(T_i)	order	MR	$\ln(T_i)$	$f(T_i)$	y_i	$(\ln T_i)^2$	$(y_i)^2$	$\ln(T_i)y_i$
10	1	10.9375	2.302585	0.109375	-2.15562	5.301898	4.64668	-4.96349
10.5	2	26.5625	2.351375	0.265625	-1.17527	5.528966	1.381261	-2.7635
11.07	3	42.1875	2.404239	0.421875	-0.60154	5.780364	0.361855	-1.44625
11.1	4	57.8125	2.406945	0.578125	-0.14729	5.793385	0.021693	-0.35451
11.17	5	73.4375	2.413232	0.734375	0.281918	5.823687	0.079478	0.680333
11.25	6	89.0625	2.420368	0.890625	0.794337	5.858182	0.630971	1.922588
Column sum			14.29874		-3.00346	34.08648	7.121938	-6.92484

β a η
21.552 -51.861 11.093

(b)

Time	Failure							
(T_i)	order	MR	$\ln(T_i)$	$f(T_i)$	y_i	$(\ln T_i)^2$	$(y_i)^2$	$\ln(T_i)y_i$
10.4	1	10.9375	2.341806	0.109375	-2.15562	5.484054	4.64668	-5.04803
10.65	2	26.5625	2.36556	0.265625	-1.17527	5.595874	1.381261	-2.78017
10.67	3	42.1875	2.367436	0.421875	-0.60154	5.604754	0.361855	-1.42412
11.2	4	57.8125	2.415914	0.578125	-0.14729	5.836639	0.021693	-0.35583
11.4	5	73.4375	2.433613	0.734375	0.281918	5.922474	0.079478	0.686079
11.67	6	89.0625	2.457021	0.890625	0.794337	6.036954	0.630971	1.951703
Column sum			14.38135		-3.00346	34.48075	7.121938	-6.97037

β a η
22.391 -54.168 11.237

Appendix D

Cost Analysis in Machining

(1) Cost of compressed air per minute

(a) Compressor cost:

The cost of compressor = Rs 85,000.00

The cost of accessories of the compressor = Rs 10,000.00

Total cost of compressor = Rs 95,000.00

If the life of the compressor is 10 years then the depreciation cost per year will be Rs.9,500.00 according to cost/life method.

Let, the machine runs for 6 hours per day for 22 days per month for each year.

The cost of compressor used per hour is equal to

$$\frac{\text{Rs. } 9,500.00}{6 \times 22 \times 12} = \text{Rs. } 6.00$$

∴ The cost of the compressor used per minute is = Rs. 0.10

(b) Electricity cost:

The compressor runs with a 2 kW motor.

The rate of electricity consumes per kW per hour is equal to Rs. 6.00

The cost of electricity consumed by the compressor per hour is Rs. 12.00

∴ The cost of electricity consumed by the compressor per minute is

$$\frac{\text{Rs.}12.00}{60} = \text{Rs. } 0.20$$

(c) Maintenance cost

The maintenance cost of the compressor is very low in comparison to the cost of compressor and electricity. There fore, the maintenance cost is negligible.

(d) Operator cost

The operator cost is assumed as Rs 0.20 per minute considering a semi-skilled labour.

The total cost of air produces in the compressor per minute is equal to the summation of compressor cost, electricity cost and the operator cost.

$$= \text{Rs. } 0.10 + \text{Rs. } 0.20 + \text{Rs. } 0.20 = \text{Rs. } 0.50$$

Let, Rs. 50.00 is equivalent to \$1 (in the month of September 2009), the total cost of air produces in the compressor per minute is equal to \$ 0.01.

(2) Tool cost per edge

A rhombus shape coated carbide tool was used for turning. The tool has 4 cutting edges and the cost of the tool is Rs. 400.00

So, the cost of the cutting tool per edge is equal to Rs 100.00 = \$ 2

(3) Critical cost of compressed air per minute when dry turning followed the air-cooled turning

The mean tool life of a cutting edge at a cutting speed of 300 m/min during dry turning is 5.63 minute (T_1).

The mean tool life of a cutting edge at a cutting speed of 300 m/min during air-cooled turning is 4.90 minute (T_3).

The mean tool life of a cutting edge at a cutting speed of 300 m/min during dry turning followed the air-cooled turning is 8.00 minute (T_2).

∴ The critical cost of air per minute at a cutting speed of 300 m/min during dry turning followed the air-cooled turning is equal to (using Equation 5.13)

$$\frac{\text{Rs.}100.00}{5.63} \left(\frac{8 - 5.63}{4.90} \right) = \text{Rs. } 8.59/\text{min} = \$ 0.17/\text{min}.$$

Similarly,

The mean tool life of a cutting edge at a cutting speed of 270 m/min during dry turning is 6.51 minute (T_1).

The mean tool life of a cutting edge at a cutting speed of 270 m/min during air-cooled turning is 6.00 minute (T_3).

The mean tool life of a cutting edge at a cutting speed of 270 m/min during dry turning followed the air-cooled turning is 9.03 minute (T_2).

∴ The critical cost of compressed air per minute at a cutting speed of 270 m/min during dry turning followed the air-cooled turning is equal to (using Equation 5.13)

$$\frac{\text{Rs.}100.00}{6.51} \left(\frac{9.03 - 6.51}{6.00} \right) = \text{Rs. } 6.45/\text{min} = \$ 0.13/\text{min}.$$

(4) Operating cost (C_o) per minute during dry turning**(a) Manpower cost for one operator**

Let, the wage of one machine operator per day is Rs. 480.00

If the operator works for 8 hours per day,

The wage of the operator per hour is Rs. 60.00

(b) Electricity cost

In the turning operation, an 11 kW motor was used in the lathe.

The present cost of electrical power per kW per hour is Rs. 6.00

For 11 kW motor, the cost of electricity per kW per hour is Rs. 66.00

(c) Machine depreciation cost

Depreciation cost is calculated utilizing either a straight line depreciation method or an accelerated depreciation method. Here, we are using the straight line (SL) method where depreciation is calculated by spreading the cost evenly over the life of the fixed asst. The equation of SL is expressed as

$$SL = \text{Cost}/\text{Life}$$

Assume that the cost of the lathe is Rs.10,000,00.00

If the life of the machine is 10 years then the depreciation cost per year will be Rs.1,00,00.00 as per SL method.

Let, the machine runs for 8 hours per day for 25 days per month for each year.

The depreciation per hour will be

$$\frac{\text{Rs. } 1,00,000.00}{8 \times 25 \times 12} = \text{Rs. } 42.00$$

(d) Machine maintenance cost

Machine maintenance cost includes engine oil, lubricating oil, grease, motor belts, cleaning of swarf etc.

Considering all these cost, let assume that the maintenance cost of the machine is Rs. 10.00 per hour per machine.

The total operating cost (C_o) per hour is equal to the summation of manpower cost, electricity cost, machine depreciation cost and machine maintenance cost

$$= \text{Rs. } 60.00 + \text{Rs. } 66.00 + \text{Rs. } 42.00 + \text{Rs. } 10.00 = \text{Rs. } 178.00$$

$$\therefore \text{Total operating cost } (C_o) \text{ per minute} = \text{Rs. } 3.00 = \$ 0.06$$

Appendix E

Calculation of Optimum Value of Factor (c)

The mean tool life of a cutting tool during dry turning at a cutting speed of 300 m/min is $T_1 = 5.63$ minute (from Table 5.2)

The mean tool life of a cutting tool during dry turning at a cutting speed of 270 m/min is $T_2 = 6.51$ minute (from Table 5.2)

Using the equation $T_c = T_1(1-10c) + 10cT_2$ and putting the value of T_1 and T_2 , we get

$$T_c = 5.63(1-10c) + (10c)6.51$$

$$T_c = 5.63 + 8.8c$$

We know that, $t_c^* = \frac{cT_1T_c}{(T_c(1-c) - T_1)}$

$$t_c^* = \frac{c \times 5.63(5.63 + 8.8c)}{(5.63 + 8.8c)(1-c) - 5.63}$$

$$t_c^* = \frac{5.63 \times 5.63 + 49.54c}{3.17 - 8.8c}$$

For $t_c = 6$ minute

$$6 = \frac{5.63 \times 5.63 + 49.54c}{3.17 - 8.8c}$$

$$19.02 - 52.8c = 31.69 + 49.54c$$

$$c = 0.12$$

Publications from the Present Thesis

1. Sarma, D.K. and Dixit, U.S., (2009), Environment-friendly strategies for efficient utilization of cutting tools in finish turning, Transactions of the American Society of Mechanical Engineers: Journal of Manufacturing Science and Engineering, **131**, 064506 (5 pages).
2. Sarma, D.K. and Dixit, U.S., (2009), Neural network modelling of forces and indirect prediction of tool wear in turning of grey cast iron with ceramic tool, International Journal of Machining and Machinability of Materials, In Press.
3. Sarma, D.K. and Dixit, U.S., (2007), A comparison of dry and air-cooled turning of grey cast iron with mixed oxide ceramic tool, Journal of Material Processing Technology, **190**, pp.160-172.