TOOL WEAR AND SURFACE ROUGHNESS PREDICTION IN TURNING STEEL UNDER MINIMUM QUANTITY LUBRICATION

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Syed Mithun Ali

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Syed Mithun Ali

Table of Contents

List of Tables viii
List of Figures ix
Nomenclature xvi
Acknowledgement xix
Abstract xx

Chapter 1 Introduction 1
1.1 Introduction 1
1.2 Machining Environment 6
1.3 Artificial Neural Network (ANN) 16
1.3.1 Performance Measure of an ANN 22
1.3.2 Types of ANNs 23
1.3.3 Learning Paradigms 27
1.3.3.1 Supervised Learning 28
1.3.3.2 Unsupervised Learning 28
1.3.3.3 Reinforcement Learning 29
1.3.4 Learning Laws 30
1.3.4.1 The Hebb's Rule 30
1.3.4.2 The Delta Rule 31
1.3.4.3 The Gradient Descent Rule 31
1.3.5 Learning Algorithms 32
1.3.5.1 Back-propagation Algorithm 32
1.3.6 Modeling of Tool Wear 35
1.3.6.1 Mathematical Models of Tool Wear 36
1.3.6.2 ANN Models of Tool Wear 40
1.3.7 Surface Roughness 43
1.3.7.1 Modeling of Surface Ronghness: A Review 45
1.4 Summary of the Review 52
1.5 Objectives of the Present Work 53
1.6 Scope of the Thesis 53

Chapter 2	**Experimental Investigations**	**55**
2.1	Introduction	55
2.2	Experimental Procedures and Conditions	56
2.3	Experimental Results	60
2.3.1	Chip Thickness ratio	60
2.3.2	Cutting Temperature	62
2.3.3	Cutting Force	64
2.3.4	Tool Wear	67
2.3.5	Surface Roughness	84
Chapter 3	**Artificial Neural Network (ANN) Model**	**90**
3.1	ANN Model Formulation	90
3.2	Input Variables	91
3.3	Output Variables	93
3.3.1	Tool wear	93
3.3.2	Surface roughness	95
3.4	ANN Model	96
3.4.1	Experimentation/ Collection of Input-Output Dataset	97
3.4.2	Pre-processing of Input-Output Dataset	98
3.4.3	Neural Network Design and Training	99
3.4.4	Testing and Performance of the Designed Network	107
Chapter 4	**Discussions on Results**	**118**
4.1	Chip Thickness Ratio	118
4.2	Cutting Temperature	120
4.3	Cutting Forces	122
4.4	Cutting Tool Wear	123
4.5	Surface Roughness	126
4.6	SEM Micrographs	128
4.7	Artificial Neural Network (ANN) Model	128

Chapter 5 Conclusions and Recommendations **132**

5.1 Conclusions 132

5.2 Recommendations 136

References **137**

Appendix **160**

List of Tables

Table 1.1	Tool wear and wear rate Models	37
Table 1.2	Factors affecting surface roughness and major investigators	47
Table 2.1	Experimental conditions	57
Table 3.1	R^2 and MAPE values between the network predictions and the experimental values using training and test dataset (n=5-20)	109
Table 3.2	R^2 and MAPE values between the network predictions and the experimental values using training and test dataset (n=25-35)	110
Table 3.3	Weight corresponding to the input layer and hidden layer	115
Table 3.4	Weight corresponding to the hidden layer and output layer	116
Table 3.5	Summary of the ANN model	117

List of Figures

Fig.1.1	Schematic diagram of a biological neuron	16
Fig.1.2	An ANN with input, output and one hidden layer	18
Fig.1.3	A single ANN neuron with its elements	19
Fig.1.4	A Perceptron network with three Perceptron outputs that share four inputs	23
Fig.1.5	A multilayer network with one hidden layer outputs, 4 inputs and 1 output	24
Fig.1.6	A feed forward ANN	25
Fig.1.7	A recurrent ANN	27
Fig.1.8	Different transfer function used in back-propagation network	34
Fig.1.9	Arithmetic average value of roughness (R_a)	45
Fig.2.1	Photographic view of the experimental set-up	58
Fig.2 2	Photographic view of surface roughness measuring technique	59
Fig.2.3	Temperature calibration curve for medium carbon steel and carbide insert	60
Fig.2.4	Variation in Chip thickness ratio (r) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL conditions at depth of cut of 1.00 mm	61
Fig.2.5	Variation in Chip thickness ratio (r) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL conditions at depth of cut of 1.50 mm	61

Fig.2.6	Variation in temperature(θ) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL conditions at depth of cut of 1.00 mm	63
Fig.2.7	Variation in temperature(θ) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL conditions at depth of cut of 1.50 mm	63
Fig.2.8	Variation in main cutting force (F_c) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL condition at depth of cut of 1.00 mm	65
Fig.2.9	Variation in main cutting force (F_c) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL condition at depth of cut of 1.50 mm	65
Fig.2.10	Variation in Feed force (F_f) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL conditions at depth of cut of 1.00 mm	66
Fig.2.11	Variation in Feed force (F_f) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL conditions at depth of cut of 1.50 mm	66
Fig.2.12	Schematic view of general pattern of wear	69
Fig.2.13	Growth of average principal flank wear (VB) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm	70
Fig.2.14	Growth of average principal flank wear (VB) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm	70

Fig.2.15	Growth of average principal flank wear (VB) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm	71
Fig.2.16	Growth of average principal flank wear (VB) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm	71
Fig.2.17	Growth of average auxiliary flank wear (VS) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm	72
Fig.2.18	Growth of average auxiliary flank wear (VS) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm	73
Fig.2.19	Growth of average auxiliary flank wear (VS) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm	73
Fig.2.20	Growth of average auxiliary flank wear (VS) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm	74
Fig.2.21	Growth of Maximum principal flank wear (VM) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm	75
Fig.2.22	Growth of maximum principal flank wear (VM) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm	75

Fig.2.23	Growth of maximum principal flank wear (VM) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm	76
Fig.2.24	Growth of maximum principal flank wear (VM) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm	76
Fig.2.25	SEM views of principal flank of worn out SNMG insert after machining medium carbon steel under (a) Dry and (b) MQL conditions with cutting speed 66 m/min, feed rate 0.10 mm/rev and depth of cut 1.0 mm	77
Fig.2.26	SEM views of principal flank of worn out SNMG insert after machining medium carbon steel under (a) Dry and (b) MQL conditions with cutting speed 66 m/min, feed rate 0.10 mm/rev and depth of cut 1.5 mm	78
Fig.2.27	SEM views of principal flank of worn out SNMG insert after machining medium carbon steel under (a) Dry and (b) MQL conditions with cutting speed 258 m/min, feed rate 0.20 mm/rev and depth of cut 1.0 mm	79
Fig.2.28	SEM views of principal flank of worn out SNMG insert after machining medium carbon steel under (a) Dry and (b) MQL conditions with cutting speed 258 m/min, feed rate 0.20 mm/rev and depth of cut 1.5 mm	80
Fig.2.29	SEM views of auxiliary flank of worn out SNMG insert after machining medium carbon steel under (a) Dry and (b) MQL conditions with cutting speed 66 m/min, feed rate 0.10 mm/rev and depth of cut 1.0 mm	81

Fig.2.30	SEM views of auxiliary flank of worn out SNMG insert after machining medium carbon steel under (a) Dry and (b) MQL conditions with cutting speed 66 m/min, feed rate 0.10 mm/rev and depth of cut 1.5 mm	82
Fig.2.31	SEM views of auxiliary flank of worn out SNMG insert after machining medium carbon steel under (a) Dry and (b) MQL conditions with cutting speed 258 m/min, feed rate 0.20 mm/rev and depth of cut 1.0 mm	83
Fig.2.32	SEM views of auxiliary flank of worn out SNMG insert after machining medium carbon steel under (a) Dry and (b) MQL conditions with cutting speed 258 m/min, feed rate 0.20 mm/rev and depth of cut 1.5 mm	84
Fig.2.33	Variation in surface roughness (R_a) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL conditions at depth of cut of 1.00 mm	86
Fig.2.34	Variation in surface roughness (R_a) with that of V and f in turning medium carbon steel by SNMG insert under Dry and MQL conditions at depth of cut of 1.50 mm	86
Fig.2.35	Variation in average surface roughness (R_a) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at a depth of cut of 1.00 mm	87
Fig.2.36	Variation in average surface roughness (R_a) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm	88

Fig.2.37	Variation in average surface roughness (R_a) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm	88
Fig.2.38	Variation in average surface roughness (R_a) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm	89
Fig. 3.1	Schematic diagram of ANN for tool wear and surface roughness	96
Fig. 3.2	ANN training performance (Network architecture: 4-5-4)	102
Fig 3.3	ANN training performance (Network architecture: 4-10-4)	103
Fig. 3.4	ANN training performance (Network architecture: 4-15-4)	103
Fig. 3.5	ANN training performance (Network architecture: 4-20-4)	104
Fig. 3.6	ANN training performance (Network architecture : 4-25-4)	104
Fig. 3.7	Proposed ANN model (Network architecture: 4-25-4)	106
Fig. 3.8	Correlation between ANN prediction and Experimental values of average principal flank wear, VB (for 4-25-4 ANN architecture)	111
Fig. 3.9	Experimental Vs. ANN prediction of average principal flank wear (VB) for 10 testing cases	112
Fig. 3.10	Experimental Vs. ANN prediction of Maximum principal flank wear (VM) for 10 testing cases	113
Fig. 3.11	Experimental Vs. ANN prediction of Average auxiliary flank wear (VS) for 10 testing cases	113

Fig. 3.12 Experimental Vs. ANN prediction of average surface roughness (Ra) for 10 testing cases 114

Nomenclature

MQL	:	Minimum quantity lubrication
MVO	:	Minimum volume of oil
BP	:	Back-propagation
AE	:	Acoustic emission
ASPN	:	Algorithm for synthesis of polynomial network
ANFIS	:	Adaptive neuro-fuzzy inference system
r_c	:	Chip-thickness ratio
θ	:	Tool-chip interface temperature
F_c	:	Main cutting force
F_f	:	Feed force
a_1	:	Chip thickness before cut
a_2	:	Chip thickness
f	:	Feed rate
V	:	Cutting velocity
d	:	Depth of cut
t_c	:	Machining time
φ	:	Principal cutting edge angle
BUE	:	Built up edge
CBN	:	Cubic boron nitride

WC : Tungsten carbide

PCBN : Polycrystalline cubic boron nitride

VB : Average Principal flank wear

VM : Maximum principal flank wear

VS : Average auxiliary flank wear

VN : Flank notch wear

R_a : Average surface roughness

AA : Arithmetic average

CLA : Centerline average

h_m : Peak value of roughness caused due to feed marks

r : Nose radius of the turning inserts

MRR : Material removal rate

SEM : Scanning electron micrograph

NN : Neural Network

RN : Recurrent Network

ANN : Artificial Neural Network

CNN : Computational Neural Network

LM : Levenberg marquardt

LMSE : Least mean squared error

PSE : Predicted squared error

DOC	:	Depth of cut
P_i	:	Input vector to NN
T_i	:	Target vector to NN
MSE	:	Mean squared error
R^2	:	Coefficient of determination/ Absolute fraction of variance.
MEP	:	Mean error percentage
APE	:	Absolute percentage of error
MAPE	:	Mean absolute percentage of error
RSM	:	Response surface methodology
t	:	Target value
O	:	Output value
p	:	Number of pattern
i, j	:	Processing elements
b	:	Bias
W	:	Weight
α	:	Learning rate
β	:	Momentum constant
IMS	:	Intelligent manufacturing system
CAPP	:	Computer aided process planning

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Abstract

Minimum quantity lubrication (MQL) refers to the use of cutting fluids of only a minute amount typically of a flow rate of 50 to 500 ml/hour which is about three to four orders of magnitude lower than the amount commonly used in flood cooling condition. The concept of minimum quantity lubrication (MQL) has been suggested since a decade ago as a means of addressing the issues of environmental intrusiveness and occupational hazards associated with the airborne cutting fluid particles on factory shop floors. This research work deals with experimental investigation on the role of MQL by VG-68 cutting oil on chip thickness ratio, cutting temperature, cutting forces, tool wear and surface roughness in turning medium carbon steel at industrial speed-feed combinations by uncoated carbide insert and also to develop an Artificial Neural Network (ANN) model to predict tool wear and surface roughness in a MQL environment. The encouraging results from experimental investigations include significant reduction in tool wear rate, dimensional inaccuracy and surface roughness by MQL over dry machining mainly through reduction in the cutting zone temperature and favorable change in the chip-tool and work-tool interaction.

Tool wear and tool life influence the productivity, quality, surface integrity, cost and profit in any machining process. So, prediction of tool wear and surface roughness plays a significant role in industry for higher productivity and surface integrity and for manufacturing process planning. Artificial Neural Network (ANN) is a very promising tool in the field of modeling and monitoring of machining operations and for process optimization. It can recognize pattern in the past data and base on that pattern it can act as

a pattern matching engine to forecast the future data. The advantage of ANNs over mathematical model is that they do not require a precise formulation of physical relationship; they only need experimental results. In this study, an Artificial Neural Network (ANN) model has been developed for prediction of tool wear and surface roughness. The input parameters of the ANN model are the four machining parameters- cutting speed, feed rate, depth of cut, machining time and the output parameters are four process parameters which are principal flank wear, maximum principal flank wear, auxiliary flank wear and surface roughness.

The proposed model can predict tool wear and surface roughness which is very close to experimental values. The results of the ANN model show that the model can be used for the optimization of the cutting process i.e. cutting parameters can be set in advance prior to perform machining operations for efficient and economic production and for the purpose of manufacturing process planning in a properly designed MQL environment.

Chapter 1

Introduction

1.1 Introduction

Metal cutting is one of the most significant manufacturing processes in material removal. Metal cutting can be defined as the removal of metal from a workpiece in the form of chips in order to obtain a finished product with desired size, shape, and surface roughness. There are different methods of metal cutting and turning is one of the commonest among these methods. Turning is the process of machining external cylindrical and conical surfaces. It is usually performed on a lathe [1].

The quality of machined components is evaluated in respect of how closely they adhere to set product specifications for length, width, diameter, surface finish, and reflective properties. Dimensional accuracy, tool wear and quality of surface finish are three factors that manufacturers must be able to control at the machining operations to ensure better performance and service life of engineering component. In the leading edge of manufacturing, manufacturers are facing the challenges of higher productivity, quality and overall economy in the field of manufacturing by machining. To meet the above challenges in a global environment, there is an increasing demand for high material removal rate (MRR) and also longer life and stability of the cutting tool. But high production machining with high cutting speed, feed and depth of cut generates large amount of heat and temperature at the chip-tool interface which ultimately reduces dimensional accuracy, tool life and surface integrity of the machined component.

Longer cuts at high cutting temperature contribute to thermal expansion and distortion of the job which results in dimensional and form inaccuracy. Such high cutting temperature influences the growth of tool wear and also premature tool failure by plastic deformation and thermal fracturing. The surface quality of the products also deteriorates with the increase in cutting temperature due to built-up-edge formation, oxidation, rapid corrosion and induction of tensile residual stress and surface micro-cracks. Such problems become more severe if the work materials are very hard, strong and heat resistive and the machined part is under dynamic or shock loading during functional operations. So, to control cutting temperature is of great importance in machining industries. In industries, the high cutting temperature and its negative impacts are tried to be controlled by optimum selection of process parameters, tool geometry and selection and application of proper cutting fluid. Introducing heat and wear resistant cutting tool materials like carbides, coated carbides and high performance ceramics can contribute to achieve higher machining efficiency to a certain extent under normal cutting conditions. Proper selection and application of cutting fluid is the worldwide acceptable and popular method to reduce machining temperature. Such cutting fluid not only cools the tool and job but also provides lubrication and cleans the cutting zone by removing chips and protects the emerging finished surface from contamination by the harmful gases present in the atmosphere.

The conventional types and methods of application of cutting fluid have been found to become less effective with the increase in cutting velocity and feed when the cutting fluid cannot properly enter into the chip-tool interface to cool and lubricate the interface due to bulk plastic contact of the chip with the tool rake surface. Besides that, often in high speed machining the cutting fluid may cause premature failure of the cutting tool by fracturing due to close curling of the chips and thermal shocks. For which, application of high cooling type water base cutting fluids are generally avoided in machining steels by brittle type cutting tools like carbides and ceramics. The more serious concern by the use of cutting fluid, particularly oil-based type is the pollution of the working environment, water pollution, soil contamination and possible damage of the machine tool slide ways by corrosion. The major socio-economic problem [2] that arise due to conventional type and method of application of cutting fluids are –inconveniences due to wetting and dirtiness of the working zone, possible damage of the machine tool by corrosion and mixing of the cutting fluid with the lubricants, environmental pollution due to break down of the cutting fluid into harmful gases and biological hazards to the operators from bacterial growth in the cutting fluids and requirements of the additional systems for local storage, pumping, filtration, recycling, re-cooling, large space and disposal of the cutting fluid, which causes soil contamination and water pollution.

The modern industries are therefore looking for possible means of dry (near dry), clean, neat and pollution free machining and grinding. Minimum Quantity Lubrication (MQL) refers to the use of cutting fluids of only a minute amount-typically of a flow rate of 50-500 ml/hour-which is about three to four orders of magnitude lower than the amount commonly used in flood cooling, where for example, up to 10 litres of fluid can be dispensed per minute. The concept of minimum quantity lubrication, sometimes referred to as 'near dry lubrication' [3] or 'micro lubrication' [4].

Tool wear and surface roughness prediction plays an important role in machining industry for gaining higher productivity and product quality. Average principal flank wear (VB) of cutting tools is often selected as the tool life criterion as it determines the diametric accuracy of machining, its stability and reliability. The productivity of a machining system and machining cost, as well as quality, the integrity of the machined surface and profit strongly depend on tool wear and tool life. Sudden failure of cutting tools leads to loss of productivity, rejection of parts and consequential economic losses. Flank wear occurs on the relief face of the tool and is mainly attributed to the rubbing action of the tool on the machined surface during turning operation.

During turning operation the average principal flank wear (VB) predominantly occurs in cutting tool, so the life of a particular tool used in the machining process depends upon the amount of average principal flank wear. The maximum principal flank wear (VM) and average auxiliary flank wear (VS) also take place during turning and can't be neglected due to their significant impact on surface integrity of machined component. Crater wear is likely to be prevalent only under certain cutting conditions, i.e. higher cutting speeds and feeds lead to more crater wear. The surface finish of the machined component primarily depends upon the amount of average principal flank wear (VB). An increase in the amount of average principal flank wear (VB) leads to reduction in nose radius of the cutting insert which in turn reduces the surface quality along the job axis. The maximum utilization of cutting tool is one of the ways for an industry to reduce its manufacturing cost. Hence tool wear has to be controlled and should be kept within the desired limits for any marching process

Tool wear mainly depends upon the machining parameters for turning a particular work piece material. In order to maximize productivity and overall economy from a manufacturing process, an accurate process model must be constructed for turning operation in a MQL environment with speed, feed, depth of cut and machining time as input machining parameters and average principal flank wear, maximum principal flank wear, average auxiliary flank wear, and surface roughness as the response or output variable. Machining under minimum quantity lubrication condition is perceived to yield favorable machining performance. Relations between technical input variants like cutting speed, feed, depth of cut and environment and resultant performance in terms of tool wear and surface roughness in turning of commercially available steel using widely available carbide insert could contribute in industrial applications along with theoretical understanding.

This research aims to develop an artificial neural network (ANN) model for the analysis and prediction of the relationship between cutting and process parameters during turning of medium carbon steel. The input parameters of the ANN model are the cutting parameters: speed, feed, depth of cut, cutting time and coolant pressure. The output parameters of the model are four process parameters measured during the machining trials, namely principal flank wear (VB), maximum principal flank wear (VM), auxiliary flank wear (VS) and surface roughness (R_a). An experimental study would be conducted to establish and validate the proposed model.

1.2 Machining Environment

In machining process, the tool removes material from the surface of a less resistant body, through relative movement and application of force. The material removed called chip slides on the face of tool submitting it to high normal and shear stresses and moreover to a high coefficient of friction during chip formation. Most of the mechanical energy used to form the chip becomes heat, which generates high temperatures in the cutting region. A major portion of the energy is consumed in the formation and removal of chips. The greater the energy consumption, the greater are the temperature and the frictional force at the tool-chip interface and consequently the higher is the tool wear. For this reason, conventional coolant is often used on the cutting tool to prevent overheating. However the main problem with conventional coolant is that it does not reach the real cutting area [5]. The extensive heat generated evaporates the coolant before it can reach the cutting area. Hence, heat generated during machining is not removed and is one of the main causes of the reduction in tool life [6].

Cutting fluids is supposed to play a significant role in improving lubrication as well as minimizing temperature at the tool-chip and tool-workpiece interfaces, consequently minimizing seizure during machining but it can only perform these functions at the point of chip formation if the coolant actually reaches the cutting zone. Cutting fluid can additionally clean the cutting zone and protect the nascent finished surface from contamination by the harmful gases present in the atmosphere. Flood cooling of the cutting zone can effectively reduce the cutting temperature when machining at lower speed. Flood cooling is not effective in terms of lowering cutting temperature when machining exotic materials or machining at high speed. The coolant does not readily access the tool-workpiece and tool-chip interfaces that are under seizure condition as it vaporized by the high temperature generated close to the tool edge.

The majority of the cooling and lubricating aspects of a flood coolant stream are lost as coolants tend to be vaporized prior to entering the cutting zone by the high temperature generated close to the tool edge, forming a high temperature blanket that renders their cooling effect ineffective. The film boiling temperatures of conventional cutting fluids is about 350^{0}C [7]. When coolant fails to reach the target, it does not perform its two necessary functions-cooling and lubricating. Besides that, often in high production machining, the cutting fluid may cause premature failure of the cutting tool by fracturing due to close curling of the chips and thermal shocks. For which application of high cooling type water base cutting fluids are generally avoided in machining steels by brittle type cutting tools like carbides and ceramics. But what is more serious concern is the pollution of the working environment caused by use of cutting fluid, particularly oil-based type.

Machining of steel by pre-cooling with liquid nitrogen may be a solution. This technique is not the same as cryogenic machining, where the material to be cut is cooled to a very low temperature prior to the machining operation. Rather, the method currently under development uses liquid nitrogen to perform the cooling and lubricating job of the cutting fluid. Much of the part remains at ambient temperature while the flow of nitrogen is carefully delivered to the point where it is needed. Reportedly tool life and finish quality are also improved by this technique due to the low temperatures at the tool/part interface. Liquid nitrogen is an inexpensive chemical that is environmentally inert. Nitrogen is the most abundant gas earth's atmosphere and when liquid nitrogen warms, it simply mixes with and diffuses harmlessly into the air. Chips generated from this technique have no residual oil on them and can be recycled as scrap metal. However, liquid nitrogen is hazardous to workers due to its extremely low temperature. Exposure can result in mild to extreme frostbite. Nitrogen that is stored in a sealed vessel will increase in pressure dramatically as it warms, potentially resulting in a non-combustion explosion. Large spills can displace all of the oxygen in a room in a short time.

Recognizing that large amount of cutting fluid can be a serious threat to health and environment, leads to adoption of minimum quantity lubrication (MQL), micro lubrication, near dry machining or 'spatter' lubrication method. MQL is a method of delivering metalworking fluids to the point of cut, or just the logical continuation of the age old technique of 'brushing on' a lubricant where it is needed. In any case, the technology recognizes that sometimes just a little fluid, when properly selected and applied can make a substantial difference in how effectively a tool performs. MQL is perceived to provide benefits of both dry machining and flood cooling as MQL results cleaner parts like dry machining and serves the basic cutting functions of metal working fluids which includes increased tool life, improved surface integrity of the workpiece, and protection of in-process corrosion (Trim Technical Bulletin: Fluid Solutions for metalworking). In addition, MQL

- Reduces mist and spray, therefore offering an attractive alternative on unenclosed machines like a typical tool room or lathe.
- Reduces or eliminate problems associated with thermal shocking of the cutting tool

- Produces a cleaner, drier workpiece than a flood or high pressure coolant.

According to Klocke and Eisenblaetter [3] cutting fluids offer several important mechanical benefits in machining processes such as cooling, lubricating and chip flushing. From a recent survey it is indicated that the cost of cutting fluids and the auxiliary equipments comprise nearly 7-17% of the total machining costs. Compared with the cost of the cutting tools (2-4%), the cutting fluid cost is significantly high. Therefore it is necessary to reduce the use of the cutting fluids. Again, small lubricant droplets in the form of mist, smoke and gases are often produced in the machining processes that are harmful to the environment and human health.

Flood or conventional coolant is applied to remove the heat generated at the cutting zone. During machining [8, 9], especially of very hard materials, much heat is generated by the friction of the cutter against the workpiece, which is one of the major causes of reduction in tool hardness and rapid tool wear. For this reason, conventional coolant is often used on the cutting tool, to prevent overheating. However, the main problem [5] with conventional coolant is that it does not reach the real cutting area. The extensive heat generated evaporates the coolant before it can reach the cutting area. The high cutting forces generated during machining will induce intensive pressure at the cutting edge between the tool tip and the workpiece. Conventional coolant might not be able to overcome this pressure and flow into the cutting zone to cool the cutting tool. Hence, heat generated during machining is not removed and is one of the main causes of the reduction in tool life. Proper selection and application of cutting fluid generally improves tool life. At low cutting speed almost four times longer tool life was obtained [10] by such cutting fluid. But surface finish did not improve significantly.

Machining leads to environmental pollution mainly because of use of cutting fluids [11, 12]. These fluids often contain sulfur (S), phosphorus (P), chlorine (Cl) or other extreme-pressure additives to improve the lubricating performance. These chemicals present health hazards. Furthermore, the cost of treating the waste liquid is high and the treatment itself is a source of air pollution. According to Aronson [2] the major problems that arise due to use of cutting fluids are:

- environmental pollution due to breakdown of the cutting fluids into harmful gases at high cutting temperature,
- biological hazards to the operators from the bacterial growth in the cutting fluids
- requirements of additional systems for pumping, local storage, filtration, temporary recycling, cooling and large space requirement.
- disposal of the spent cutting fluids which also offer high risk of water pollution and soil contamination.

Skin exposure to cutting fluid can cause various skin diseases [13]. In general, skin contact with straight cutting oils cause folliculitis, oil acne, and keratoses while skin exposure to soluble, semi-synthetic and synthetic cutting fluid would result in irritant contact dermatitis and allergic contact dermatitis. Another source of exposure to cutting fluids is by inhalation of mists or aerosols. Airborne inhalation diseases have been occurring with cutting fluid aerosols exposed workers for many years. These diseases include lipid pneumonia, hypersensitivity pneumonitis, asthma, acute airways irritation, chronic bronchitis, and impaired lung function [13]. In response to these health effects through skin contact or inhalation, the National Institute for Occupational Safety and

Health (NIOSH) has recommended that the permissible exposure level (PEL) is 0.5 mg/m^3 as the metalworking fluid concentration on the shop floor [13, 14]. Bennett and Bennett [15] stated that during machining operations, workers could be exposed to cutting fluids by skin contact and inhalation. Skin contact usually occurs when:

- worker directly touches cutting fluid without any protective equipment;
- worker handles work, machine, and equipment that are covered with cutting fluid;
- Worker is exposed to cutting fluid splashes from the machine tool or workpiece.

Enormous efforts to reduce the use of lubricant in metal cutting are being made from the viewpoint of cost, ecological and human health issues [2, 16-18]. Minimal quantity lubrication (MQL) can be considered as one of the solutions to reduce the amount of lubricant. Again Concern for the environment, health and safety of the operators, as well as the requirements to enforce the environmental protection laws and occupational safety and health regulations are compelling the industry to consider a Minimum Quantity Lubricant (MQL) machining process as one of the viable alternative instead of using conventional cutting fluids. In some applications the consumption of cutting fluids has been reduced drastically by using mist lubrication. However, mist in the industrial environment can have a serious respiratory effect on the operator [19]. Consequently, high standards are being set to minimize this effect. Use of cutting fluids will become more expensive as these standards are implemented leaving no alternative but to consider environmentally friendly manufacturing.

Apart from the cost aspects, Heisel et al. [20] found that cutting fluids represents a serious problem to the preservation of the environment and to human health. Therefore, Minimum Volume of Oil technique may represent a compromise between the advantages and disadvantages of completely dry cutting and cutting with abundant soluble oil. MVO is a technique, which consists of the application (pulverisation) of a very small volume of cutting oil (usually less than 100 ml/h), in a flow of compressed air. This small amount of oil, most of the time is enough to substantially reduce friction and to avoid the adhesion of the chip on the tool. When abundant cutting fluid is used, the machined surface is flooded, while when MVO is used the lubricant is placed just in the contact area of the tool-chip and tool-workpiece. In this technique, the lubrication function is carried out by the oil and cooling is provided mainly by compressed air. Comparing the above two wet cutting, Heisel et al. [21], pointed out some advantages: (a) the amount of fluid used is much lower; (b) reduction of costs with oil maintenance, recycling and rejection; (c) the workpieces remain almost dry, eliminating washing operation; (d) the low content of oil which stays on the chips makes their drying unnecessary.

When turning AISI 1040 steel the influence of near dry lubrication on cutting temperature, chip formation and dimensional accuracy was investigated by Dhar et al. [22]. The lubricant was supplied at 60 ml/hr through an external nozzle in a flow of compressed air (7 bar). Based on the machining tests, the authors found that near dry lubrication resulted in lower cutting temperatures compared with dry and flood cooling The dimensional accuracy under near dry lubrication presented a notable benefit of controlling the increase of the workpiece diameter when the machining time elapsed where tool wear was observed. Dimensional accuracy was improved with the use of near dry lubrication due to the diminution of tool wear and damage.

The effects of cutting fluid on tool wear in high speed milling were studied by Lopez et al. [23]. Both near dry lubrication and flood cooling were applied when cutting aluminum alloys. In addition to experiments, they also performed computational fluid dynamics (CFD) simulations for estimating the penetration of the cutting fluid to the cutting zone. The oil flow rates of 0.04 and 0.06 ml/min were studied. The pressurized air was applied at 10 bars. The results showed that (i) with the help of compressed air, the oil mist could penetrated the cutting zone and provide cooling and lubricating while the CFD simulation showed that the flood coolant was not able to reach the tool teeth; (ii) the nozzle position relative to feed direction was very important for oil flow penetration optimization. Sasahara et al. [24] reported that in the case of helical feed milling for boring aluminum alloy, cutting forces, cutting temperature and dimension accuracy under near dry lubrication were close to those under flood cooling condition. Rahman et al. [25] performed experiments in end milling with the use of lubricant at 8.5 ml/hr oil flow rate. The oil was supplied by the compressed air at 0.52 MPa. The workpiece material was ASSAB 718HH steel. The experimental results showed that: (1) tool wear under near dry lubrication was comparable to that under flood cooling when cutting at low feed rates, low speeds and low depth of cuts; (2) the surface finish generated by near dry machining was comparable to that under flood cooling; (3) cutting forces were close in both near dry machining and flood cooling; (4) fewer burrs formed during near dry machining compared to dry cutting and flood cooling application; (5) the tool-chip interface temperature under near dry lubrication was lower than in dry cutting but higher than that in flood cooling.

The effect of minimum quantity lubricant on tool life when drilling carbon steels with high speed steel twist drills was investigated by Heinemann et al. [26]. The cutting fluid flow rate was 18 ml/hr. It was found that a continuous supply of minimum quantity lubricant conveyed a longer tool life while a discontinuous supply of lubricant resulted in a reduction of tool life. A low-viscous and high cooling-capable lubricant provided a longer tool life when different lubricants were used for an external MQL-supply in the tests. Brinksmeier et al. [27] applied minimum quantity lubrication in grinding. Two different work materials were used: hardened steel (16MnCr5) and tempered steel (42CrMo4V). The minimum quantity lubrication was implemented under 0.5 ml/min oil flow rate and 6 bar pressurized air. With reference to the grinding tests, the following results were observed: (i) both dry and near dry grinding would cause thermal damage on the hardened material with the creep feed grinding operation; (ii) acceptable surface finish was obtained under minimum quantity lubrication if the material removal rate was low; (iii) the type of lubricant used in minimum lubrication had a significant influence on the surface finish. The analysis of the cooling effect of cutting fluid for both minimum quantity lubrication and flood cooling was also presented. However, there was not a comparison between predicted and measured cutting temperatures.

Minimum quantity lubrication refers to the use of cutting fluids of only a minute amount – typically of a flow rate of 50 to 500 ml/hour – which is about three to four orders of magnitude lower than the amount commonly used in flood cooling condition. The concept of minimum quantity lubrication sometimes referred to as "near dry lubrication" [3] or "micro-lubrication" [4] has been suggested since a decade ago as a means of addressing the issues of environmental intrusiveness and occupational hazards associated with the airborne cutting fluid particles on factory shop floors. The minimization of cutting fluid also leads to economical benefits by way of saving lubricant costs and workpiece/tool/machine cleaning cycle time. A recent survey conducted on the production of the European automotive industry revealed that the expense of cooling lubricant comprises nearly 20% of the total manufacturing cost [28].

In comparison to cutting tools (7.5%), the cooling lubricant cost is significantly higher. As a result, the need to reduce cutting fluids consumption is strong. Furthermore, the permissible exposure level (PEL) for metalworking fluid aerosol concentration is 5.0 m g/m^3, per the U.S. Occupational Safety and Health Administration (OSHA) [2], and is 0.5 mg/m^3 according to the U.S. National Institute for Occupational Safety and Health (NIOSH) [13]. The oil mist level in U.S. automotive parts manufacturing facilities has been estimated to be generally on the order of 20-90 mg/m^3 with the use of traditional flood cooling and lubrication [29]. This suggests an opportunity for improvement of several orders of magnitude.

Itoigawa et al. [30] investigated the effects and mechanisms in minimal quantity lubrication by use of an intermittent turning process of aluminum silicon alloy. Especially a difference between minimal quantity lubrication (MQL) and MQL with water is inspected in detail to elucidate boundary film behavior on the rake face. He concluded that MQL with water droplets gives good lubrication performance if the appropriate lubricant, such as synthetic ester, is used. MQL with synthetic ester, without water, shows a lubrication effect. However, tool damage and material pick-up onto the tool surface cannot be suppressed.

1.3 Artificial Neural Network (ANN)

An artificial neural network (ANN), often just called a "neural network" (NN), is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. Neural networks can be defined as "A neural network is a system composed of many simple processing elements operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing element or nodes

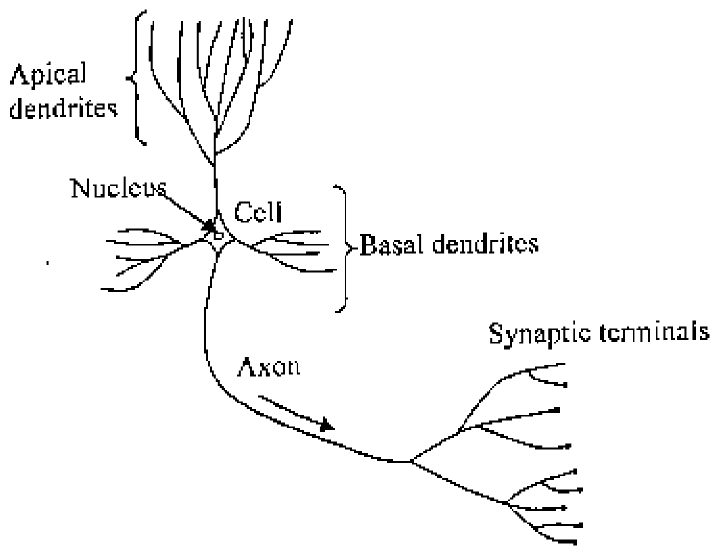


Fig.1.1 Schematic diagram of a biological neuron

Neural network architecture is inspired by the architecture of biological nervous systems, which use many simple processing elements operating in parallel to obtain high computation rates" [31].

In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.

In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. In other words neural network can be defined as a series of algorithms that attempt to identify underlying relationships in a set of data by using a process that mimics the way the human brain operates. Neural networks have the ability to adapt to changing input so that the network produces the best possible result without the need to redesign the output criteria.

The original inspiration for the technique was from examination of the central nervous system and the neurons which constitute one of its most significant information processing elements (Fig.1.1). The neural networks resemble the brain mainly in two respects-knowledge is acquired by the network from its environment and interneuron connection strengths, known as synaptic weights are used to store the acquired knowledge [32].

Figure1.1 shows the parts of a nerve cell or neuron. Each neuron consists of a cell body, or soma that contains a cell nucleus. Branching out from the cell body are a number of fibers called dendrites and a single long fiber called the axon. Typically they are 1 cm long (100 times the diameter of a cell body), but can reach up to 1 meter. A neuron makes connections with 10 to 100,000 other neurons at junctions called synapses. Signals are propagated from neuron to neuron by a complicated electrochemical reaction. The signals control brain activity in the short term, also enable –long term changes in the position and connectivity of neurons. These mechanisms are thought to form the basis for learning in the brain. Most information processing goes on in the cerebral cortex, the outer layer of the brain. The basic organizational unit appears to be a column of tissue about 0.5 mm in diameter, extending the full depth of the cortex, which is about 4 mm in humans. A column contains about 20,000 neurons and human brain contains 10^{14} synapses and 10^{11} neurons.

In a neural network model, simple nodes (called neurons) are connected together to form a network of nodes hence the term neural network. Other names for the field include connectionism, parallel distributed processing, neural computation or computational neural network (CNN). Neural networks are composed of nodes or units connected by directed links. Each link has a numeric weight associated with it which determines the strength and sign of the connection. Fig.1.2 shows ANN with input, output and one hidden layer with four neurons.

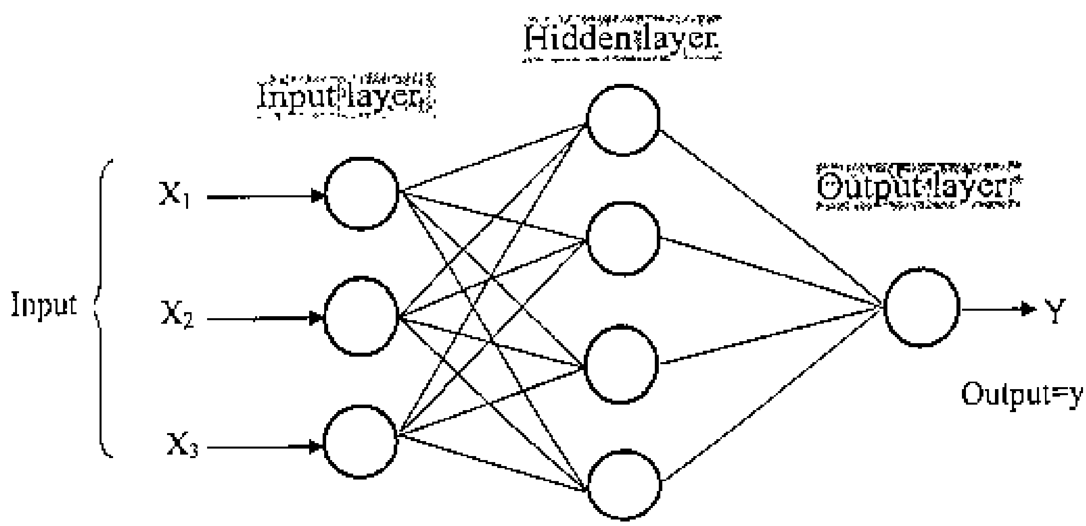


Fig.1.2 An ANN with input, output and one hidden layer

Here there are three inputs which are X_1, X_2, and X_3 and they produce a single output Y. The hidden layer establishes the complex relationship between the inputs and the outputs. The number of hidden neuron and hidden layer various depending on the nature and complexity of the problems and distributions of the data set.

Artificial neural networks attempt to mimic the basic operation of the brain. Information is passed between the neurons, and based upon the structure and synapse weights, a network behavior (or output mapping) is provided. Neural networks are very simple implementations of local behavior observed within our own brains. The brain is composed of neurons, which are the individual processing elements.

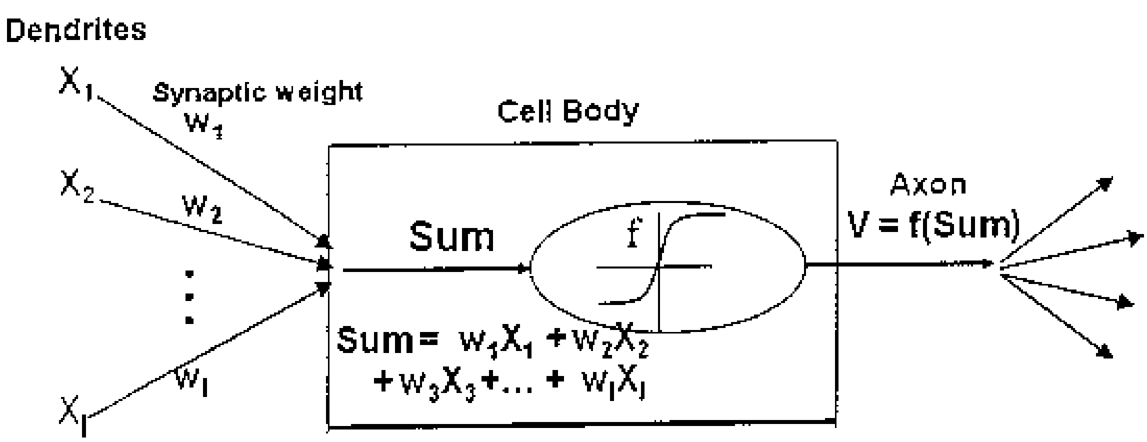


Fig.1.3 A single ANN neuron with its elements

The cell body in the human neuron receives incoming impulses via *dendrites* (receiver) by means of chemical processes. If the number of incoming impulses exceeds certain threshold value the neuron will discharge it off to other neurons through its *synapses*, which determines the impulse frequency to be fired off. Fig.1.3 shows a typical neuron and its elements. A neuron is the basic element of neural networks, and its shape and size may vary depending on its duties. Analyzing a neuron in terms of its activities is important, since understanding the way it works also helps us to construct the ANNs.

An ANN may be seen as a *black box* which contains hierarchical sets of neurons (e.g., processing elements) producing outputs for certain inputs. Each processing element consists of data collection, processing the data and sending the results to the relevant consequent element. The whole process may be viewed in terms of the inputs, weights, the summation function, and the activation function (Fig.1.3) [33, 34]. The description of the Fig. 1.7 and the working principle is given below:

1. The inputs (e.g. X_1, X_2.......X_l are the activity of collecting data from the relevant sources. These data are fed to the neural network.
2. The weights control the effects of the inputs on the neuron. In other words, an ANN saves its information over its links and each link has a weight (e.g. W_1, W_2.......W_l). These weights are constantly varied while trying to optimize the relation in between the inputs and outputs. Synaptic weights characterize themselves with their strength (value) which corresponds to the importance of the information coming from each neuron. In other words, the information is encoded in these strength-weights.
3. Summation function is to calculate of the net input readings from the processing elements. (E.g. Sum= $W_1 X_1 + W_2 X_2 + W_3 X_3 + \ldots\ldots + W_l X_l$)
4. Transfer (activation) function (f) determines the output of the neuron by accepting the net input (Sum= $W_1 X_1 + W_2 X_2 + W_3 X_3 + \ldots\ldots + W_l X_l$) provided by the summation function.

Depending on the nature of the problem, the determinations of transfer and summation function are made. A transfer function generally consists of algebraic equations of linear or nonlinear form [35]. The use of a nonlinear transfer function makes a network capable of storing nonlinear relationships between the input and the output. A commonly used function is sigmoid function because it is self-limiting and has a simple derivative. An advantage of this function is that the output cannot grow infinitely large or small [36]. Any differentiable function can qualify as an activation function in theory. In practice, only a small number of "well-behaved" (bounded, monotonically increasing, and differentiable) activation functions are used. These include:

The sigmoid (logistic) function:

$F(x) = (1 + \exp(-x))^{-1}$

The hyperbolic tangent function:

$F(x) = (\exp(x)-\exp(-x))/(\exp(x)+ \exp(-x))$

The sine or cosine function:

$F(x) = \sin(x)$ or $F(x) = \cos(x)$

The linear function:

$F(x) = x$,

Among them, the logistic transfer function is the most popular.

5. Outputs accept the results of the transfer function and present them either to the relevant processing element or to the outside of the network.
6. Each input has its own weight plus there is an additional weight called bias

1.3.1 Performance Measure of an ANN

Like the Perceptron learning rule, the least mean square error (LMS) algorithm is an example of supervised training, in which the learning rule is provided with a set of examples of desired network behavior:

$$\{P_1, T_1\}, \{P_2, T_2\}, \ldots\ldots, \{P_Q, T_Q\}$$

Here $\mathbf{P}_Q$ is an input to the network, and $\mathbf{T}_Q$ is the corresponding target output. As each input is applied to the network, the network output is compared to the target. The error is calculated as the difference between the target output and the network output. We want to minimize the average of the sum of these errors.

$$\mathbf{mse} = \frac{1}{Q}\sum_{k=1}^{Q} e(\mathbf{k})^2 = \frac{1}{Q}\sum_{K=1}^{Q}(t(\mathbf{k}) - a(\mathbf{k}))^2 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[1.1]$$

The LMS algorithm adjusts the weights and biases of the linear network so as to minimize this mean square error. Fortunately, the mean square error performance index for the linear network is a quadratic function. Thus, the performance index will either have one global minimum, a weak minimum or no minimum, depending on the characteristics of the input vectors. Specifically, the characteristics of the input vectors determine whether or not a unique solution exists

1.3.2 Types of ANNs

ANNs can have different number of hidden layers of neuron depending upon the complexity of the problem. Based on the number of hidden layers ANNs are two types – single layer perceptron and multi-layer perceptron.

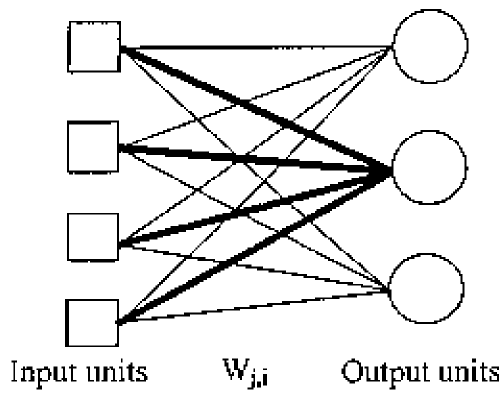


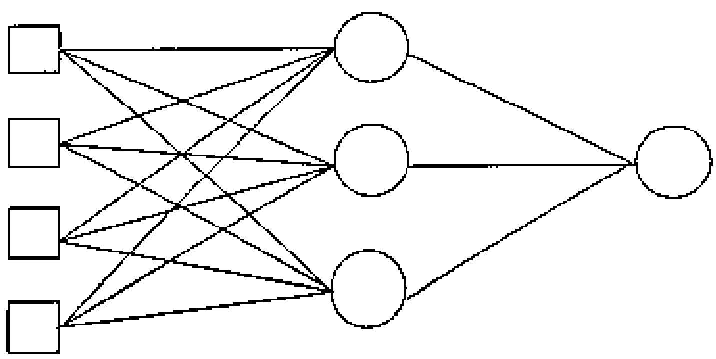
Fig. 1.4 A Perceptron network with three Perceptron outputs that share four inputs

Single-layer Perceptron

A network with all the inputs connected directly to the outputs is called a single-layer network or a Perceptron network. Since each output unit is independent of the others-each weight affects only one of the outputs-we can limit our study to Perceptron with a single output unit as shown in the figure 1.4

Multi-layer Perceptron

This class of networks consists of multiple layers of computational units [Fig. 1.5], usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. In many applications the units of these networks apply a sigmoid function as an activation function.



Input units, a_k W_{kj} Hidden units, a_j W_{kj} Output units, a_i

Fig. 1.5 A multilayer network with one hidden layer outputs, 4 inputs and 1 output

There are several different types of ANNs in use that basically differ on the basis of their network structure organization (topology/architecture) and their presence or absence of random elements. Among them, most commons are - feedforward ANNs and recurrent ANNs.

Feed-forward ANNs

The feedforward neural network [Fig.1.6] was the first and arguably simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. : A feed forward ANN is characterized by its architecture and determined by the number of layers, the number of nodes in each layer, the transfer or activation function used in each layer, as well as how the nodes in each layer are connected to nodes in adjacent layers.

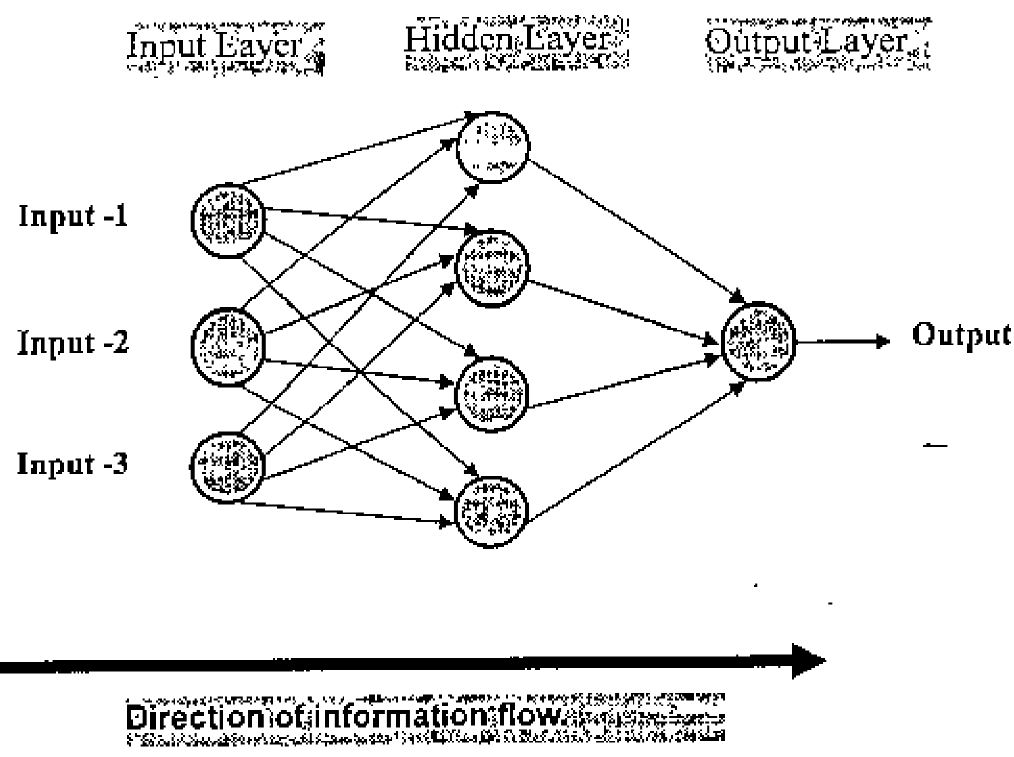


Fig.1.6 A feed forward ANN

Although partial connections between nodes in adjacent layers and direct connections from input layer to output layer are possible, the most commonly used ANN is the so-called "fully connected" network in that each node at one layer is fully connected only to all of the nodes in the adjacent layers.

The first layer is known as input layer, the last as output layer, and any intermediate layer(s) as hidden layer(s). A multiple feed forward layer can have one or more layers of hidden units. The number of units at the input layer and output layer is determined by the problem at hand. Input layer units correspond to the number of independent variables while output layer units correspond to the dependent variables or the predicted values. While the numbers of input and output units are determined by the task at hand, the numbers of hidden layers and the units in each layer may vary. There are no widely accepted rules for designing the configuration of a neural network. A network with fewer than the required number of hidden units will be unable to learn the input-output mapping, whereas too many hidden units will generalize poorly of any unseen data. Several researchers attempted to determine the appropriate size of hidden units. Kung and Hwang [37] suggested that the number of hidden units should be equal to the number of distinct training patterns while Arai [38] concluded that N input patterns required N-1 hidden nnits in a single layer. However, as remarked by Lee [39], it is rather difficult to determine the optimum network size in advance. Other studies suggested that ANNs generalize better when succeeding layers are smaller than the preceding ones [40, 41]. Although a two-layer network is commonly used in most problem solving approaches, the determination of an appropriate network configuration usually requires many trial and error methods. Another way to select network size is to use constructive approaches. In constructive approaches, the network starts with a minimal size and grows gradually during the training procedure [42, 43]

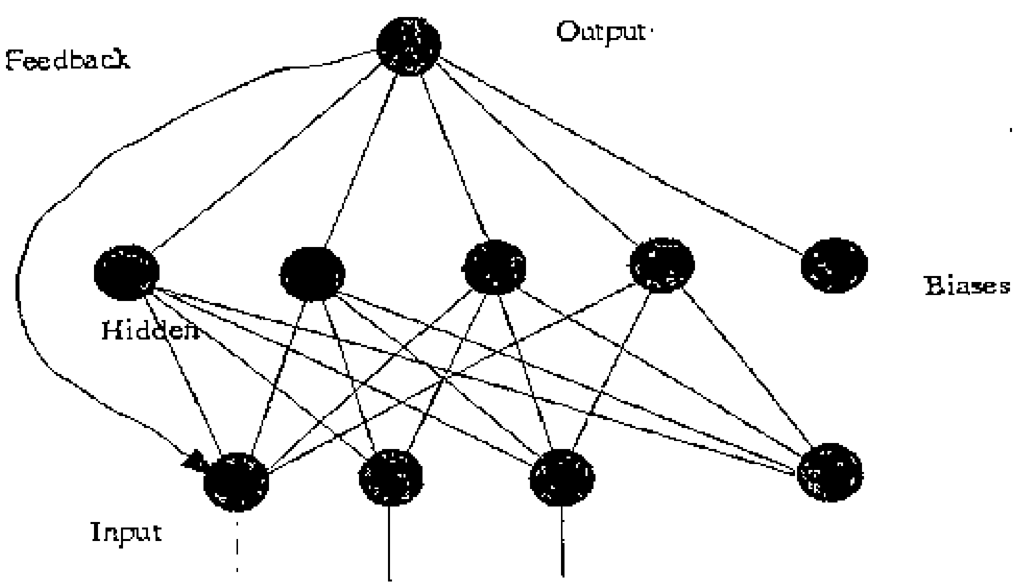


Fig.1.7 A recurrent ANN

Recurrent Network

Contrary to feedforward networks, recurrent neural networks (RNs) are models with bi-directional data flow. While a feedforward network propagates data linearly from input to output, RNs also propagate data from later processing stages to earlier stages. That is, closed loops are present in the architecture and network is modified depending on those feedback loops. Fig. 1.7 shows explicitly the feedback links.

1.3.3 Learning Paradigms

There are three major learning paradigms, each corresponding to a particular abstract learning task. These are supervised learning, unsupervised learning and reinforcement learning. Usually any given type of network architecture can be employed in any of those tasks.

1.3.3.1 Supervised Learning

In supervised learning, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually adjusted. The set of data which enables the training is called the "training set." During the training of a network the same set of data is processed many times as the connection weights are ever refined. Summary of Supervised training are:

- Adjust weights such that the differences between desired and actual outputs are minimized
- Desired output: dependent variable in training data
- Each training example specifies- (Independent variables, dependent variables)

1.3.3.2 Unsupervised Learning

The types of neural networks that don't use any external human influence, or any data set, in order to adjust their weights are called unsupervised. Unsupervised learning models are sometimes called self-supervised learning or clustering. As mentioned before the supervised models give a result as well as on the correct output. In an unsupervised learning procedure no correct output is provided to the network. Presentation of an output is accompanied by depend only on the actual state that the system is arrived and not on any externally provided correct output. The network is looking for patterns in the input signals and then makes matching according to the function of the network. The network identifies the patterns and differences in the inputs without any external assistance. In unsupervised learning, the network is provided with inputs but not with desired outputs. The system itself must then decide what features it will use to group the input data. This is often referred to as self-organization or adaptation. Summary of unsupervised learning are:

- Only supplies input
- No dependent variable specified in training data
- The neural network adjusts its own weights so that similar inputs cause similar outputs.

1.3.3.3 Reinforcement Learning

In reinforcement learning, data x is usually not given, but generated by an agent's interactions with the environment. At each point in time t, the agent performs an action y_t and the environment generates an observation x_t and an instantaneous cost c_t, according to some (usually unknown) dynamics. The aim is to discover a policy for selecting actions that minimizes some measure of a long-term cost, i.e. the expected cumulative cost. The environment's dynamics and the long-term cost for each policy are usually unknown, but can be estimated.

1.3.4 Learning Laws

Many learning laws are in common use. Most of these laws are some sort of variation of the best known and oldest learning law, Hebb's Rule. Research into different learning functions continues as new ideas routinely show up in trade publications. Some researchers have the modeling of biological learning as their main objective. Others are experimenting with adaptations of their perceptions of how nature handles learning. Either way, man's understanding of how neural processing actually works is very limited. Learning is certainly more complex than the simplifications represented by the learning laws currently developed. A few of the major laws are presented as examples.

1.3.4.1 The Hebb's Rule

The first, and undoubtedly the best known, learning rule was introduced by Donald Hebb. The description appeared in his book The Organization of Behavior in 1949. His basic rule is: If a neuron receives an input from another neuron and if both are highly active (mathematically have the same sign), the weight between the neurons should be strengthened. Hopfield Law: It is similar to Hebb's rule with the exception that it specifies the magnitude of the strengthening or weakening. It states, "if the desired output and the input are both active or both inactive, increment the connection weight by the learning rate, otherwise decrement the weight by the learning rate.

1.3.4.2 The Delta Rule

This rule is a further variation of Hebb's Rule. It is one of the most commonly used. This rule is based on the simple idea of continuously modifying the strengths of the input connections to reduce the difference (the delta) between the desired output value and the actual output of a processing element. This rule changes the synaptic weights in the way that minimizes the mean squared error of the network. This rule is also referred to as the Widrow-Hoff Learning Rule and the Least Mean Square (LMS) Learning Rule. The way that the Delta Rule works is that the delta error in the output layer is transformed by the derivative of the transfer function and is then used in the previous neural layer to adjust input connection weights. In other words, this error is back-propagated into previous layers one layer at a time. The process of back-propagating the network errors continues until the first layer is reached.

1.3.4.3 The Gradient Descent Rule

This rule is similar to the Delta Rule in that the derivative of the transfer function is still used to modify the delta error before it is applied to the connection weights. Here, however, an additional proportional constant tied to the learning rate is appended to the final modifying factor acting upon the weight. This rule is commonly used, even though it converges to a point of stability very slowly. It has been shown that different learning rates for different layers of a network help the learning process converge faster. In these tests, the learning rates for those layers close to the output were set lower than those layers near the input. This is especially important for applications where the input data is not derived from a strong underlying model.

1.3.5 Learning Algorithms

Training a neural network model essentially means selecting one model from the set of allowed models (or, in a Bayesian framework, determining a distribution over the set of allowed models) that minimizes the cost criterion. There are numerous algorithms available for training neural network models; most of them can be viewed as a straightforward application of optimization theory and estimation. Most of the algorithms used in training artificial neural networks are employing some form of gradient descent. This is done by simply taking the derivative of the cost function with respect to the network parameters and then changing those parameters in a gradient-related direction. Evolutionary methods, simulated annealing, and Expectation-maximization and non-parametric methods are among other commonly used methods for training neural networks.

1.3.5.1 Back-propagation Algorithm

Back propagation is a supervised learning technique used for training ANNs. It was first described by Paul Werbosin in 1974, and further developed by David E.Rumelhart, Georcy E.Hinton and Ronald J.Williams in 1986. The backpropagation (BP) neural network is a multiple layer network with one input layer, one output layer and some hidden layers between the input and output layers [44]. Its learning procedure is based on gradient search with least sum squared optimality criterion. It is most useful for feed-forward networks (networks that have no feedback, or simply, that have no connections that loop). The term is an abbreviation for back-wards propagation of errors. Back-propagation requires that the activation function used by the artificial neurons (or nodes) be differentiable. One such function used as the activation function is sigmoid function:

$$f(u) = 1 / 1+e^{-u} \qquad \text{.................................[1.2]}$$

Other transfer functions can also be used. The most commonly used transfer functions are shown in Fig.1.8.

Stepwise procedure of back-propagation algorithm:

- Present a training sample to the ANN.
- Compare the net works output to the desired output from that sample.
- Calculate the error in each output neuron.
- For each neuron, calculate what the output should have been, and a scaling factor, how much lower or higher the output must be adjusted to match the desired output. This is the local error.
- Adjust the weights of each neuron to lower the local error.
- Assign blame for the local error to neurons at the previous level, giving greater responsibility to neurons connected by stronger weights.
- Repeat the steps above on the neurons at the previous level, using each ones blame as its error.

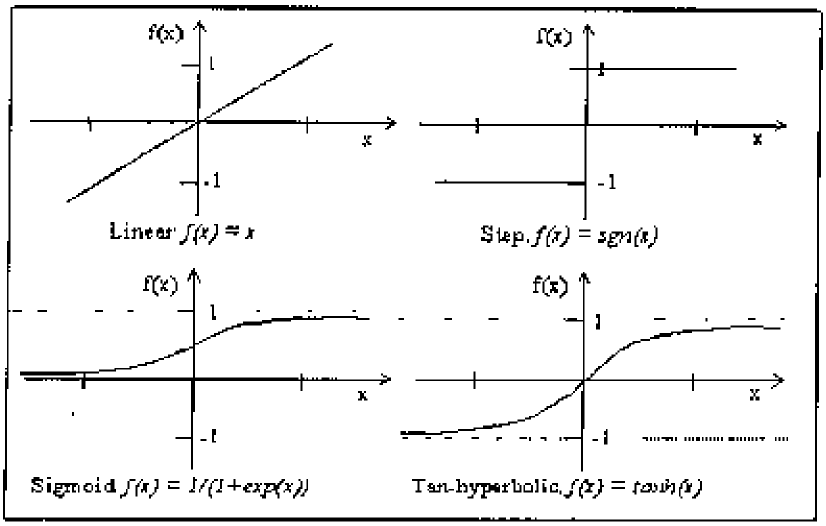


Fig. 1.8 Different transfer function used in backpropagation network

As the algorithms name implies, the errors (and therefore the learning) propagate backwards from the output nodes to the inner nodes. So technically speaking, back-propagation is used to calculate the gradient of the error of the network with respect to the networks modifiable weights. This gradient is almost always then used in a simple stochastic gradient descent algorithm to find weights that minimize the error. Often the term back-propagation is used in a more general sense, to refer to the entire procedure encompassing both the calculation of the gradient and its use in stochastic gradient descent. Back-propagation usually allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited. It is important to note that back-propagation networks are necessarily multilayer (usually with one input, one hidden and one output layer). In order for the hidden layer to serve any useful function, multilayer networks must have non-linear activation functions for the multiple layers. It is the most common method of obtaining the many weights in the network. It is a form of supervised training.

The standard BP algorithm suffers from the serious drawbacks of slow convergence and inability to avoid local minima. Therefore, BP with the Levenberg-Marquardt (LM) approximation is used in most of the work. The LM learning rule uses an approximation of Newton's method to get better performance [45]. This technique is relatively faster but requires more memory. The LM update rule is:

$$\nabla W = \left(J^{T} J + \mu I\right)^{-1} J^{T} e \qquad \text{[1.3]}$$

Where, J is the Jacobean matrix of derivatives of each error to each weight, μ is a scalar and e is an error vector. If the scalar is very large, the above expression approximates the gradient descent method while if it is small the above expression becomes the Gauss-Newton method. The Gauss–Newton method is faster and more accurate near error minima. Hence, the aim is to shift towards the Gauss-Newton as quickly as possible. The μ is decreased after each successful step and increased only when the step increases the error.

1.5 Modeling of Tool Wear

In the survey of literature we see different models of tool that can be classified as mathematical model, regression based model. artificial neural network model, and fuzzy approach model. Some of the surveys of the literature have been highlighted in this study.

1.3.6.1 Mathematical Models of Tool Wear

The ability to predict tool wear or tool life is obviously important for tool management and manufacturing process planning and also in Computer Aided Process Planning (CAPP). From the beginning, the effort to predict tool wear or tool life takes into account the dependence on the combination on the properties of tool (material, geometry, surface integrity, and internal defects), the work (hardness, strength, chemical composition etc), the cutting conditions (speed, feed, depth of cut, cutting fluids), the cutting mode (turning, milling, drilling and others) and the machine tool (for example stiffness, state of maintenance).

Moreover, the studies concerning tool wear are mainly experimental ones and few numerical investigations may be recognized in technical literatures. However, it must be acknowledged that a universal model considering all aspects is a theoretical and practical impossibility. It is however possible to develop tool wear or tool life equations or developing Artificial Neural Network (ANN) model if the cutting mode and machine tool are limited and the tool wear is simple and dominated by a single mechanism. Many mathematical and neural network models are developed to quantify tool wear. Mathematical models can be categorized into two types: tool life models and tool wear rate models (Table 1.1).

Since the tool wear in cutting operations involves complex wear mechanisms, researchers have attempted to directly correlate the results of tool life to the applied machining parameters (cutting speed, feed rate, etc.). The well known Taylor's tool life relationship and its various extended equations are of this type [46, 47], these equations describe the relationship between tool life and machining parameters and involve a few constraints that need to be experimentally determined for the given combination of tool and workpiece materials.

Table 1.1 Tool Wear and Wear Rate Models

Empirical Tool Life Models	**Differential Tool Wear Rate Models**
Taylor's Tool Life Equation: $VT^{\alpha} = C_1$ (α, C_1 = constants)	Takeyama & Murata Model, considering Abrasive Wear and Diffusive Wear [1963]: $\frac{dW}{dt} = G(V,S) + D.\exp(\frac{-E}{R\theta})$ (G, D = constants)
Taylor's Extended Equation: $T = \frac{C_2}{V^{\alpha}S^{\beta}a^{\gamma}}$ (α, β,γ,C_2 = constants)	
Taylor's Extended Equation: $T = \frac{C_3}{V^{\alpha}S^{\beta}a^{\gamma}(BHN/200)^{\varepsilon}}$ (α, β,γ,C_3 = constants)	Usui's Model, derived from equation of adhesive wear [48] $\frac{dW}{dt} = C\sigma_n V_s \exp\left(\frac{-\lambda}{\theta}\right)$ (C, λ = Wear Characteristics constants)
Temperature Based Equation [49]: $T\theta^{n} = C_4$ (n, C_4 = Constants)	
$\left(\frac{dW}{dt}\right)$ = Wear Rate T = Tool Life R = Universal Gas Constant E = Process Activation Energy V = Cutting Speed	S = Feed VS = Sliding Velocity BHN = Workpiece Hardness σ_n = Normal Stress θ = Cutting Temperature

The tool life equation of Taylor relates influence of cutting speed on tool life over limited ranges of cutting speed. In mathematical form the equation can be expressed as:

$$VT^{\alpha} = C \quad \text{[1.4]}$$

Where V is the cutting speed, T the tool life, α the slope of the log T-log V and C is the Taylor constant; that is the cutting speed for a 1 min tool life. This formula indicates that a linear relationship between log T and log V (that is α is a constant). The Taylor equation seems to be valid reasonably when machining carbon and low alloy steels with all types of material in semi roughing conditions (depth of cut 0.050-0.150 in and feeds of less than 0.020 in) when cutting with speeds to give tool lives of 10-50 min, because it is in this region that optimum economic conditions are approached.

Barrow [50] has found that the tool wear depends on in addition to temperature, normal stress which acts on the flank face of the cutting tool. He proposed that temperature will exert a strong influence on the primary wear either through its influence on the properties of the tool material, the thermal stressing of the tool material or by facilitating of diffusion process.

In contrast to the above tool life models, the tool wear rate models describe the rate of local volume loss on the tool contact face per unit area per unit time. These models are derived from one or several wear mechanisms. They provide information about wear growth rate due to some wear mechanisms. In these models, the wear growth rate i.e. the rate of volume loss at the tool face per unit contact area per unit time (mm/min), are related to several cutting process variables that have to be decided by experiment or using some methods [51]. Chowdhury [52] developed an empirical tool flank wear rate model as a function of cutting velocity, feed, depth of cut, and variation of the normal load with respect to flank wear, wear coefficient, hardness of the cutting tool and the index of the diffusion coefficient. Based on Archard [53] model of volumetric wear rate depending on the deformation producing particles and considering diffusion of materials from the tool material, the model employs regression analysis to determine the constants defining the model. He found that all the input variables parameters influences tool wear rate, however, at different extent. The cutting velocity is the predominant factor affecting tool wear. The flank wear increases with increase in feed and depth of cut through the influence of feed is much significant than depth of cut.

It is generally accepted that for carbide tools under practical cutting tools under practical conditions, the wear rate is dominated by a temperature sensitive diffusion process, in particular at higher cutting speeds [48, 54-55]. Takeyama and Murata derived a fundamental wear rate equation by considering abrasive wear, which is proportional to cutting distance and diffusive wear. Mathew [54] analyzed the tool wear of carbide tools when machining carbon steels and results have shown that the Takeyama and Murata's diffusion equation can be used to effectively relate the tool wear rate to the average contact temperature of the tool.

Fillice et. al [56] developed a finite element model based on Takeyma and Murata model as it is able to properly describe the diffusion wear effects. Considering diffusion as the dominant phenomenon at high machining, Fillice rewrote Takeyma and Murata model. However, Fillice proposed a parameter which can be described using a polynomial function of temperature. Molinari and Nouari [55] proposed a model of tool wear by diffusion, taking into account cutting parameters, working material properties and frictional aspects, and underlined the influence of contact temperature at the interface between tool and chip. Experimental investigations on tungsten carbide tool wear were performed by Yang [57], who focused his attention on the evaluation of the wear coefficient by several pin-on-disc experiments.

Usai et al. [48] in the tool wear study for carbide tools derived a wear rate model based on the equation of adhesive wear, which involves temperature, normal stress, and sliding velocity at the contact surface. Their results in machining different carbon steels (0.15-0.46% C) showed that both flank wear crater wear obey the same wear mechanism and can be described by the proposed wear It should be noted that despite considering different tool wear mechanisms, Mathew [54] could fit the experimental wear data well due to the fact that the diffusive and adhesive wear models used, respectively, have the same form with the temperature dependence in the experimental term.

1.3.6.2 ANN Models of Tool Wear

ANN approach ensures efficient and fast selection of the optimum cutting conditions and processing of available technological data [58]. ANNs have been widely applied in modeling many metal cutting operations, such as turning, milling and drilling [59]. There is an extensive research interest in the application of ANNs in modeling and monitoring of machining operations [60, 61].

The advantage of ANNs over mathematical model is that they do not require a precise formulation of physical relationship, they only need experimental results. Applications of neural networks in computer-integrated production are adaptive control of cutting process, prediction of surface roughness, cutting forces, vibrations, prediction of tool wear and tool failure, solving of optimization problems [62-64].

Elanayar and Shin [65] proposed a model, which approximates flank and crater, wear propagation and their effects on cutting force by using radial basis function neural networks. The generic approximation capabilities of radial basis function neural networks are used to identify a model and a state estimator is designed based on this identified model. Ghasempoor et al. [66] proposed a tool wear classification and continuous monitoring neural network system for turning by employing recurrent neural network design. In the study of Li et al. [67], neural network models have also been integrated with analytical models such as Oxley's theory to form a hybrid machining model for the prediction of tool wear and workpiece surface roughness.

Neural networks are used to predict difficult-to-model machining characteristic factors. Liu and Altintas [68] derived an expression to calculate flank wear in terms of cutting force ratio and other machining parameters. The calculated flank wear, force ratio, feed rate and cutting speed are used as an input to a neural network to predict the flank wear in the next step. Sick [60] demonstrated a new hybrid technique, which combines a physical model describing the influence of cutting conditions on measured force signals with neural model describing the relationship between normalized force signals and the wear of the tool. Time-delay neural networks are used in his studies.

Choudry and Bartarya [69] compared the design of experiments technique and neural networks techniques for predicting tool wear. They established the relationships between temperature and tool flank wear. The amount of flank wear on a turning tool was indirectly determined without interrupting the machining operation by monitoring the temperature at the cutting zone and the surface finish by using a naturally formed thermocouple. They concluded that neural networks perform better than design of experiments technique.

Azouzi and Guillot [70] examined the feasibility of neural network based sensor fusion technique to estimate the surface roughness and dimensional deviations during machining. This study concludes that depth of cut, feed rate, radial and z-axis cutting forces are the required information that should be fed into neural network models to predict the surface roughness successfully. In addition to those parameters, Risbood et al. [71] added the radial vibrations of the tool holder as additional parameter to predict the surface roughness. Benardos and Vosniakos [72] made an extensive literature review on predicting surface roughness in machining and confirmed the effectiveness of neural network approaches.

Bisht et al. [73] developed a back propagation neural network model for the prediction of flank wear in turning operations. Large numbers of experiments have been performed by them on mild steel workpiece material using high speed steel (HSS) as the cutting tool. Process parametric conditions including cutting speed, feed-rate, depth of cut, and the measured parameters such as cutting force, chip thickness and vibration signals are used as inputs to the neural network model. Flank wear of the cutting tool corresponding to these conditions was the output of the neural network .The performance of the trained neural network has been tested with the experimental data, and is found to be in good agreement. Yongjin and Fischer [74] developed tool wear index (TWI) and the tool life model for analysing wear surface areas and material loss from the tool using micro-optics and image processing/analysis algorithms. They proposed optimal control strategy demonstrates how production cost can be minimized by adjusting machining parameters and extending the tool usage within the constraints for specific machining conditions. Oraby and Hayhurst [75] developed models for wear and tool life determination using nonlinear regression analysis techniques in terms of the variation of a ratio of force components acting at the tool tip. Kuo et al. [76] proposed an on-line estimation system applied in the area of tool wear monitoring through integration of two promising technologies: artificial neural network and fuzzy logic. The proposed system is able to accurately predict the amount of tool wear. The results showed that the proposed system can significantly increase the accuracy of the product profile when compared to the conventional approaches

1.3.7 Surface Roughness

Each machined surface is a part of engineering component made by any metal removal process, and each engineering component consists of definite set of surfaces. In assembly, an engineering component becomes a part of final product that carries out a certain role. Thus, machined surface comes into contact either with another surface or with fluid, accomplishing functioning of assembled device. In contact, in functioning or in loading, an arbitrary surface has its own functioning properties or perhaps its behaviour that contribute to quality of assembled device, as for instance power transmission (clutch, brake, transmission, driving device), information processing (measurement device, video head) and so on.

The surface finish of machined parts is known to have considerable effect on some properties such as wear resistance and fatigue strength. Thus the quality of the surface is a significantly importance for evaluating the productivity of machine tools, and mechanical parts. A proper cutting condition is extremely important task because these determine surface quality of manufactured parts [77].

Surface roughness is predominantly considered as the most important feature of practical engineering surface due to its crucial influence on the mechanical and physical properties of machined parts. As a significant design specification, surface roughness influences on properties such as wear resistance, cleanability, assembly tolerances, coefficient of friction, wear rate, corrosion resistance and aesthetics and fatigue strength. The quality of the surface is a factor of importance in the evaluation of machine tool productivity [78]

Surface roughness has received serious attentions for many years. It has been an important design feature and quality measure in many situations such as parts subjected to fatigue loads, precision fits, fastener holes and aesthetic requirements. Furthermore, surface roughness in addition to tolerances imposes one of the most critical constraints for cutting parameter selection in manufacturing process planning. As competition grows closer, customers now have increasingly high demands on quality, making surface roughness become one of the most competitive dimensions in today's manufacturing industry [79]

There are several measurements that describe the roughness of a machined surface. Average roughness, R_a for the characterization of surface roughness is used most widely in the industry for specifying surface roughness. The R_a value is obtained by measuring the height and depth of the valleys on a surface with respect to an average centerline [Fig. 1.9].

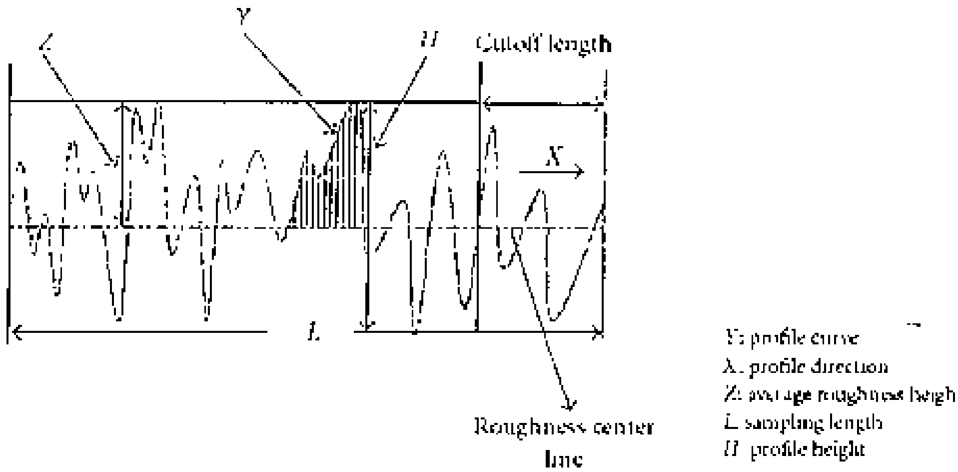


Fig. 1.9 Arithmetic Average value of roughness (R_a) [80]

Since turning is the primary operation in most of the production process in the industry, surface roughness of turned components has greater influence on the quality of the product. Surface finish in turning has been found to be influenced in varying amounts by a number of factors such as feed rate, work material characteristics, work hardness, unstable built up edge, depth of cut, cutting time, tool nose radius and tool cutting edge angles, stability of machine tool and work-piece setup, chatter, and use of cutting fluids in varying application methods and composition.

1.3.7.1 Modeling of Surface Roughness: A Review

Almost all the workers have taken into account the variables of speed and feed in surface roughness study. Groover [81] and Boothroyd and Knight [82] considers the impact of three factors, namely the feed, nose radius, and cutting edge angles, on surface roughness is depicted. Assuming a nonzero cutter nose radius (r), they developed the following equation to estimate the ideal roughness value

$$R_a = \frac{S_0^{\ 2}}{32r} \qquad \text{...} [1.5]$$

Where, R_a =ideal arithmetic average surface roughness (in. or mm), S_0=feed (in/rev or mm/rev) and r = cutter nose radius (in or mm). If the nose radius would be zero, then the following equation is use to estimate the ideal surface roughness, Boothroyd and knight [82]

$$R_a = \frac{S_0}{4(\cot\alpha + \cot\beta)} \qquad \text{...} [1.6]$$

Where α and β are the working major cutting edge angle and end cutting edge angle respectively.

Shaw [83] presented a case when the feed lies between the above two. Denoting the peak-to-valley roughness by R_{th}, then

$$\frac{f}{r} = \sqrt{\left(\frac{2R_{th}}{r} - \left(\frac{R_{th}}{r}\right)^2\right)} + Sin\beta + \left(\frac{R_{th}}{r} - 1 + Cos\beta\right)Cot\beta \qquad \text{.......................} [1.7]$$

A considerable amount of studies has investigated the general effects of the speed, feed, depth of cut, nose radius and others on the surface roughness. A summary of these representative studies is presented in the table 1.2. Almost all studies presented in Table 1.2 have considered speed and feed. In addition, the work hardness was also studied by Bhattacharya et al. [84] and Sundaram and Lambert [85]. The surface roughness models developed by Grieve et al. [86], Dickinson [87], and Fischer and Elrod [88] considered the effect of feed rate and nose radius. These models concluded that the effect of cutting speed is insignificant. However, different conclusions were presented in Chandiramani and Cook

[89], Shaw [90], Boothroyd and Knight [82], Sundaram and Lambert [91], Miller et al. [92], Feng and Wang [93], and Feng [79]. They have demonstrated that the cutting speed had a significant impact on surface roughness despite its complex nature of impact. In a certain range, the surface roughness improves as the speed increases. However, the surface roughness will deteriorate due to the impact of built-up edge (BUE) and chatter when speeds reach a certain region. After this region, the surface roughness will be found to improve again [82, 83]

Table 1.2 Factors affecting surface roughness and major investigators

Investigators	Major factors studied	Material studied
Karmakar [94]	Speed, feed, depth of cut	Steel C-45
Bhattacharya et al.[84]	Speed, feed, nose radius, work-piece hardness	Plain carbon steel
Rasch and Rolstadas [95]	Speed, feed	Carbon steel
Selvam and Radhakrishnan [96]	Speed, built-up edge, work-piece strain hardening	Steel
Lambert and Taraman [97]	Speed, feed, depth of cut	Steel SAE 1018
Petropoulos [98]	Tool wear, surface roughness distribution	Steel
Boothroyd and knight [82]	Speed, feed	Mild steel
Selvam [99]	Vibrations, chatter speed	Steel
Sundaram and Lambert [100]	Speed, feed, nose radius, depth of cut	Steel 4140
Miller et al. [92]	Speed, feed, tool condition, cutting fluid	Alloy, cast iron
Lambert [101]	Speed, feed, nose radius	Steel D6AC

The depth of cut was considered in the mathematical models developed by Karmakar [94], Lambert and Taraman [97], and Sundaram and Lambert [100]. Miller et al. [92] considered the effect of cutting fluid on surface roughness. Dawson and Kurfess [102] examined the impact of tool wear on surface quality in hard turning. Although a qualitative analysis of such machining variables as speed, feed and depth of cut (DOC) on the surface roughness has been widely available in the literature, few comprehensive predictive models have been developed. Accordingly, the past modeling methods on surface roughness prediction can be classified into two categories: geometric modeling example, [87-88, 103] and regression analysis. As a type of analytical modeling method, geometric modeling is based on the motion geometry of a metal cutting process regardless the cutting dynamics. As described previously, analytical models tend to be general and computationally straightforward. The first major drawback with the geometric modeling method is that they missed other parameters in cutting dynamics including speed, depth of cut and the and the work piece material in their models, such as in Equations [1.5] and [1.6]. The second major drawback with this modeling method is that they did not verify their model with any experimental data.

One of the major drawbacks with the regression method, a kind of empirical modeling method, is that these studies did not apply the factorial experimentation approach to design the experiments. Therefore, the data and conclusions obtained were biased and factor interactions were not clearly examined. Another drawback is that each study limited to only a small number of parameters. Furthermore, the regression analysis (RA) method in surface roughness modeling possesses the general drawbacks of an empirical modeling method as described previously.

This research is able to use the Artificial Neural Networks (ANN) method in developing the empirical models for tool wear and surface roughness prediction. The two methods –Regression analysis and artificial neural network have been recently termed data mining techniques [104, 105. Jang et al. [106] applied ANN in surface roughness study and correlate surface roughness with cutting vibrations Grzesik [107] used the minimum undeformed chip thickness to predict surface roughness in turning. A surface topography simulation model was established by Lin and Chang [108] to simulate the surface finish profile generated after a turning operation with known vibration characteristics. The model incorporated the effects of tool geometry, cutting parameters and the relative motion between the cutting tool and the workpiece on the surface finish profile, which was 'decomposed' into three directions, namely, the radial, tangential and axial direction.

The relationship between tool life, surface roughness and vibration was examined by Abouelatta and Madl [109].The variables that were considered included the cutting speed, feed rate, depth of cut, tool nose radius, tool overhang, approach angle, workpiece length and workpiece diameter and the accelerations in both radial and feed directions. The acceleration signals were fed to an FFT analyzer that produced ASCII files. The experimental data were analyzed to produce regression analysis models. Ghani and Choudhury [110] followed a similar approach in which the vibration signals were used to monitor tool wear and to verify the correlation between tool wear progression and surface roughness during turning. The experiments were conducted on nodular cast iron with ceramic tool, something that lead to very short tool life (approximately 1.5 min).

Jang et al. [106] focused on the development of an online roughness measuring technique by studying the effects of cutting vibration during hard turning. A series of experiments that aimed at determining the cutting speed for built-up-edge formation in turning was conducted by Munoz-Escalona and Cassier [111] and based on the experimental data two mathematical models which correlate surface roughness with cutting parameters were established. The first one included the effects of the cutting tool's nose radius, feed rate, cutting speed and depth of cut while the second added the effect of the material's hardness on surface finish. The most important terms were found to be the feed rate, tool's nose radius and cutting speed, in that order.

A detailed investigation was carried out by Thiele and Melkote. [112] concerning the effects of the cutting edge geometry and workpiece hardness on the surface finish and cutting forces in the finish hard turning of steel. An Ultrasonic system was developed by Coker and Shin [113] for in-process monitoring and control of surface roughness. The objective of Davim et. al [114] was to establish a correlation between cutting velocity, feed and depth of cut with the surface roughness in turning. For that purpose, a plan of experiments, based on Taguchi techniques, was designed and executed. The results showed that the cutting velocity had the greater influence, followed by the feed and that the error achieved was smaller than that of a geometric theoretical model. An effort to predict surface roughness in turning of high-strength steel based on RSM was made in the work of Choudhury and El-Baradie [115]. The adequacy of the developed model results was not very good but the conclusion was that the effect of feed is much more pronounced than the effects of cutting speed and depth of cut on the surface roughness. Feng and Wang [116] included a total of six parameters, namely the workpiece hardness, feed, tool point angle, depth of cut, spindle speed and cutting time to build a model for finish turning operations.

An extensive work was reported Thomas et al. [117] concerning the role of cutting tool vibrations on surface roughness during dry turning operations. A sensor fusion technique was presented by Azoui and Guillot [118]. They evaluated the surface roughness and dimensional deviation during turning. The systematic method for the selection of the candidate sensors determined the average effect of each in the performance of the measuring system. The sensors that affected it the most were fused using ANN modeling.

The work of Chien and Chou [119] can be divided in two parts. The first part deals with the building of three predictive models, using multilayer functional-link networks, for surface roughness, cutting force and tool life, respectively. The second part focused on finding the optimum cutting conditions by combining surface roughness and tool life network with a genetic algorithm. In that way, the cutting conditions that maximized the metal removal rate were obtained, under the constraints of surface roughness and cutting tool life. Suresh et al. [120] also adopted a two stage approach towards optimizing for surface roughness. First, experimental results were used to build two mathematical models for surface roughness by a regression method according to RSM. Secondly, the second-order mathematical model was taken as an objective function and was optimized with a GA to obtain the machining conditions for a desired surface finish.

Polynomial networks were considered in the work of Lee et al [121] to construct the relationships between the cutting parameters (cutting speed, feed rate, depth of cut) and cutting performance (tool life, surface roughness and cutting force). Li et al. [122] developed a hybrid machining model that integrated analytical models and neural network models for predicting all of the machining characteristic factors. Another approach that used a criterion for determining a network's architecture automatically can be found by Lin et al. [123] The aim was to develop a prediction model prior to the implementation of the actual machining process to determine certain cutting conditions (cutting speed, feed rate and depth of cut) in order to obtain a desired surface roughness value and cutting force value. Matsumura et al [124] adopted an approach that could evaluate the influence of machine tool characteristics on cutting processes using adaptive prediction was presented. The network for predicting surface roughness had as inputs the cutting speed, the affinity between cutting tool and workpiece, the chip discontinuity (evaluated by the chip strain), the built-up-edge formation (evaluated by average temperature around the cutting edge), the width of flank wear and the theoretical roughness considering tool wear. An adaptive neuro-fuzzy inference system (ANFIS) and computer vision were used to predict surface roughness by Ho et al. [125] in turning. The computer vision system, comprising a digital camera connected to a PC and the appropriate light sources, provided surface images that were analyzed to calculate the arithmetic average of gray levels (number of shades of gray). This information as well as the cutting parameters were given, for a total of four inputs, to the ANFIS and the roughness value could then be obtained.

1.4 Summary of the Review

A review of the literature on prediction of tool wear and surface roughness reveals that no ANN model has been steel developed to predict tool wear and surface roughness while machining medium carbon steel under Minimum Quantity Lubrication Condition with uncoated carbide insert designated as SNMG 120408 and Considering the four cutting parameters -cutting speed, feed rate, depth of cut and marching time. No ANN model is still found which determines the surface roughness and three response variable related to tool wear (VB, VM, VS) and tool life friendly. The rationale behind this study is to predict tool wear and surface roughness using an Artificial Neural Network (ANN) so that optimization of machining parameters can be done in advance while turning medium carbon steel in a properly designed MQL environment.

1.5 Objectives of the Present Work

The objectives of the present investigation are

a) Systematic experimental study on the effects of minimum quantity lubrication on the cutting performance of medium carbon steel at different cutting velocities and feeds in terms of

   i. cutting forces i.e. main cutting force and feed force

   ii. average chip-tool interface temperature and work tool temperature

   iii. tool wear (principal flank wear, maximum principal flank wear and auxiliary flank wear)

   iv. surface finish

b) Develop a model for tool wear and surface roughness using an Artificial Neural Network (ANN) while turning medium carbon steel by carbide insert under minimum quantity lubrication from the characterization of the physical processes taking place during machining and its validation.

1.6 Scope of the Thesis

The thesis is organized into five chapters including this one. The chapters are structured in the following way: Chapter 1 presents the concepts of machining, general requirements in machining industries, significance of prediction of tool wear and surface roughness, techno-environmental and socio-economical problems associated with the high cutting temperature and the conventional dry machining and expected role of minimum quantity lubrication (MQL) jet on marching performance and overall economy of machining. Survey of previous work and objective of the present work are also presented in **Chapter 1.**

Chapter 2 presents the procedure and conditions of the machining experiments carried out and the experimental results on the effects of Minimum Quantity Lubrication (MQL) , relative to dry machining, on cutting ratio, cutting zone temperature, cutting forces, cutting tool wear, and surface integrity in turning medium carbon steel by using uncoated carbide insert under different cutting conditions

Chapter 3 provides development of an artificial neural network (ANN) model for tool wear and surface roughness from the characterization of the physical processes taking place during machining and its validation.

Chapter 4 contains the detailed discussion on the experimental results and possible interpretations on the results obtained.

Finally, a summary of major investigations of this research work with some recommendations is given in **Chapter 5** and references and appendix are provided at the end.

Chapter 2

Experimental Investigations

2.1 Introduction

The concept of minimum quantity lubrication (MQL) may be considered as a rigorous solution in achieving reduced tool wear and improved surface finish while maintaining cutting forces or power at reasonable levels, if the MQL system can be properly designed. Minimum quantity lubrication (MQL) technique not only provides reduction in tool wear or increase in tool life and improvement in surface roughness but also reduces the consumption of cutting fluid. The aim of the present work is to develop an artificial neural network (ANN) model for prediction of tool wear and surface roughness in turning medium carbon steel using minimum quantity lubrication which would contribute in manufacturing planning, optimization of machining parameters and overall economy of machining productivity. Before developing an artificial neural network (ANN) model, experimental study on the effects of minimum quantity lubrication on the cutting performance of medium carbon steel at different cutting velocities, feeds and depth of cuts in terms of cutting forces (main cutting force and feed-force), chip-tool interface temperature, tool wear and surface roughness will be conducted to realize the performance of MQL over dry machining.

2.2 Experimental Procedure and Conditions

The machining tests have been carried out by straight turning of medium carbon steel on a lathe (7.5 kW) by a standard uncoated carbide insert with ISO designation-SNMG 120408 at different cutting velocities (V) and feed rates (f) and depth of cuts under dry and MQL condition. Minimum quantity lubrication (MQL) machining has been considered to be an effective semidry application because MQL offers positive part on environment friendliness as well as techno-economical benefit. To explore the beneficial effects of MQL on the machinability distinctiveness of a tool-work combination, frequently used in machining industries in terms of cutting ratio, cutting temperature, cutting force, tool wear and surface finish, which deals with product quality, productivity and overall economy is an attempt of this research work.

The conditions under which the machining tests have been carried out are briefly given in Table 2.1. Experiments have been carried out by turning a medium carbon steel bars of initial diameter 173 mm and length 404 mm in a high speed rigid lathe by uncoated carbide insert at different cutting speed (V) and feeds (f) ranging from 66 to 266 m/min and 0.10 to 0.20 mm/rev respectively and depth of cut (d) have been selected as 1.0 and 1.5 mm for cutting ratio, temperature, force and surface roughness under both dry and MQL condition. For assessing tool wear, tool life, roughness during tool wear, cutting speed was selected as 66 and 266 m/min, feed rate was 0.10 and 0.20 mm/rev and depth of cut was 1.0 and 1.5 mm. All these parameters have been selected as per tool manufacturer's recommendation as well as industrial practices for machining medium carbon steel with uncoated carbide insert.

Effectiveness of cooling and the related benefits entirely depends on how closely the MQL jet can reach the chip-tool and the work-tool interfaces where, apart from the primary shear zone, heat is generated. The tool geometry is reasonably expected to play significant role on such cooling effectiveness. Keeping this view tool configuration namely SNMG-120408 has been undertaken for present investigation. The insert was clamped in a PSBNR-2525 M12 type tool holder.

Table 2.1 Experimental conditions

Machine tool	: Lathe Machine(China), 7.5 kW
Work materials	: Medium Carbon Steel
Size	: Initial Diameter = 173 mm and length = 404 mm
Cutting tool	: Uncoated Carbide, (p-30 grade), SNMG-120408, Sandvik 
Geometry	: -6°,-6°,6°,15°,75°,0.8 mm
Tool holder	: PSBNR 2525 M12 (ISO specification), Widia
Process parameters	
Cutting velocity, V	: 66, 68, 95, 133, 190, 258 and 266 m/min
Feed rate, f	: 0.10, 0.12, 0.14, 0.16, 0.18 and 0.20 mm/rev
Depth of cut, d	: 1.0 and 1.5 mm
MQL supply	: Flow Rate 150 ml/hr, Air Pressure 23 bar, Oil Pressure 25 bar
Environment	: i. Dry ii. MQL (VG-68 Cutting oil)

The positioning of the nozzle tip with respect to the cutting insert was fixed after a number of trials. The final arrangement made and used is given below in Fig. 2.1. The MQL jet is directed along the auxiliary cutting edge at an angle 30^0 to reach at the principal flank and partially under the flowing chips through the inbuilt groove parallel to the cutting edges. The thin but high velocity stream of MQL has been heading for along the auxiliary cutting edge of the insert, so that the coolant reaches as close to the chip-tool and work-tool interfaces as possible and cools the above mentioned interfaces and both the principal and auxiliary flanks effectively as well. The photographic view of the experimental set-up is shown in Fig. 2.1

Fig.2.1 [illegible]

An MQL system using cutting fluid and compressed air essentially consists of

i. compressor for compressing and delivering compressed air at the desired pressure
ii. mixing chamber for mixing cutting fluid and compressed air
iii. suitable nozzle to impinge MQL to the cutting zone
iv. pressure and flow control valves for effective economical use of cutting fluid

A cylindrical bar of medium carbon steel of 173 mm diameter was selected for straight turning. During machining, the cutting insert was withdrawn at regular intervals and then VB, VM, VS were measured under metallurgical microscope (Carl Zesis, 351396, Germany) fitted with micrometer of least count 1 μm.

Surface roughness was measured respectively by a Talysurf (Surtronic 3+ Roughness checker, Taylor Hobson, UK) using a sampling length of 4.00 mm. The photographic view of the surface roughness measuring technique is shown in Fig 2.2:

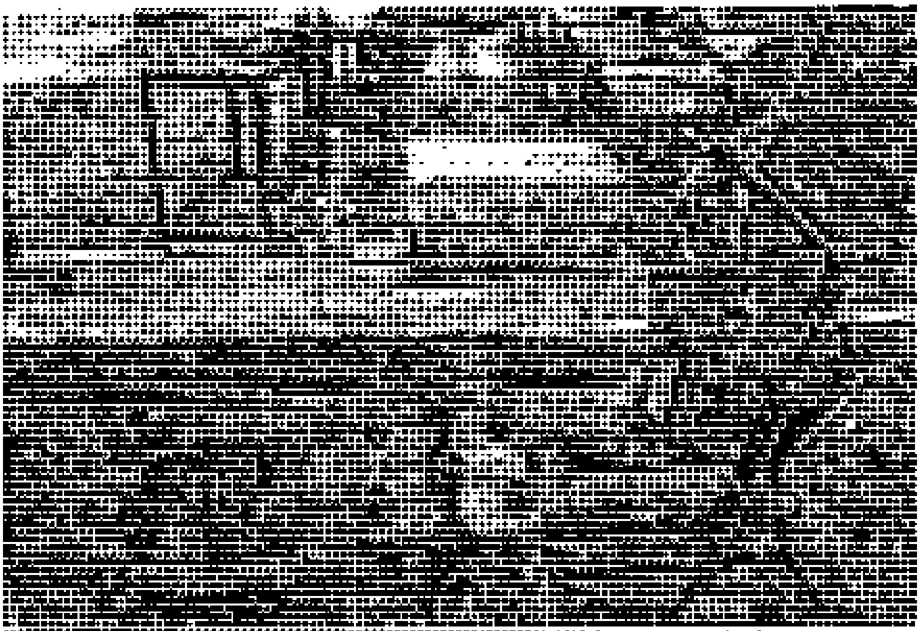


Fig.2.2

For the improvement of cutting performance, the knowledge of temperature at the chip-tool interface with good accuracy is essential. Several experimental and analytical techniques have been developed for the measurement of temperatures generated in cutting zone. The average chip-tool interface cutting temperature was measured under dry and MQL conditions undertaken by simple but reliable tool-work thermocouple technique with proper calibration (Fig. 2.3).

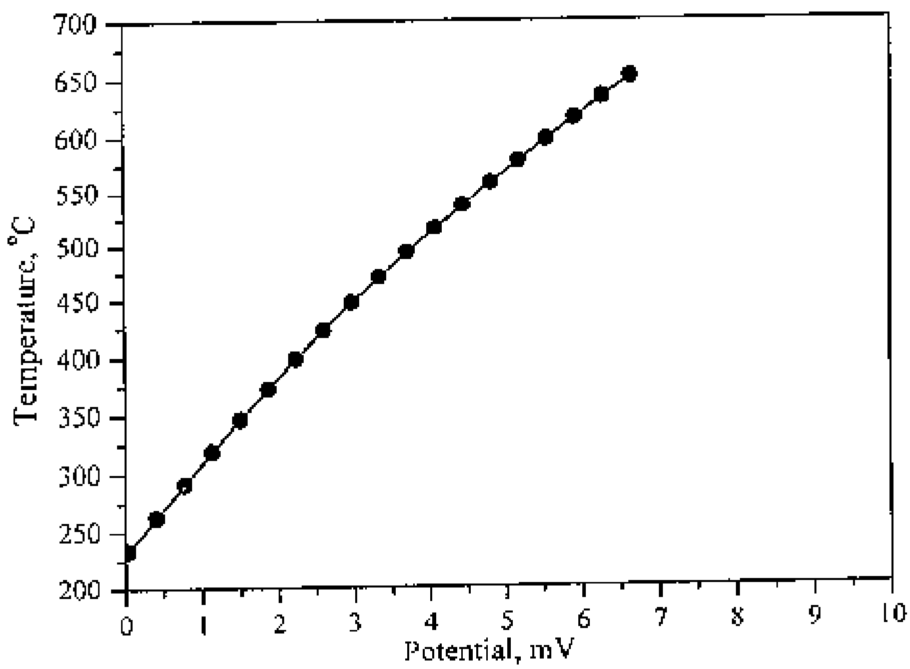


Fig.2.3 Temperature calibration curve for medium carbon steel and carbide insert [126]

2.3 Experimental Results

2.3.1 Chip Thickness Ratio

Chip thickness ratio, r_c (ratio of chip thickness before and after cut) is an important machinability index for identifying machining performance. For given tool geometry and cutting conditions, the value of r_c depends upon the nature of chip-tool interaction, chip contact length and chip form, all of which are expected to be influenced by MQL in addition to the levels of V and f. The variation in value of r_c with change in cutting velocity, V and feed rate, f and as well as machining environment evaluated for medium carbon steel for the depth of cuts of 1.0 and 1.5 mm have been plotted and shown in the fig. 2.4 and 2.5 respectively.

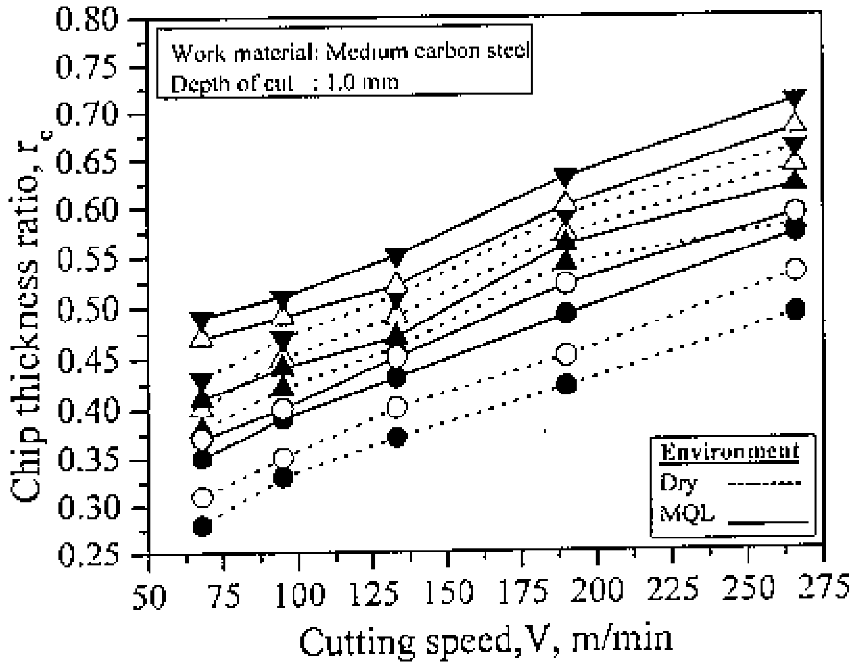


Fig.2.4 Variation in **Chip thickness ratio (r_c)** with that of V and f in turning **medium carbon steel** by **SNMG** insert under **Dry** and **MQL** conditions at depth of cut of 1.00 mm

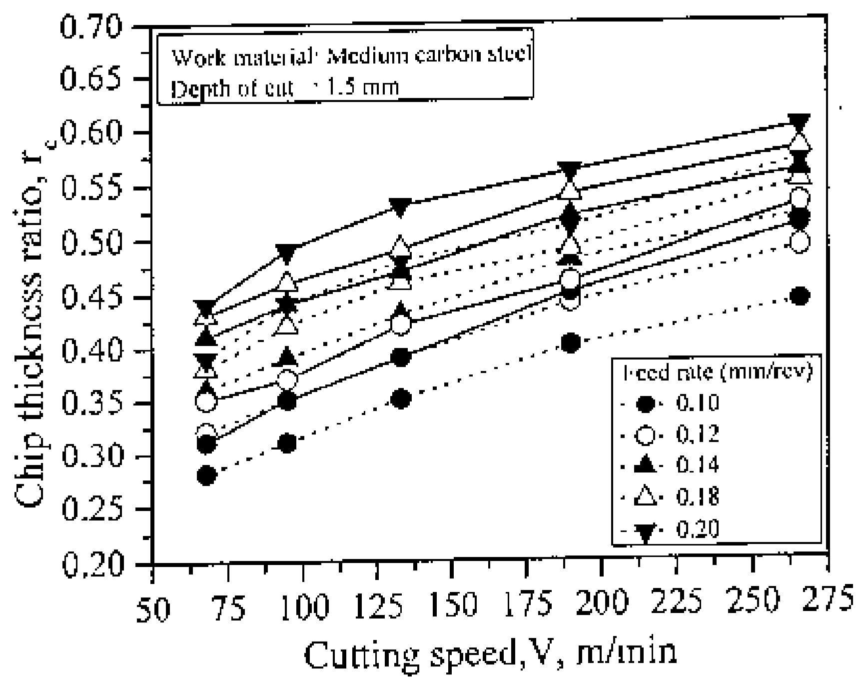


Fig.2.5 Variation in **Chip thickness ratio (r_c)** with that of V and f in turning **medium carbon steel** by **SNMG** insert under **Dry** and **MQL** conditions at depth of cut of 1.50 mm

2.3.2 Cutting Temperature

Any machining process associated with high velocity and feed rate inherently generate large amount of heat as well as high cutting zone temperature. The magnitude of this cutting temperature increases, though in different degree, with the increase of cutting velocity, feed and depth of cut, as a result, high production machining is constrained by rise in temperature The cutting temperature if not controlled properly, cutting tools undergo severe flank wear and notch wear, loose sharpness of the cutting edge either wearing or become blunt by welded built-up edge and weaken the product quality. In normal cutting condition all such heat sources produce maximum temperature at the chip-tool interface, which substantially influence the chip formation mode; cutting forces, tool life and product quality. High production machining needs to increase the process parameters further for meeting up the growing demand and cost competitiveness. Cutting temperature is increased with the increase in process parameter as well as with the increase in hardness and strength of the work material. Therefore, attempts are to be made to reduce this detrimental effect of cutting temperature.

The average chip-tool interface temperature was measured under both dry and MQL condition by tool-work thermocouple techniques with proper calibration during turning of medium carbon steel at different cutting velocities and feeds in the present investigation. The evaluated role of MQL on average chip-tool interface temperature in turning medium carbon steel by uncoated carbide insert (SNMG-120408) at different V–f combinations for the depth of cuts of 1.0 and 1.5 mm under both dry and MQL condition have been shown in Fig.2.6 and Fig.2.7.

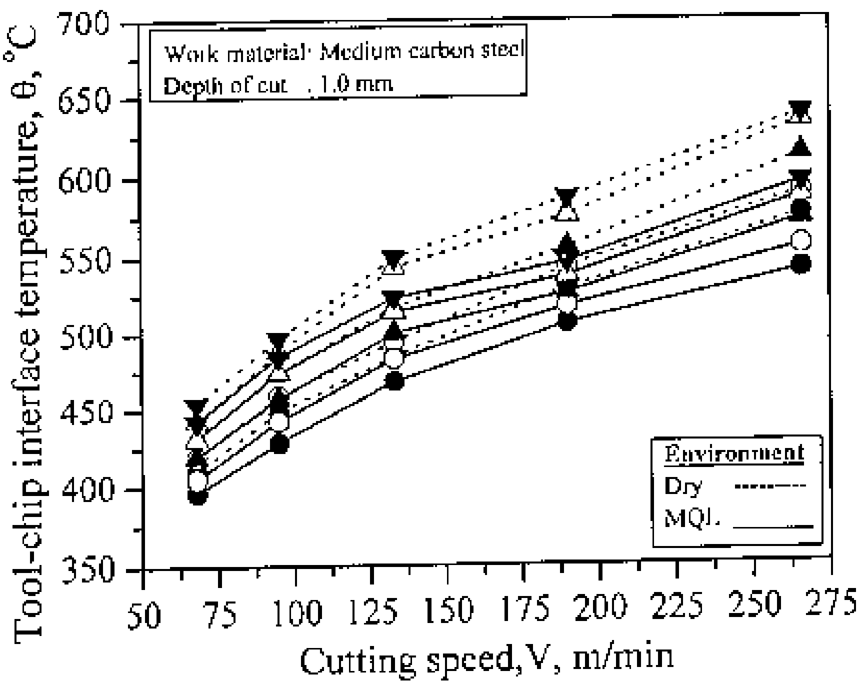


Fig.2.6 Variation in **temperature (0)** with that of V and f in turning **medium carbon steel** by **SNMG** insert under **Dry** and **MQL** conditions at depth of cut of 1.00 mm

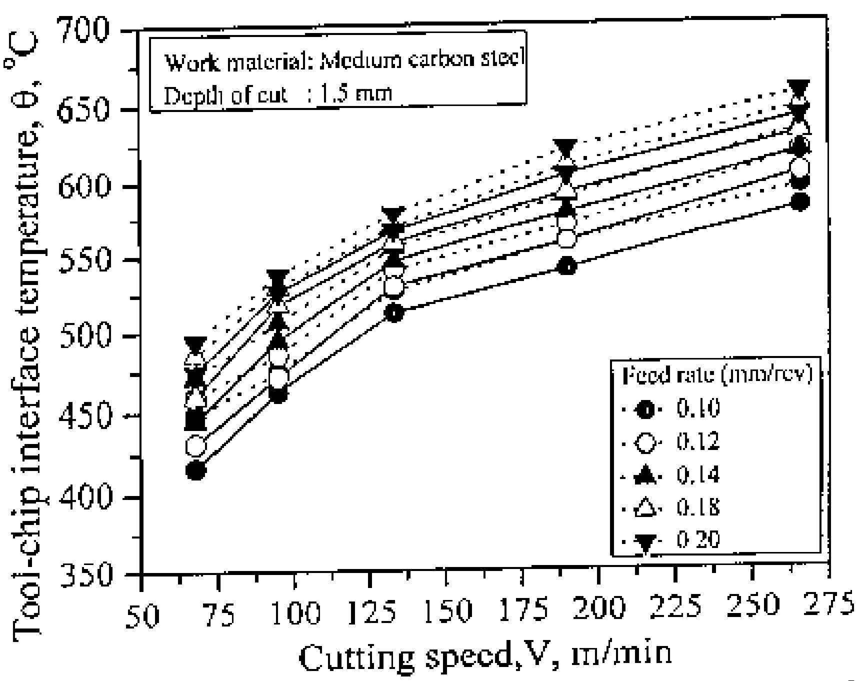


Fig.2.7 Variation in **temperature (0)** with that of V and f in turning **medium carbon steel** by **SNMG** insert under **Dry** and **MQL** conditions at depth of cut of 1.50 mm

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2.3.3 Cutting Force

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

In the present work, the magnitude of F_c and F_f have been monitored by dynamometer for all the combinations of cutting speeds, feeds, depth of cuts and environments undertaken.

The effect of MQL on F_c and F_f that have been observed while turning medium carbon steel specimen by the uncoated carbide inserts SNMG-120408 under different V and f with depth of cuts of 1.0 and 1.5 mm have been graphically shown in Fig. 2.8, Fig. 2.9, Fig. 2.10, and Fig. 2.11.

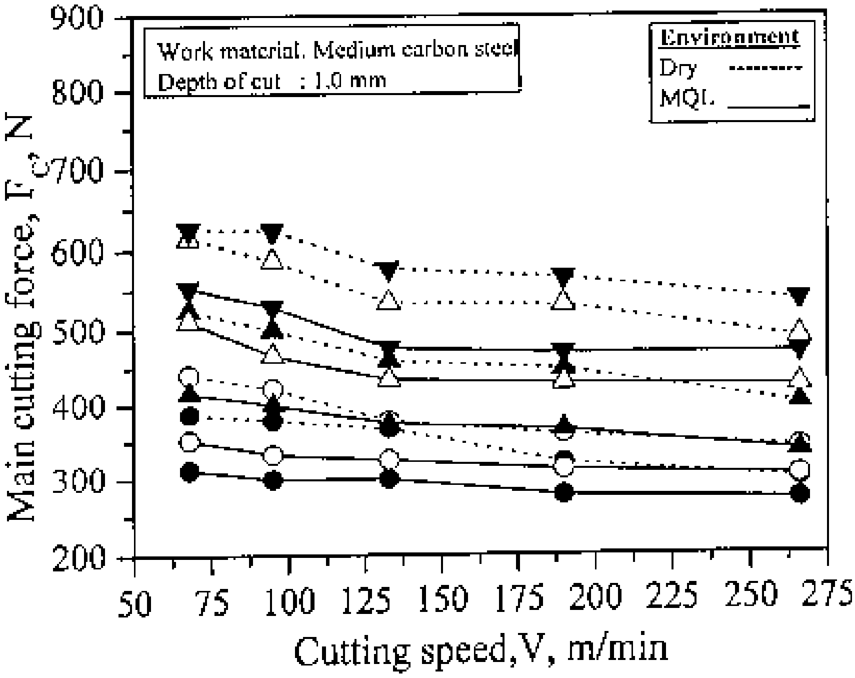


Fig.2.8 Variation in **main cutting force** (F_c) with that of V and f in turning **medium carbon steel** by **SNMG insert** under **Dry** and **MQL** conditions at depth of cut of 1.00 mm

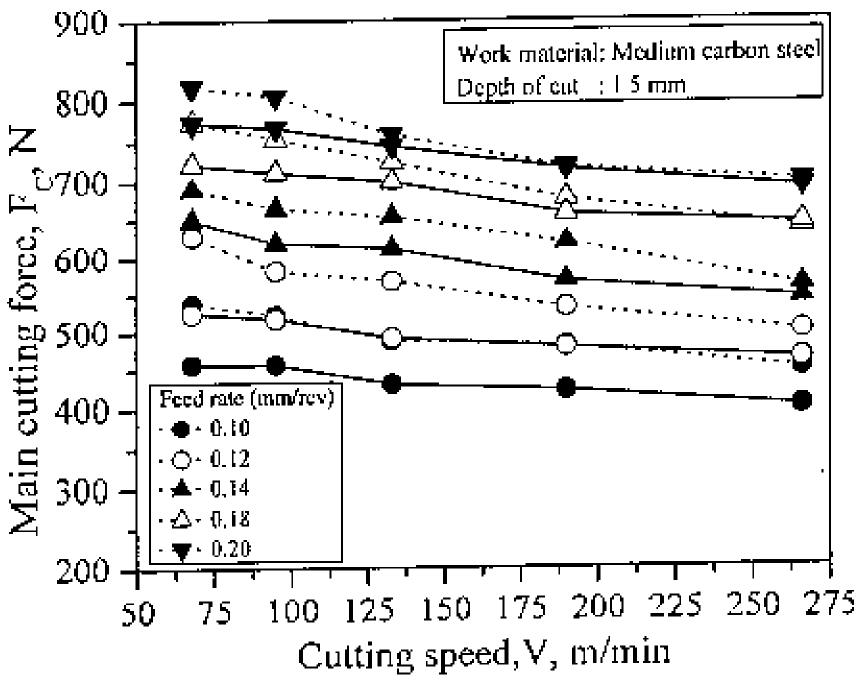


Fig.2.9 Variation in **main cutting force** (F_c) with that of V and f in turning **medium carbon steel** by SNMG insert under **Dry** and **MQL** conditions at depth of cut of 1.50 mm

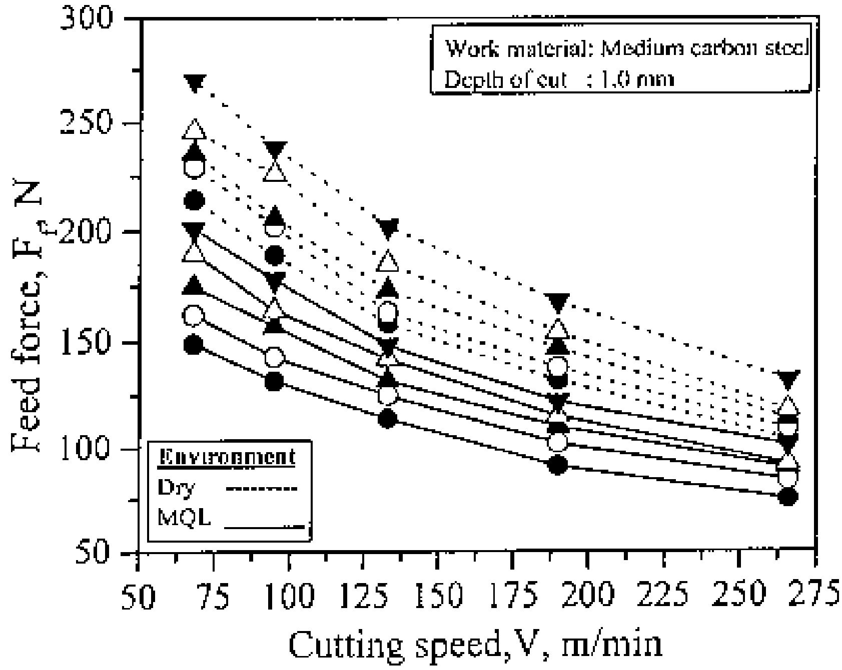


Fig.2.10 Variation in **Feed force** (F_f) with that of V and f in turning **medium carbon steel** by **SNMG** insert under **Dry** and **MQL** conditions at depth of cut of 1.0 mm

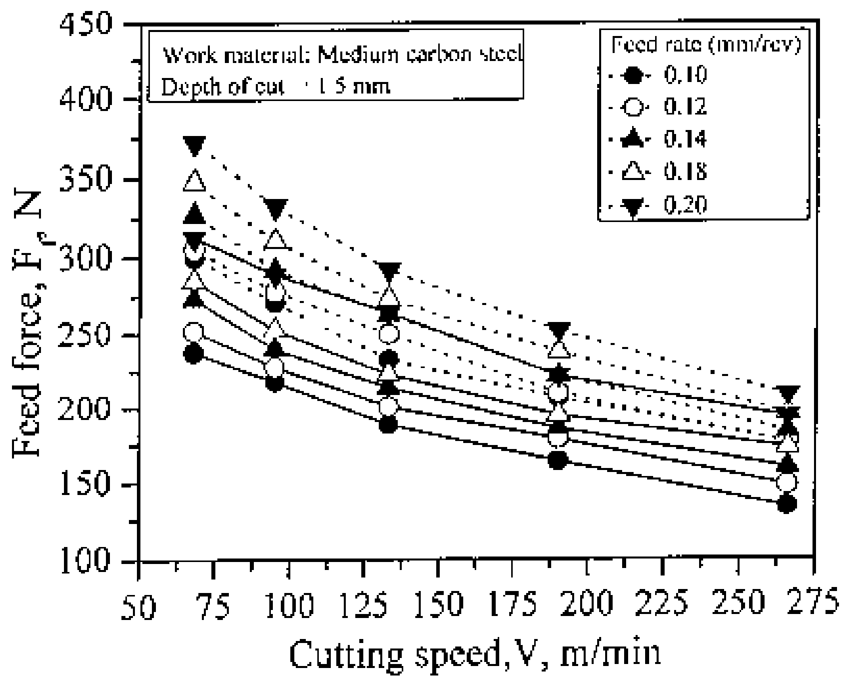


Fig.2.11 Variation in **Feed force** (F_f) with that of V and f in turning **medium carbon steel** by **SNMG** insert under **Dry** and **MQL** conditions at depth of cut of 1.50 mm

2.3.4 Tool Wear

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

The need for accurate assessment of tool wear has increased considerably in order to produce the required end products so that a new tool may be introduced at the instant at which the existing tool has worn out, thus preventing any hazards occurring to the machine or deterioration of the product surface finish. The importance of maximizing a tool's working time and doing the utmost to keep tools from breaking is directly related with cutting-process optimization. Tool life improvement is essential to reduce the cost of production as much as possible. Cutting tools have a limited life due to inevitable wear and consequent failure, and avenues must be found to increase tool life, the critical parameter of the cutting process. Tool wear sensing should be one of the primary objectives in order to produce the required end products in an automated industry so that a new tool may be introduced at the instant at which the existing tool has worn out, thus preventing any hazards occurring to the machine or deterioration of surface finish.

With the progress of machining the tools attain crater wear at the rake surface and flank wear at the clearance surfaces due to continuous interaction and rubbing with the chips and the work surfaces respectively. The principal flank wear is the most important because it raises the cutting forces and related problems. Again the life of the tools, which ultimately fail by the systematic gradual wear, is generally assessed at least for R&D work, by the average value of the principal flank wear (VB), which aggravates cutting forces and temperature and may induce vibration with progress of machining. Wear may grow at a relatively faster rate at certain locations within the zones of flank wear apart from notching. The width of such excessive wear are expressed by VM (maximum flank wear), VS (average auxiliary flank wear) and VSM (maximum auxiliary flank wear). The reason of these preferential wears are the presence of some initial defect or variation in geometry, temperature and chip-tool interaction along the cutting edges depending upon the tool geometry, tool-work materials and the conditions of machining. The pattern and extent of the auxiliary flank wear (VS) affects surface finish and dimensional deviation of the machined parts. Growth of tool wear is sizeable influenced by the temperature and nature of interactions of the tool-work interfaces, which again depend upon the machining conditions for given tool-work pairs. In the present investigations the given insert attained significant values of VM, VS and VSM in different degree under different conditions. Fig. 2.12 shows the schematic view of general pattern of wear.

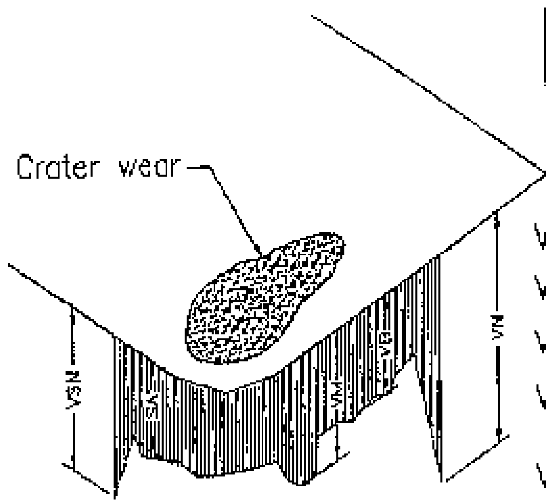


Fig. 2.12 Schematic view of general pattern of wear **[Dhar, 2001]**

During machining under each condition, the cutting insert was withdrawn at regular intervals and then the salient features like, VB, VM, VS, etc. were measured under metallurgical microscope fitted with micrometer of least count 1.0 μm. At the end of the machining and attaining sufficient wear the pattern and extent of wear of each tool was examined under Scanning Electron Microscope (SEM) and the photographs are taken for onward comparative study.

To reduce the rate of growth of VB, attempts should be made in all possible ways without much give up MRR. The growth of principal flank wear, VB with progress of machining time recorded while turning the medium carbon steel by uncoated SNMG insert at lower speed and feed (V=66m/min, f=0.10 mm/rev) and higher speed and feed (V=258 m/min, f=0.20 mm/rev) with two depth of cut (d=1.0mm and 1.5 mm) under dry and MQL (cutting oil) conditions have been shown in Fig.2.13, Fig.2.14, Fig 2.15 and Fig.2.16. Fig.2.14, Fig.2.15, Fig.2.16 and Fig.2.17 show the growth of average flank wear (VB) with time observed while turning medium carbon steel by SNMG insert at a particular V, f and d combination under dry and MQL (cutting oil) environments.

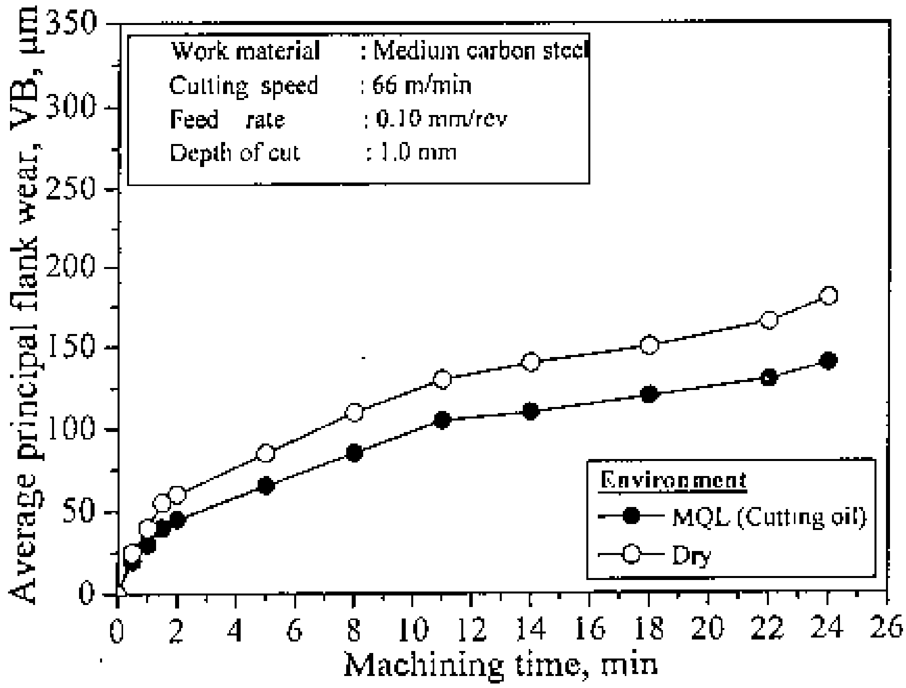


Fig.2.13 Growth of average principal flank wear (VB) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut 1.00 mm

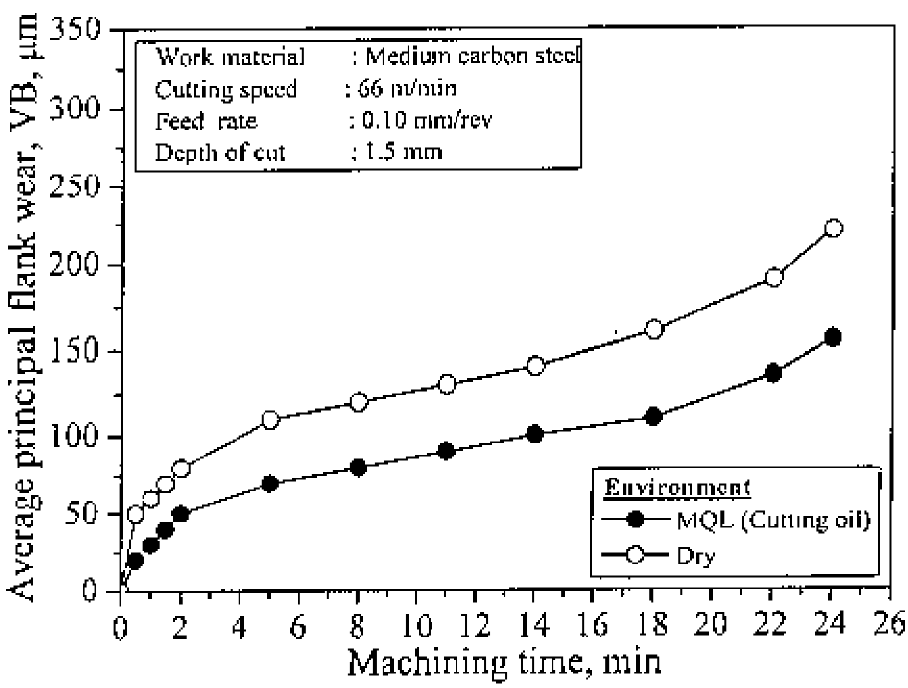


Fig.2.14 Growth of average principal flank wear (VB) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut 1.50 mm

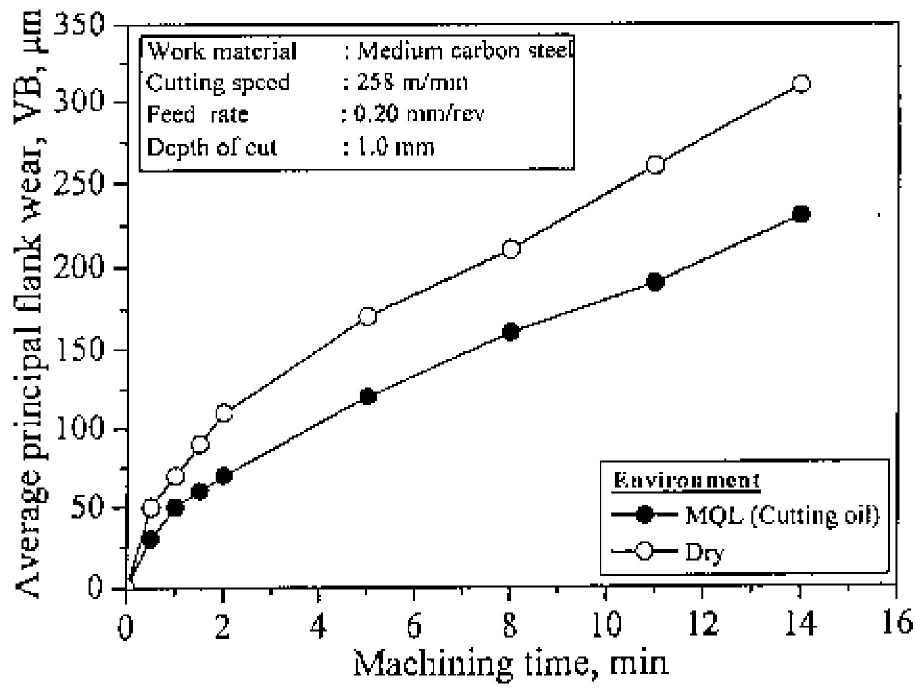


Fig.2.15 Growth of average principal flank wear (VB) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut 1.00 mm

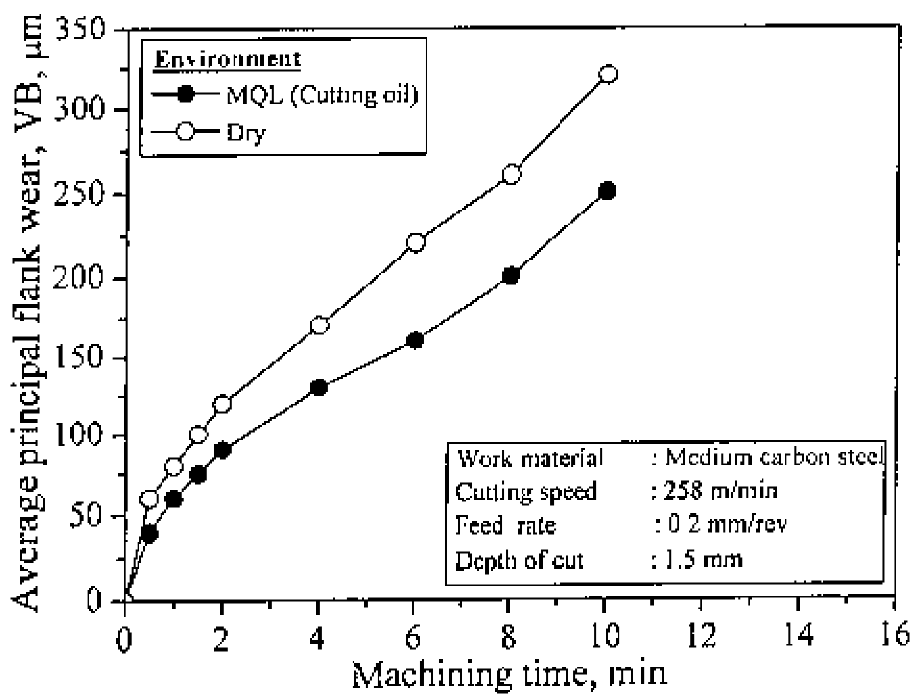


Fig.2.16 Growth of average principal flank wear (VB) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut 1.50 mm

The growth of auxiliary flank wear, VS with progress of machining time recorded while turning the medium carbon steel by uncoated SNMG insert at lower speed and feed (V=66m/min, f=0.10 mm/rev) and higher speed and feed (V=258 m/min, f=0.20 mm/rev) with two depth of cut (d=1.0mm and 1.5 mm) under dry and MQL (cutting oil) conditions have been shown in Fig.2.17, Fig.2.18, Fig.2.19 and Fig.2.20.

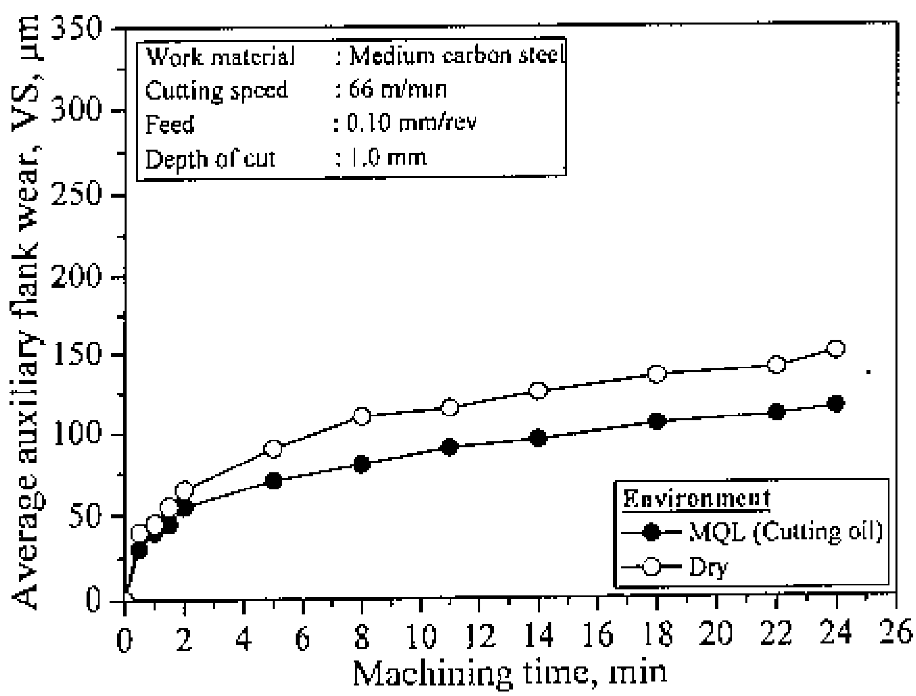


Fig.2.17 Growth of average auxiliary flank wear (VS) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm

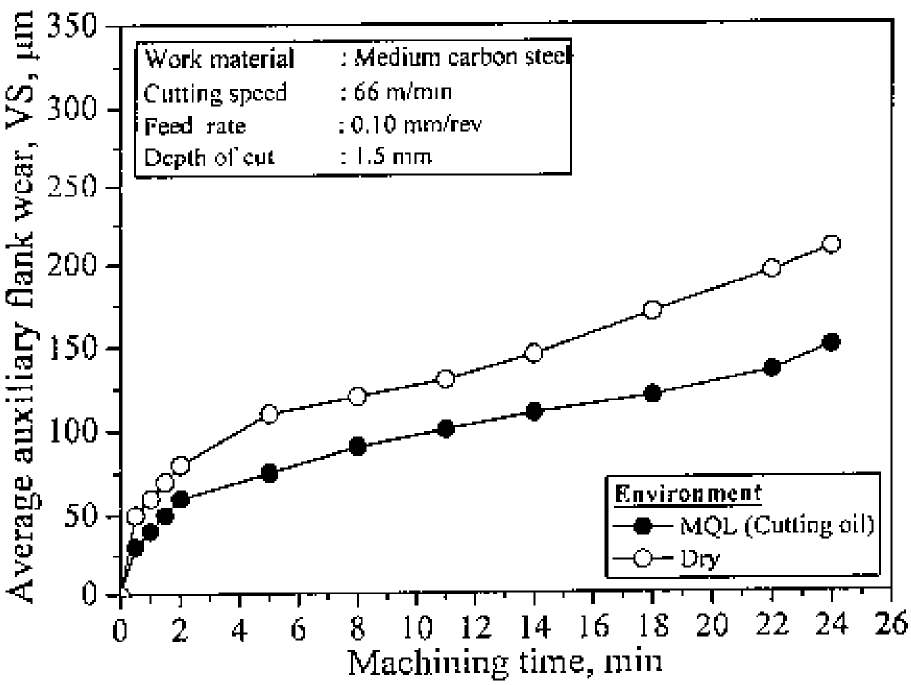


Fig.2.18 Growth of average auxiliary flank wear (VS) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm

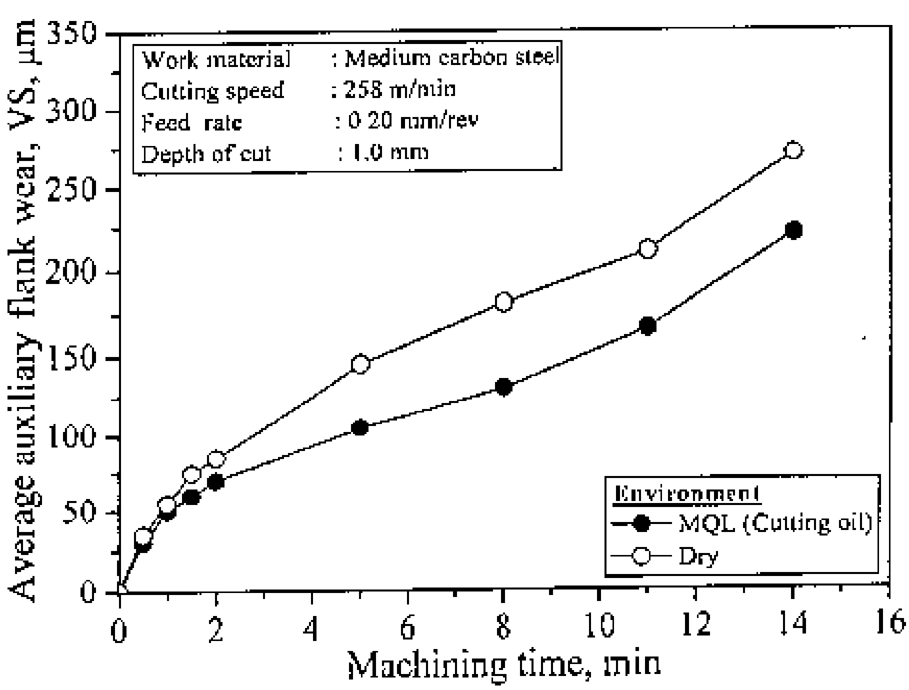


Fig.2.19 Growth of average auxiliary flank wear (VS) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm

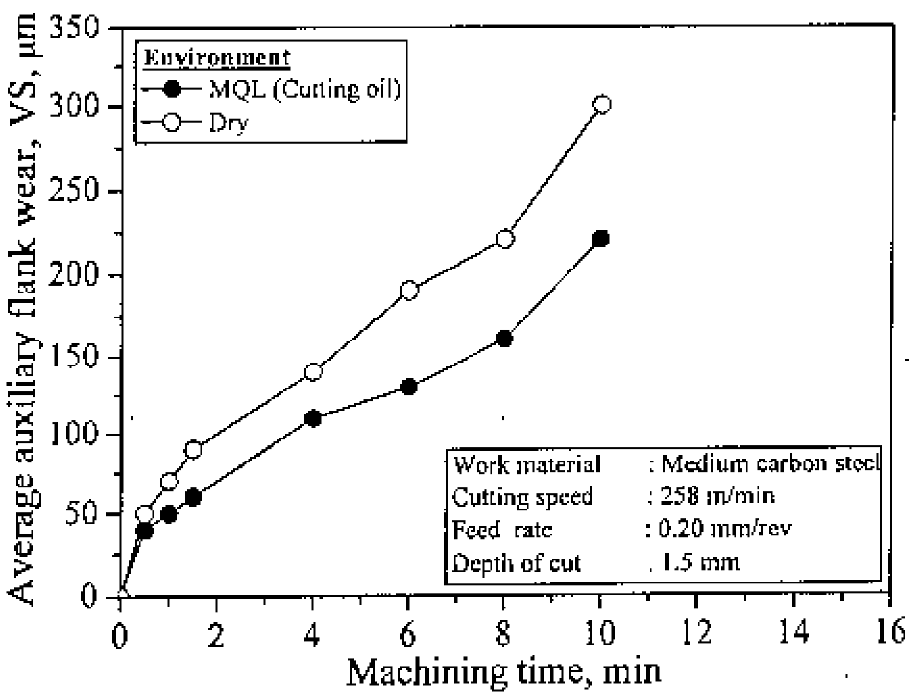


Fig.2.20 Growth of average auxiliary flank wear (VS) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm

The growth of maximum principal flank wear, VM with progress of machining time recorded while turning the medium carbon steel by uncoated SNMG insert at lower speed and feed (V=66m/min, f=0.10 mm/rev) and higher speed and feed (V=258 m/min, f=0.20 mm/rev) with two depth of cut (d=1.0mm and 1.5 mm) under dry and MQL (cutting oil) conditions have been shown in Fig.2.21, Fig.2.22, Fig.2.23 and Fig.2.24.

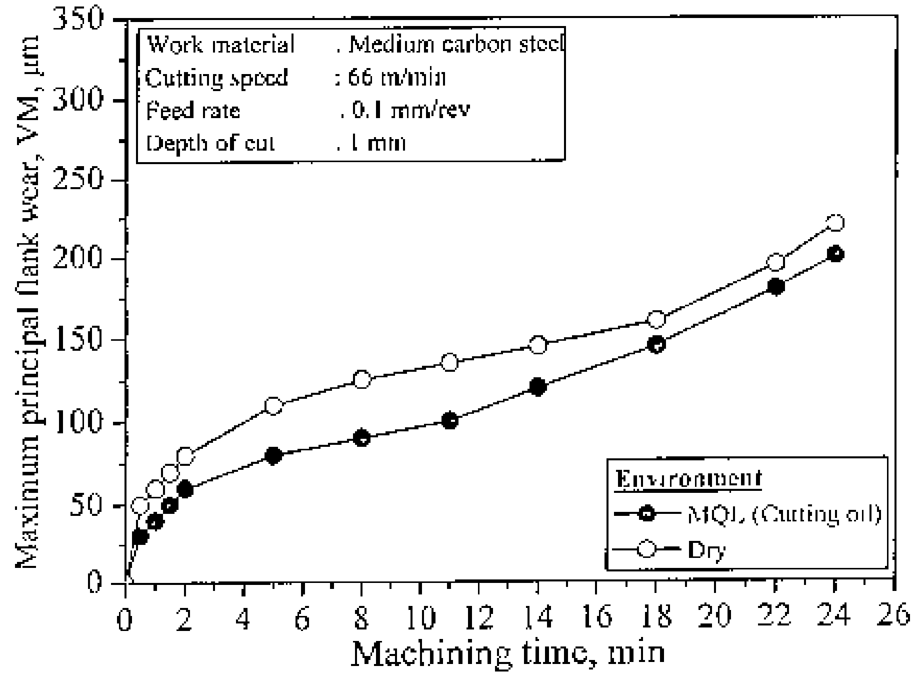


Fig.2.21 Growth of Maximum principal flank wear (VM) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm

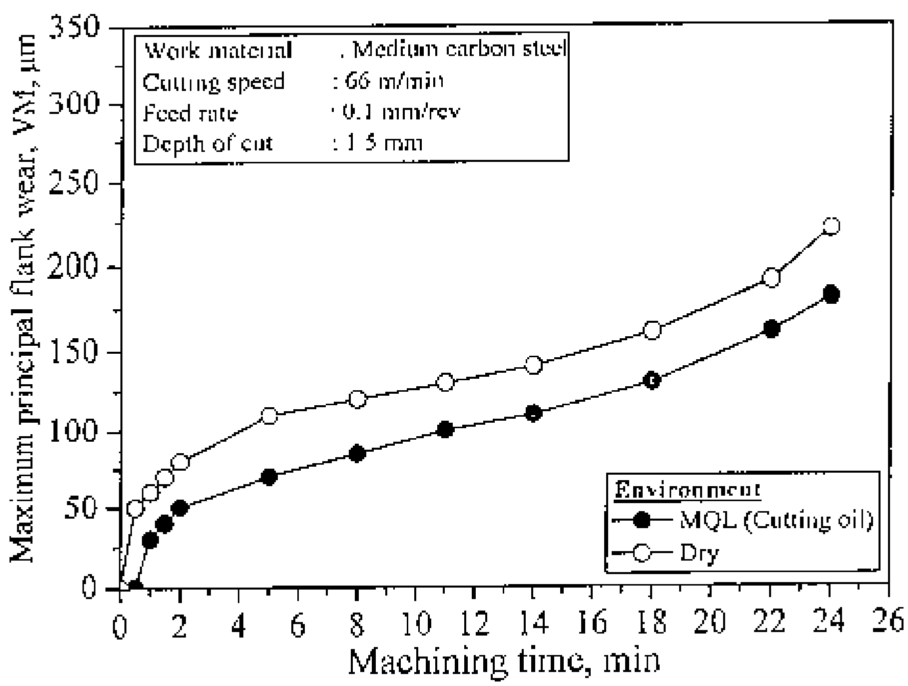


Fig.2.22 Growth of maximum principal flank wear (VM) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm

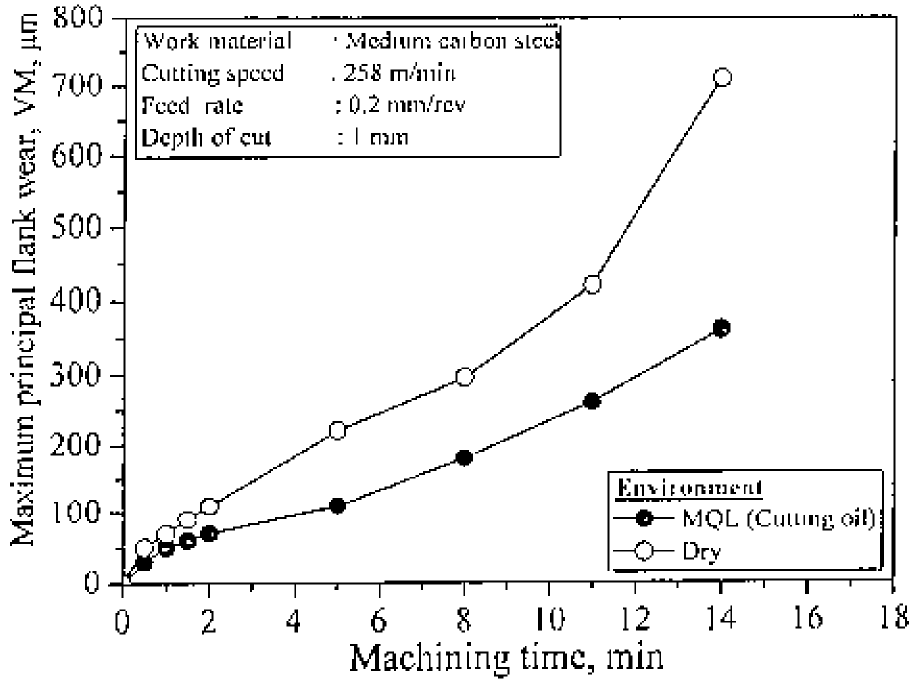


Fig.2.23 Growth of maximum principal flank wear (VM) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm

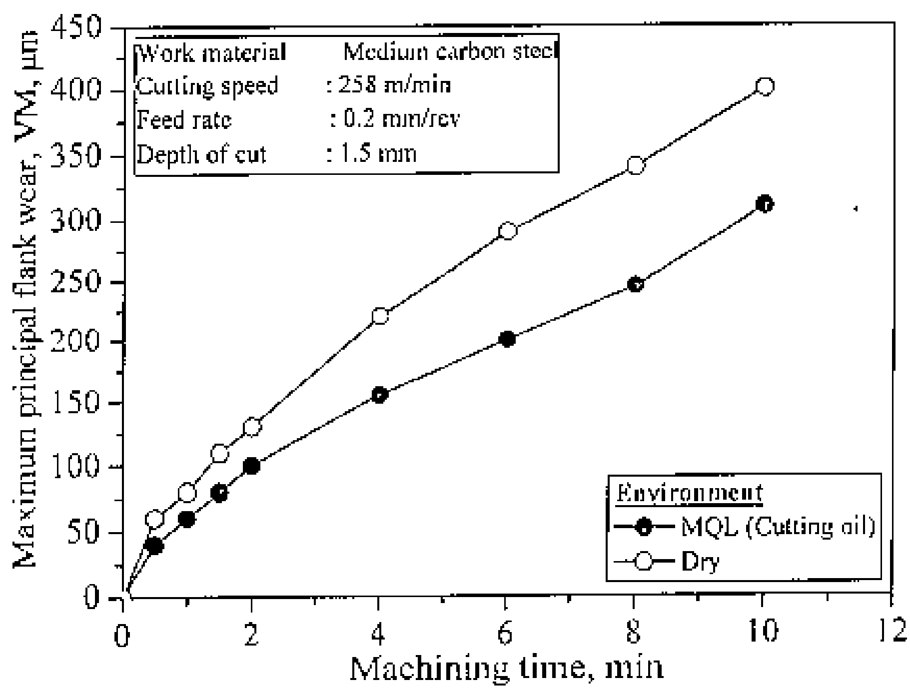
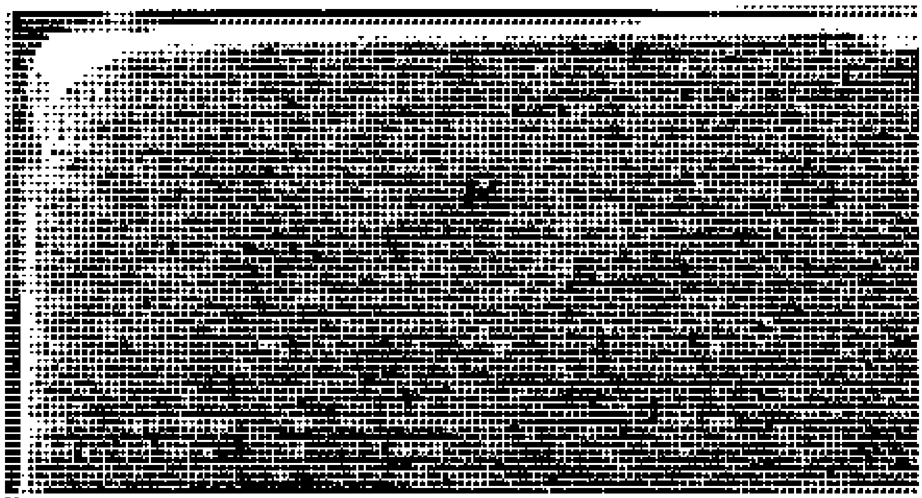
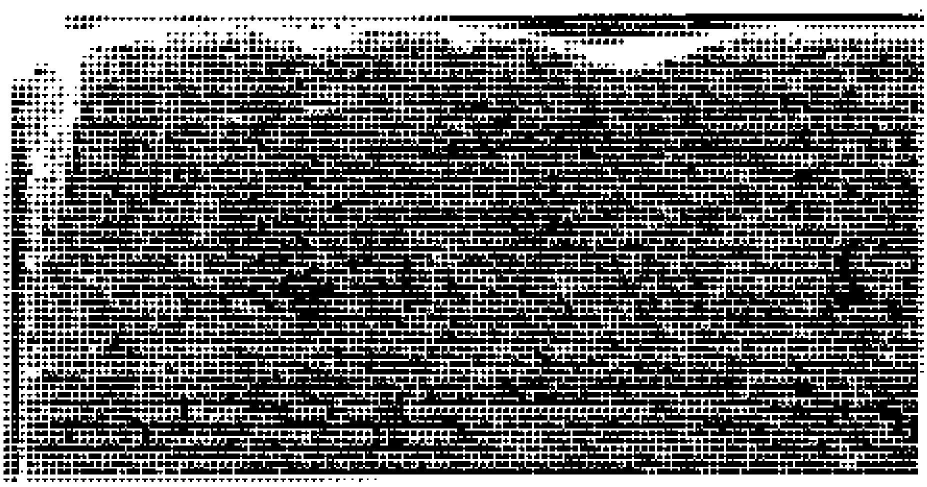


Fig.2.24 Growth of maximum principal flank wear (VM) with machining time turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm

SEM micrograph of worn out principal flank and auxiliary flank of SNMG insert after machining at lower speed and feed (V=66m/min, f=0.10 mm/rev) and higher speed and feed (V=258 m/min, f=0.20 mm/rev) with two depth of cut (d=1.0mm and 1.5 mm) under dry and MQL (cutting oil) conditions have been shown in Fig.2.25, Fig.2.26, Fig.2.27, Fig.2.28. Fig.2.29, Fig.2.30, Fig.2.31 and Fig.2.32.

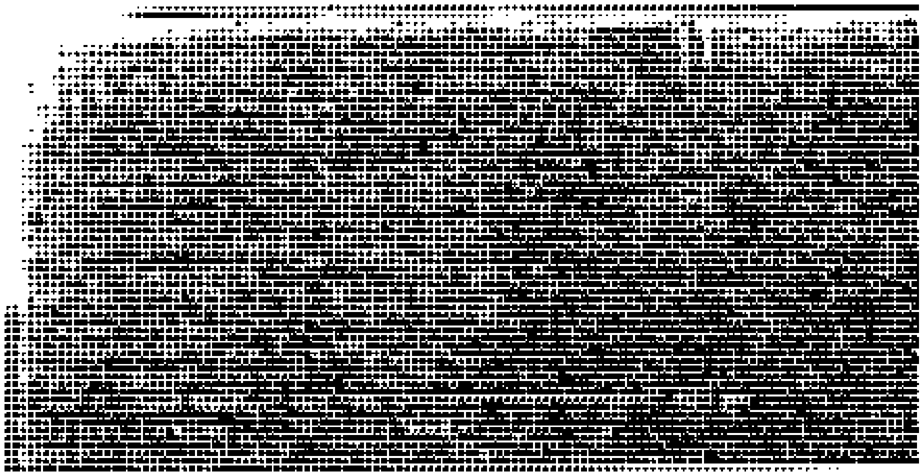


(a) **Dry** condition, 24 min

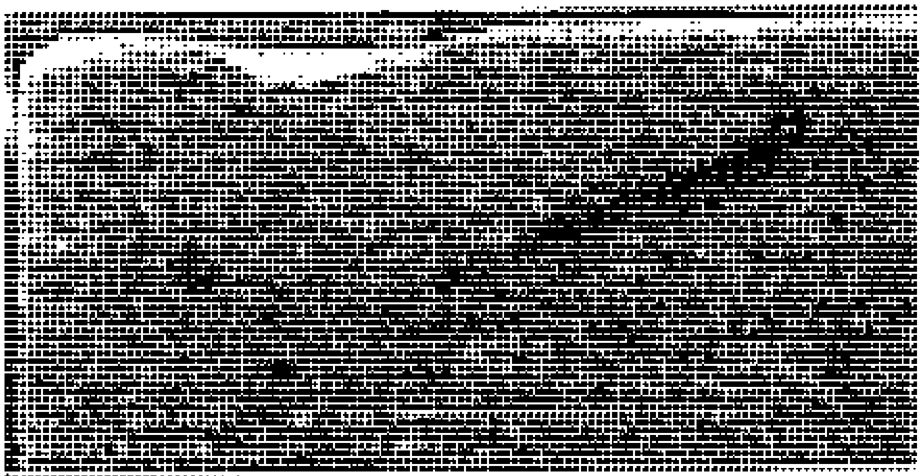


(b) **MQL** condition, 24 min

Fig.2.25 SEM views of **principal flank** of worn out SNMG insert after machining **medium carbon steel** under (a) **Dry and** (b) **MQL** conditions with cutting speed 66 m/min, feed rate 0.10 mm/rev and depth of cut 1.0 mm



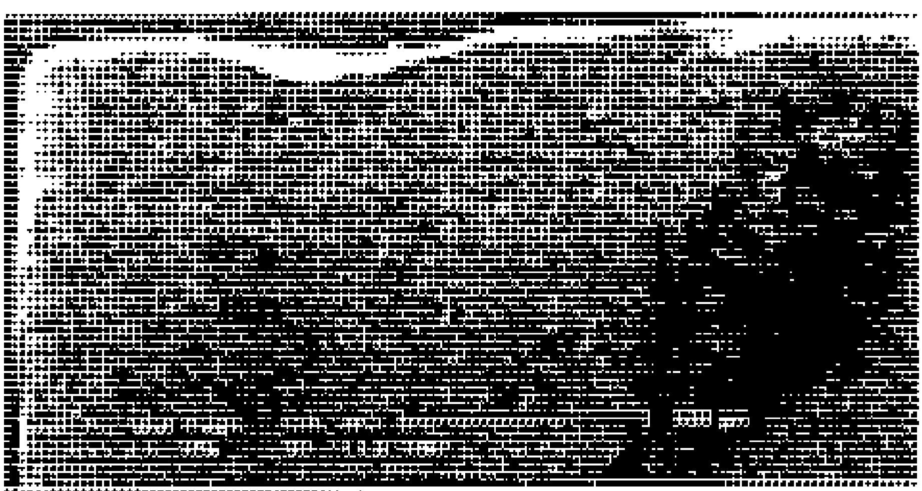
(c) **Dry** condition, 24 min



(d) **MQL** condition, 24 min

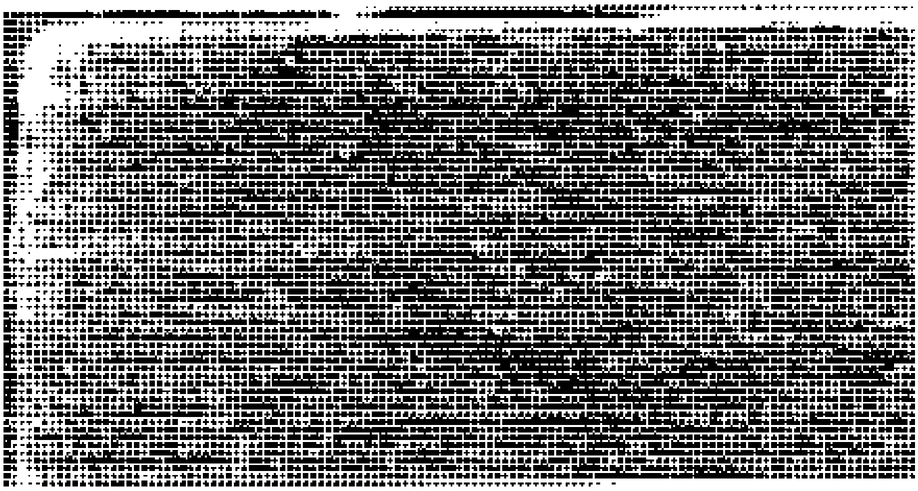
Fig.2.26 SEM views of **principal flank** of worn out **SNMG** insert after machining **medium carbon steel** under (c) **Dry and** (d) **MQL** conditions with cutting speed 66 m/min, feed rate 0.10 mm/rev and depth of cut 1.5 mm

(e) Dry condition, 14 min

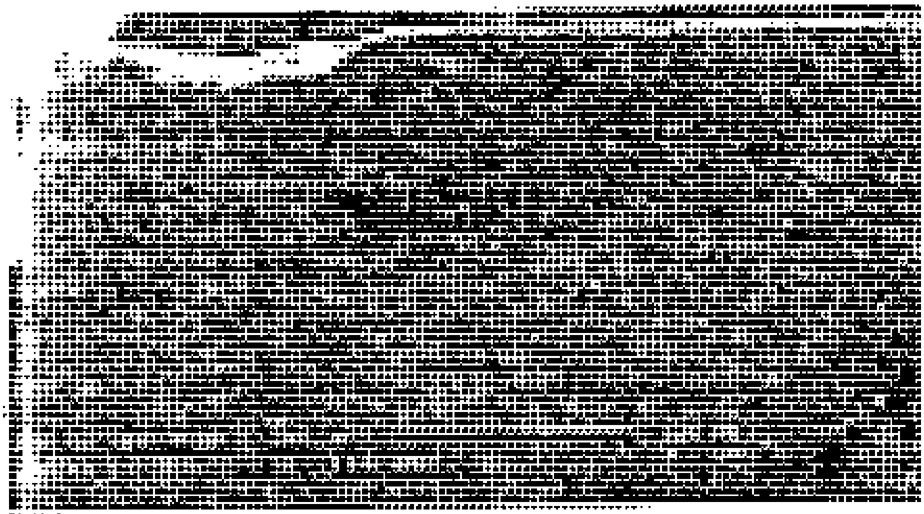


(f) MQL condition, 16 min

Fig.2.27 SEM views of principal flank of worn out SNMG insert after machining medium carbon steel under (e) Dry and (f) MQL conditions with cutting speed 258 m/min, feed rate 0.20 mm/rev and depth of cut 1.0 mm

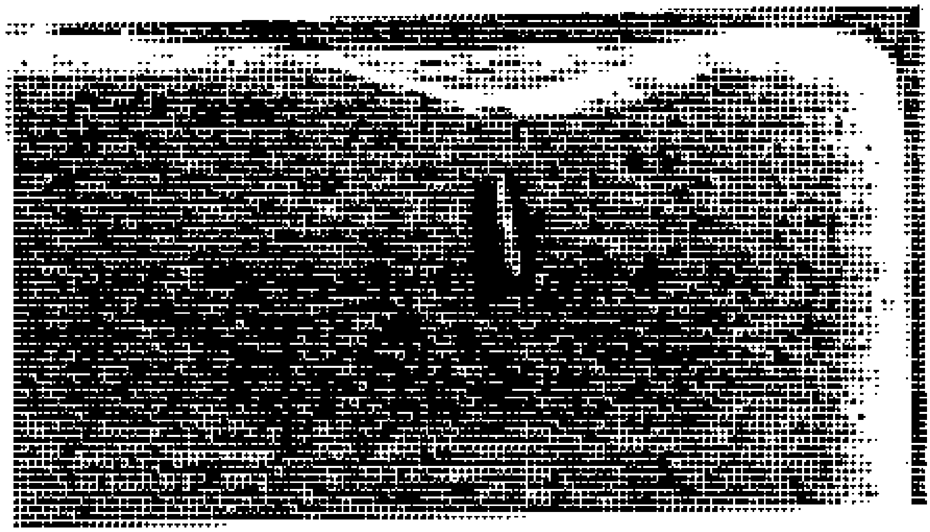


(g) Dry condition, 10 min

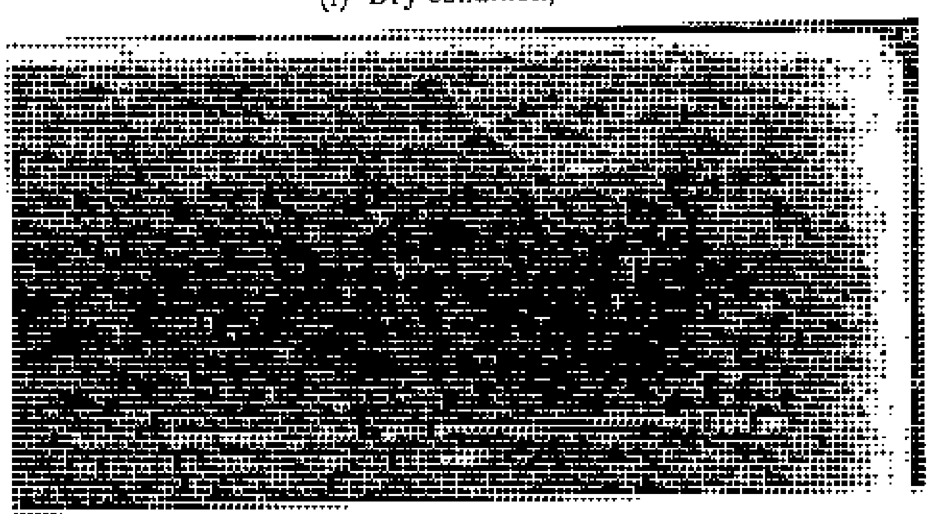


(h) MQL condition, 10 min

Fig.2.28 SEM views of **principal flank** of worn out SNMG insert after machining **medium carbon steel** under (g) **Dry and** (h) **MQL** conditions with cutting speed 258 m/min, feed rate 0.20 mm/rev and depth of cut 1.5 mm

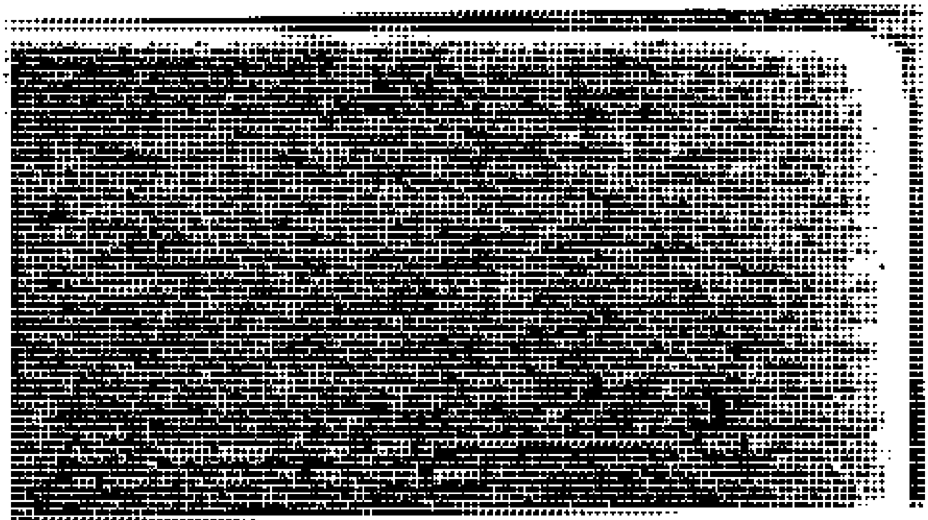


(i) **Dry** condition, 24 min

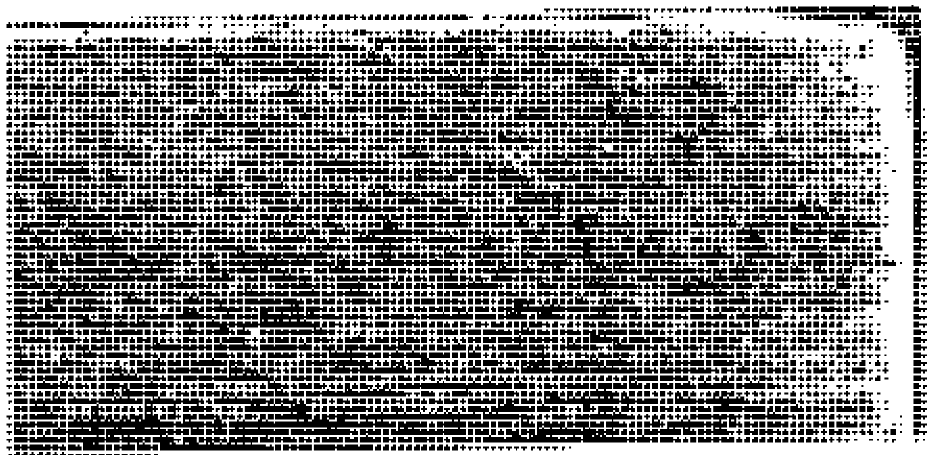


(j) **MQL** condition, 24 min

Fig.2.29 SEM views of **auxiliary flank** of worn out SNMG insert after machining **medium carbon steel** under (i) **Dry and** (j) MQL conditions with cutting speed 66 m/min, feed rate 0.10 mm/rev and depth of cut 1.0 mm

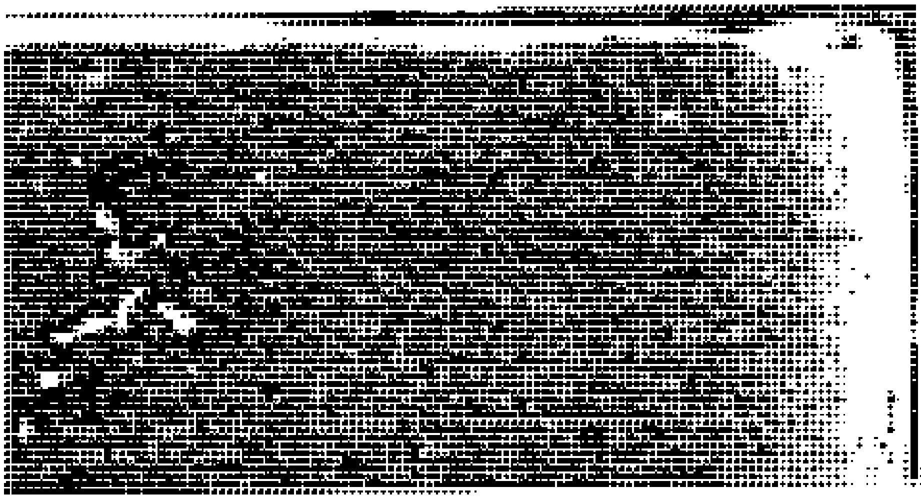


(k) Dry condition, 24 min



(l) MQL condition, 24 min

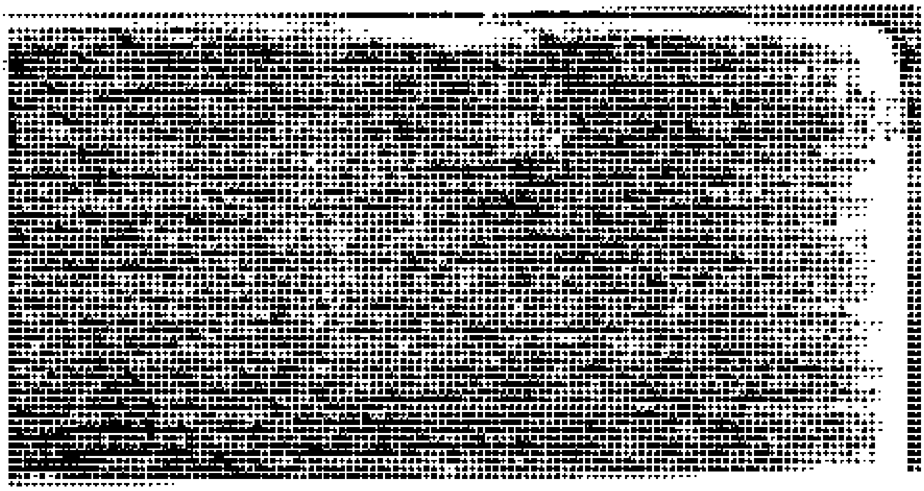
Fig.2.30 SEM views of auxiliary flank of worn out SNMG insert after machining medium carbon steel under (k) Dry and (l) MQL conditions with cutting speed 66 m/min, feed rate 0.10 mm/rev and depth of cut 1.5 mm



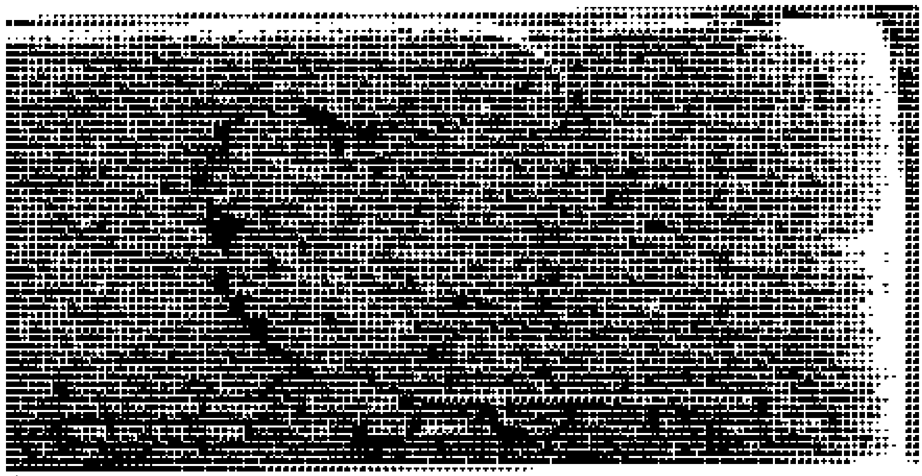
(m) Dry condition, 14 min

(n) MQL condition, 16 min

Fig.2.31 SEM views of **auxiliary flank** of worn out **SNMG** insert after machining **medium carbon steel** under (m) **Dry and** (n) **MQL** conditions with cutting speed 258 m/min, feed rate 0.20 mm/rev and depth of cut 1.0 mm



(o) Dry condition, 10 min



(p) MQL condition, 10 min

Fig.2.32 SEM views of auxiliary flank of worn out SNMG insert after machining medium carbon steel under (o) Dry and (p) MQL conditions with cutting speed 258 m/min, feed rate 0.20 mm/rev and depth of cut 1.5 mm

2.3.5 Surface Roughness

Surface roughness is a widely used index of product quality and in most cases a technical requirement for mechanical products. The performance and surface life of any machined component is influenced by surface integrity of that component. Achieving the desired surface quality is of great importance for the functional behavior of a part. Therefore, the estimation of the magnitude of surface roughness under given cutting conditions resulting from resulting from metal removal operations is one of the major roles in this area.

The surface roughness of machined parts is a significant design specification that is known to have considerable influence on properties such as wear resistance, clean ability, assembly tolerances, coefficient of friction, wear rate, corrosion resistance, fatigue strength and aesthetic appearance. The quality of surface finish is a factor of importance in the evaluation of machine tool productivity. As roughness of the machined surface is an important quality measure in metal cutting, it is important to monitor and control surface roughness over time during the machining operation.

Surface roughness has been measured at two stages; one, after a few seconds of machining with the sharp tool while recording the cutting temperature and forces and second, with the progress of machining while monitoring growth of tool wear with machining time. Here the surface finish has been measured by a Talysurf (Surtronic 3+, Rank Taylor Hobson Limited) by the machining of the steel bar by the uncoated carbide insert at different V-f combination for the depth of cuts of 1.0 and 1.5 mm under dry and MQL using a sampling length of 4.00 mm. The arithmetic average value is measured several times and it is then averaged to obtain the surface roughness value for the combinations of cutting speed, feed and depth of cut.

Fig.2.33 and Fig 2.34 show the variation in surface roughness observed during machining of the medium carbon steel bar by the SNMG insert at variable V-f and under two different depth of cut (1.0mm and 1.5 mm) respectively under dry and MQL conditions.

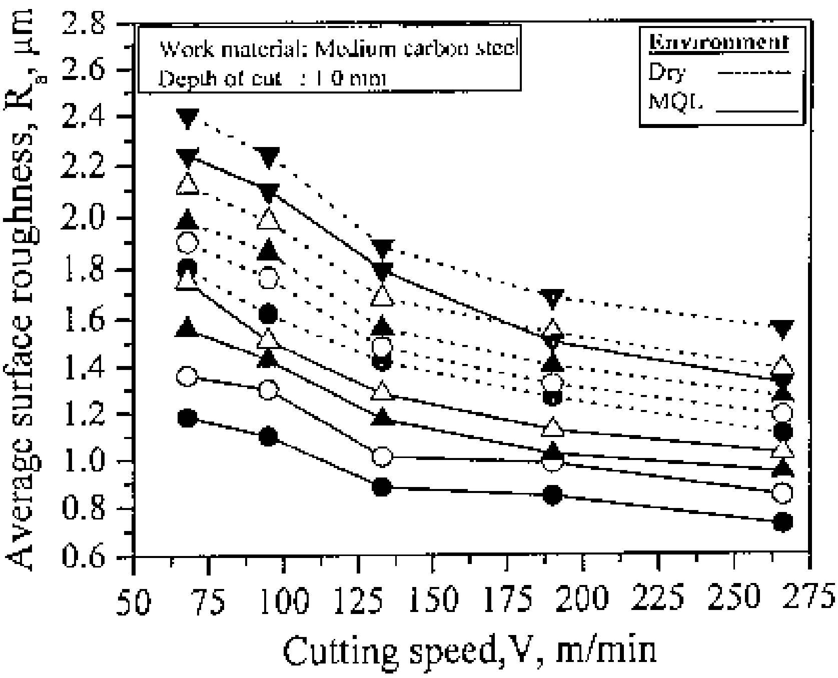


Fig.2.33 Variation in **surface roughness** (R_a) with that of V and f in turning **medium carbon steel** by SNMG insert under **Dry** and **MQL** conditions at depth of cut of 1.00 mm

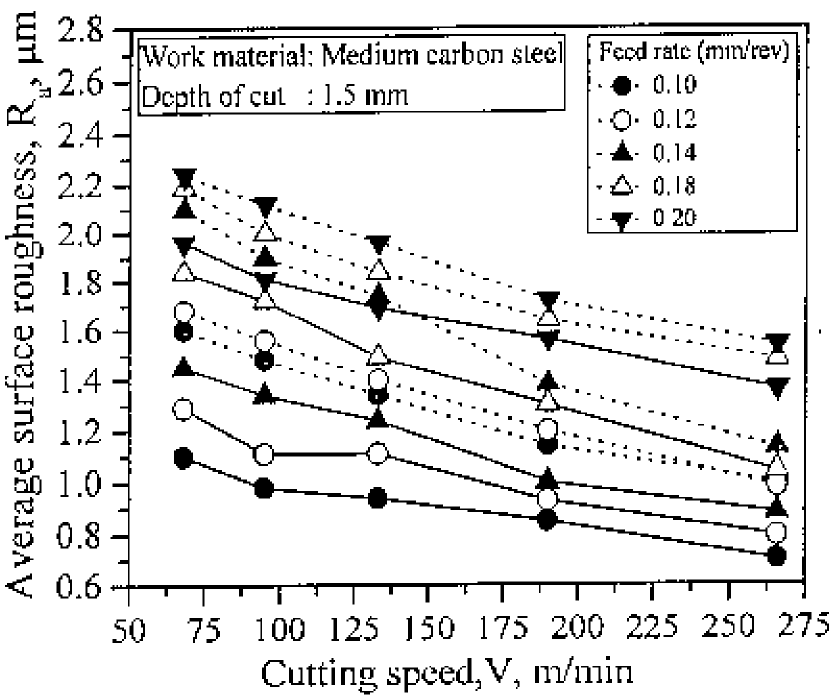


Fig.2.34 Variation in **surface roughness** (R_a) with that of V and f in turning **medium carbon steel** by **SNMG** insert under **Dry** and **MQL** conditions at depth of cut of 1.50 mm

Variation of surface roughness with progress of machining time at lower speed and feed (V=66m/min, f=0.10 mm/rev) and higher speed and feed (V=258 m/min, f=0.20 mm/rev) with two depth of cut (d=1.0mm and 1.5 mm) under dry and MQL (cutting oil) conditions have been shown in Fig.2.35, Fig.2.36, Fig.2.37 and Fig 2.38

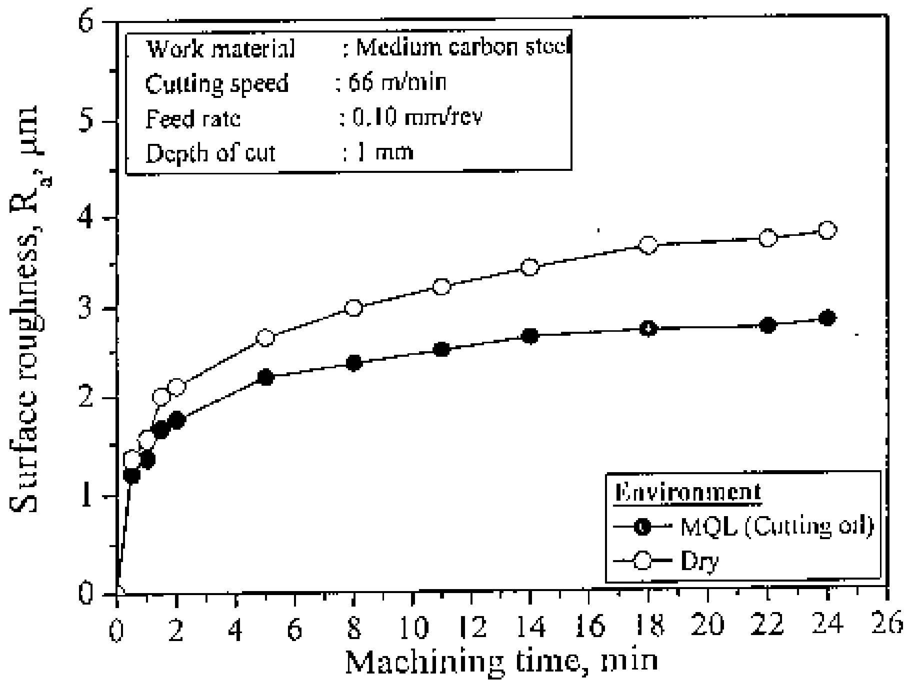


Fig.2.35 Variation in average surface roughness (R_a) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at a depth of cut of 1.00 mm

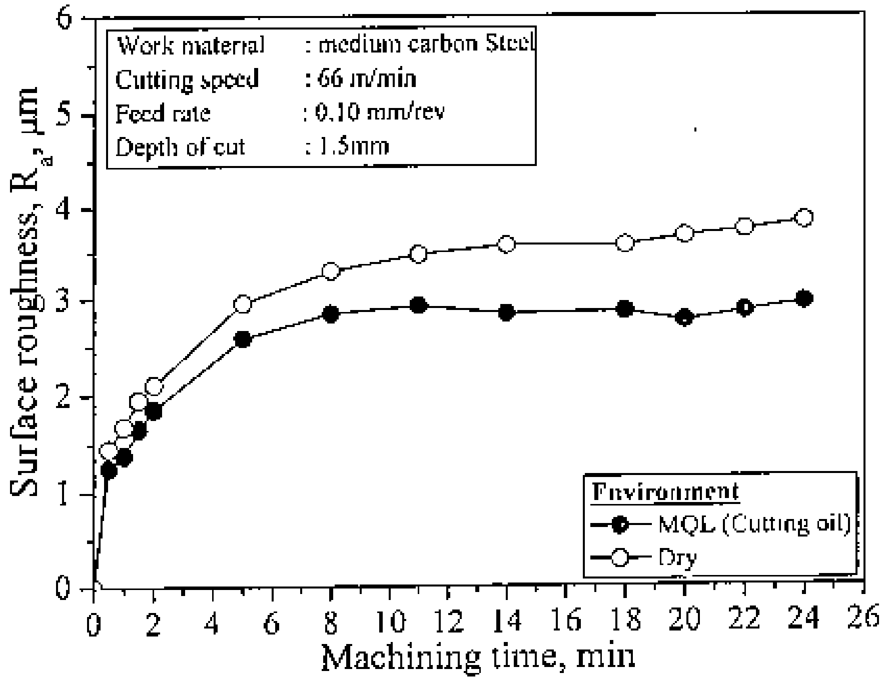


Fig.2.36 Variation in average surface roughness (R_a) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm

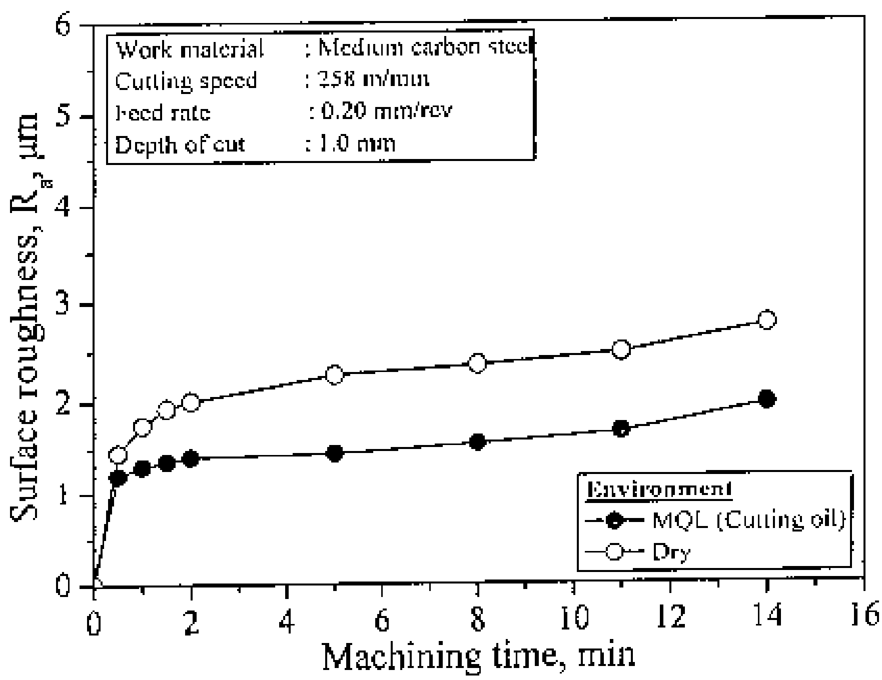


Fig2.37 Variation in average surface roughness (R_a) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.00 mm

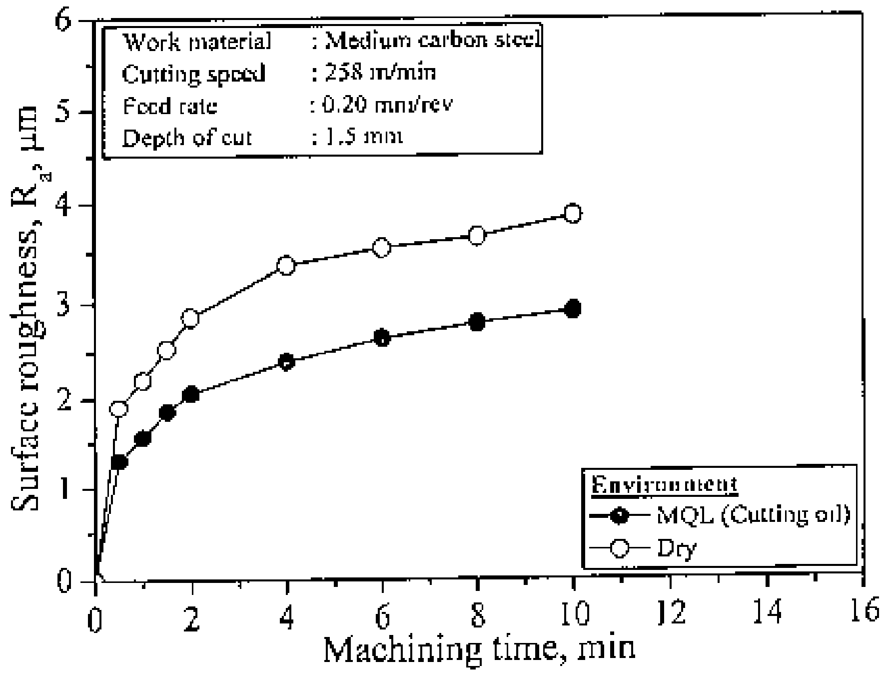


Fig.2.38 Variation in average surface roughness (R_a) with time recorded during turning medium carbon steel by SNMG insert under dry and MQL environments at depth of cut of 1.50 mm

Chapter 3

Artificial Neural Network (ANN) Model

3.1 ANN Model Formulation

Artificial neural networks (ANNs) are one of the most powerful computer modeling techniques, based on statistical approach, currently being used in many fields of engineering for modeling complex relationships which are difficult to describe with physical models.

ANNs have been extensively applied in modeling many metal-cutting operations such as turning, milling, and drilling [Ezugwu et al [128], Dimla and Lister [129], Dimla [130]. However, this study was inspired by the very limited or no work on the application of ANNs in modeling the relationship between cutting conditions and the process parameters during machining of medium carbon steel by uncoated carbide insert under minimum quantity lubrication (MQL) condition.

The importance of predicting the tool wear and surface finish in any machining process help us for proper planning and control of machining parameters and optimization of the cutting conditions to minimize production cost and time and producing products of desired quality to satisfy our purposes.

3.2 Input Variables

Before developing ANN model to predict tool wear and surface roughness, the factors that affects the process performance needs to be considered first:

(i) The machining variables or set up variables, which include cutting speed (V), feed rate (f) and depth of cut (d). These parameters can be set up in advance. It means that these parameters are controllable. These parameters have been used in our proposed model. In turning operation [Fig. 1.1] a workpiece is rotated and a cutting tool removes a layer of material as it moves to the left. The cutting tool is set at a certain depth of cut (measured in mm or inch) and travels to the left with a certain velocity as the workpiece rotates. Two values of depth of cuts (DOC) have been selected over the permissible range: which are 1.00 mm and 1.50 mm in order to formulate the ANN model. The feed or feed rate is the distance the tool travels per unit revolution of the workpiece (mm/rev or inch/rev). As a result of this action a chip is produced which moves up the face of the tool. Two values of feed rate have been selected in this research work, they are 0.1mm/rev and 0.2 mm/rev

(ii) The tool geometry like nose radius, rake angle, side cutting edge angle, cutting edge. These factors depend on the tool to be chosen for a particular machining process. If the tool is qualitative-predictable, then parameters are considered to be controllable. Anyway, it is necessary to keep in mind that such a factor like built up edge can occur. In such case tool geometry can not be considered as predictable parameter. In our research, the experiment was carried out for a particular tool-work combination, tool geometry was constant. So, it has not been considered in the ANN model which was proposed to predict tool wear and surface roughness.

(iii) Workpiece and their mechanical properties. If used materials are produced under quality control, the parameter (workpiece properties) can be considered as controllable. As mentioned above, the experiment was carried out for a particular tool-work combination; chemical and physical properties of machined material can be considered constant. So, it has not been considered in the ANN model which was proposed to predict tool wear and surface roughness.

(iv) Auxiliary tooling, and used lubrication. Auxiliary tooling, for example clamping system, can be considered as controllable, if clamping process is done correctly. Clamping problems can be figured out by controlling machined parts waviness or cutting machine, for example lathe, vibration parameters. In our experiment, lubrication or cooling liquids are not used. In such cases, the factor is omitted in the proposed ANN model.

(v) Vibrations between workpiece, machine tool and cutting tool. These factors influence process performance to a great extent. For simplicity this has not been considered in the proposed neural network model.

(vi) Machining time influences the process performance to a great extent. As machining time increases, tool wear also increases and so significantly influence the surface quality. Considering this, machining time has been considered as one of input parameters of the model.

3.3 Output Variables

3.3.1 Tool Wear

Cutting tools are subjected to high localized stresses, high temperatures, sliding of the tool along the machined surface. These condition induced tool wear, which in turn adversely affects tool life, the quality of the machined surface and its dimensional accuracy and consequently the economics of cutting operations. Tool wear is generally a gradual process. In an automated production line, for manufacturing process planning the prediction of tool wear is of much significant. The rate of tool wear depends on tool and workpiece material, tool shape, cutting fluids; process parameters (such as cutting speed, feed and depth of cut) and machine-tool characteristics [131].There are two basic types of wear: flank wear and crater wear (Fig.2.12).

Flank wear is caused by friction between the flank face (primary clearance face) of the tool and the machined workpiece surface. At the tool flank-workpiece surface contact area, tool particles adhere to the workpiece surface and are periodically sheared off. Flank wear occurs on the relief face of the tool and the side relief angle and is generally attributed to rubbing of the tool along the machined surface, causing adhesive and/or abrasive wear and high temperatures which affect tool-material which affect tool-material properties as well as the workpiece surface. Cutting speed is the most significant process variable in tool life, although depth of cut and feed rates is also important [131]

After selecting the lubricant, cutting tool material, and geometry to be used in marching a particular work material, the best engineering approach is to identify a machinability speed that corresponds to the critical temperature limits of both cutting tool and work material. The tool-work material interface temperature must be below the diffusion and melting limits of the materials used in the cutting tool; otherwise binding materials such as cobalt in the WC or TiN or Al_2O_3 in cubic boron nitride (CBN) tools may diffuse towards the chip leading to a chain of diffusion, adhesion, and abrasive wear mechanisms.

It is a well known fact that cutting forces increases in the feed direction when flank wear grows. Friction between the flank and finish surface produces additional forces to the shearing. These forces have greater influence in the direction normal to the flank surfaces. However correlating the increase in cutting force with tool wear is still difficult, since the cutting forces may also increase due to the changes in the workpiece geometry and material properties of the workpiece [132].

The productivity of a machining system and machining cost, as well as quality, the integrity of the machined surface and profit strongly depend on tool wear and tool life During turning operation the average principal flank wear (VB) predominantly occurs in cutting tool, so the life of a particular tool used in the machining process depends upon the amount of average principal flank wear. The maximum principal flank wear (VM) and average auxiliary flank wear (VS) also take place during turning and can't be neglected due to their significant impact on surface integrity of machined component.

3.3.2 Surface Roughness

The surface parameter used to evaluate surface roughness in this study is the roughness average (R_a). This parameter is also known as the arithmetic mean roughness value, arithmetic average (AA), or centerline average (CLA). Within the presented research framework, the discussion of surface roughness is focused on the universally recognized. R_a is recognized universally as the commonest international parameter of roughness. The average roughness is the area between the roughness profile and its center line, or the integral of the absolute value of the roughness profile height over the evaluation length [Fig. 1.9] **[80, 133-134]**. Therefore, R_a is specified by the following equation:

$$R_a = \frac{1}{L}\int_0^L |Y(x)|\,dx, \qquad \text{..................................[3.1]}$$

When R_a is evaluated from digital data, the integral is normally approximated by a trapezoidal rule:

$$R_a = \frac{1}{n}\sum_{i=1}^{n}|Y_i| \qquad \text{..................................[3.2]}$$

Where, R_a is the arithmetic average deviation from the mean line (μm), L is the sampling length, and Y is the ordinate of the profile curve. Graphically, the average roughness is the area (shown in Fig.1.9) between the roughness profile and its center line divided by the evaluation length. Surface roughness is a widely used index of product quality and in most cases a technical requirement for mechanical products. The performance and surface life of any machined component is influenced by surface integrity of that component To develop the model of tool wear along with surface roughness the value of average surface roughness, R_a was measured with the progress of machining while monitoring the growth of tool wear with machining time. Here the surface finish has been measured by a Talysurf (Surtronic 3+, Rank Taylor Hobson Limited) by the machining of the steel bar by the uncoated carbide insert at different V-f combination for the depth of cuts of 1.0 and 1.5 mm under MQL environment using a sampling length 4.00 mm. The arithmetic average value is measured several times and it is then averaged to obtain the surface roughness value for the combinations of cutting speed, feed and depth of cut.

3.4 ANN Model

There has been continual in research interest in the applications of ANNs in the modeling and monitoring of machining operations and for process optimization.

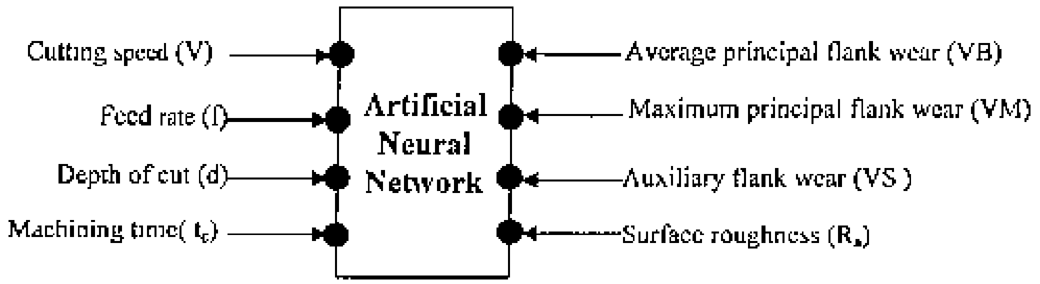


Fig. 3.1 Schematic diagram of ANN for Tool Wear and Surface Roughness

The input/output dataset of the ANN model that we are to going to be formulated to predict tool wear and surface roughness in a MQL environment is illustrated schematically in Fig. 3.1

The input parameters of the neural network are the cutting conditions, namely cutting speed (V), feed rate (f), depth of cut (d) and cutting time (t_c). The output parameters of the model are four process parameters measured during the machining trials, namely principal flank wear (VB), maximum principal flank wear (VM), auxiliary flank wear (VS) and surface roughness (R_a). An experimental study would be conducted to establish and validate the proposed model. The five basic steps used in general application of neural network have been adopted in the development of the model: assembly or collection of data; analysis and pre-processing of the data; design of the network object; training and testing of the network; and performing simulation with the trained network and post-processing of results.

3.4.1 Experimentation (Collection of Input-Output Dataset)

The machining tests have been carried out by straight turning of medium carbon steel on a lathe (7.5 kW) by a standard uncoated carbide insert with ISO designation-SNMG 120408 at different cutting velocities (V) and feed rates (f) and depth of cuts (d) under MQL (cutting oil) condition. In total four machining tests were conducted for different cutting speeds, feed rates, depth of cuts and machining time. During machining trials the cutting insert was withdrawn at regular intervals to examine the pattern and extent of wear under a metallurgical microscope. After each trial, the average surface roughness value was also measured by a Talysurf. We have thus obtained several pairs of output variables in response to the different combinations of process parameters. The data range selected was as follows: low speed (68 m/min)- low feed (0.1mm/rev) and high speed (258 m/min)-high feed (0.20 mm/rev). All the machining trials were carried with and between these two ranges for the depth of cut of 1.0 mm and 1.5 mm respectively.

3.4.2 Pre-processing of Input-Output Dataset

The generalization capability of the neural network is totally dependent on: (i) the selection of appropriate input-output parameters of the system (ii) the distribution of the dataset (iii) the format of the presentation of the dataset to the network. For our ANN model, the input parameters used are the four main cutting parameters (cutting speed, feed rate, depth of cut, marching time), while the output dataset are the four process parameters (average principal flank wear, maximum principal flank wear, average auxiliary flank wear, average surface roughness). In this study four machining test were carried out and a total of 38 input-output dataset pairs were obtained during the machining trials.

$$P_i = \begin{bmatrix} \text{Cutting speed}, V \\ \text{Feed rate}, f \\ \text{Depth of cut}, d \\ \text{Machining time}, t_c \end{bmatrix}, \qquad T_i = \begin{bmatrix} \text{Average principal flank wear}, VB_{..} \\ \text{Maximum principal flank wear}, VM \\ \text{Average auxiliary flank wear}, VS \\ \text{Average surface roughnes}, R_a \end{bmatrix}$$

Before the ANN can be trained and the mapping learnt, it is important to process the experimental data into patterns. Training and testing pattern vectors are formed before input-output dataset are fed to network. Each pattern is formed with an input condition vector, P_i and the corresponding target vector, T_i which is shown in the above matrix.

Before training the network, the input-output dataset were normalized within the range of ±1, using the Matlab command 'premnmx'. The normalized value (x_i) for each raw input-output dataset (d_i) was calculated as

$$x_i = \frac{2}{d_{max} - d_{min}}(d_i - d_{min}) - 1 \qquad \text{.................................[3.3]}$$

Here, x_i =normalized value

d_i=original value of input/output

d_{min} =minimum value of input/output

d_{max}=maximum value of input/output

3.4.3 Neural Network Design and Training

The network architecture/ topology or features such as number of neurons and layers are very important factors that determine the functionality and generalization capability of the network [135]. The selection of the activation function and training algorithm also play a significant role to obtain better forecast of response variable. In this work, standard multilayer feed-forward back-propagation hierarchical neural network is adapted for the prediction of tool wear and surface roughness in turning medium carbon steel in MQL environment. The neural network has been deigned with MATLAB 7.1 software. The back propagation algorithm is a gradient decent error-correcting algorithm which updates the weights in such a way that network output error is minimized [136]. The feed forward backpropagation network consists of an input layer (where the inputs of the problems are received), one hidden layer (where the relationship between the inputs and outputs are determined represented by synaptic weights) and an output layer which emits the outputs of the problem. The input layer has four neurons corresponding to each of the four cutting parameters and four neurons in the output layer corresponding to each of the four response parameter (Fig.3.7). In order to find out the best network architecture different networks with different number of layers and neurons in the hidden layer were designed and tested; different training algorithm were used; transfer function in the hidden layer and output layer were changed and finally select the optimal network to predict tool wear and surface roughness. The issue of determining the optimum number of hidden nodes is a crucial yet complicated one. In general, network with fewer hidden nodes are preferable as they usually have better generalizations ability and less over fitting problems. But network with too few hidden nodes may not have enough power to model and learn the data. The most common way in determining the number of hidden nodes is via trial and error. Several rule of thumbs have also been proposed, such as, the number of hidden nodes depends on the number of input patterns and each weight should have at least ten input patterns (sample size). In the case of one hidden layer network, several practical guidelines exist. These include 2n+1, 2n, n\2 where n is the number of input nodes. Lawrence and Fredrick [137] suggested that the number of hidden neuron = (n_1+n_2), where n_1 and n_2 are the number of input and output nodes respectively.

For the optimal network architecture, tangent sigmoid transfer function 'tansig' has been used in the hidden layer and linear transfer function 'purelin' has been used in the output layer. The ANN configuration is represented as 4-25-4 that is input layer consists of four inputs, the hidden layer twenty five neurons and the output layer consisting of four outputs (neurons). The number of neurons in the hidden layer is determined by trial and error method after designing and investigating many networks. As mentioned above, there is no fixed rule for determining the number of neurons in the hidden layer The number of neurons in this layer must be large enough to allow for enough partitions of the non-linear evaluation space.

Training of an ANN plays a significant role in designing the direct ANN-based prediction. The accuracy of the prediction depends on how it is trained. The training of the neural network using a feed-forward back propagation algorithm has been carried out. The network performs two phases of data flow. First the input pattern is propagated from the input layer to the output layer and, as a result of this forward flow of data, it produces an output. Then the error signals resulting from the difference between the computed and the actual are back propagated from the output layer to the previous layers for them to update their weights.

The number of neurons in the hidden layer is intentionally chosen to start with five (5) neuron and hidden neurons are added to the hidden layer by 5 incrementally. The addition of hidden neurons continues until there is no further improvement in network performance. The performance of the network was evaluated by mean sum of squared error (MSE) between the measured and the predicted values for every output nodes in respect of training the network. The feedback from that processing is called the "average error" or "performance". Once the average error is below the required goal or reaches the required goal, the neural network stops training and is, therefore, ready to be verified.

The training performance of different network architectures (4-5-4, 4-10-4, 4-15-4, 4-20-4, 4-25-4) has been shown in the Fig. 3.2, Fig. 3.3, Fig. 3.4, Fig. 3.5 and Fig. 3.6 respectively. It is seen from the Fig. 3.2 and Fig. 3.5 that the network architectures consisting of five and 10 hidden neurons do not converges to the required error goal (0.0001) that has been set in this study. Fig. 3.4 shows that the 4-15-4 architecture meets the error goal at the end of 143 cycles. After exceeding 15 numbers of hidden neurons, all other designed network meets the performance goal but their generalization or prediction accuracy is not same. The best network configuration was selected on the basis of coefficient of determination (R^2) and mean absolute percentage of error (MAPE) for each of the output parameters in respect to both training and testing performance.

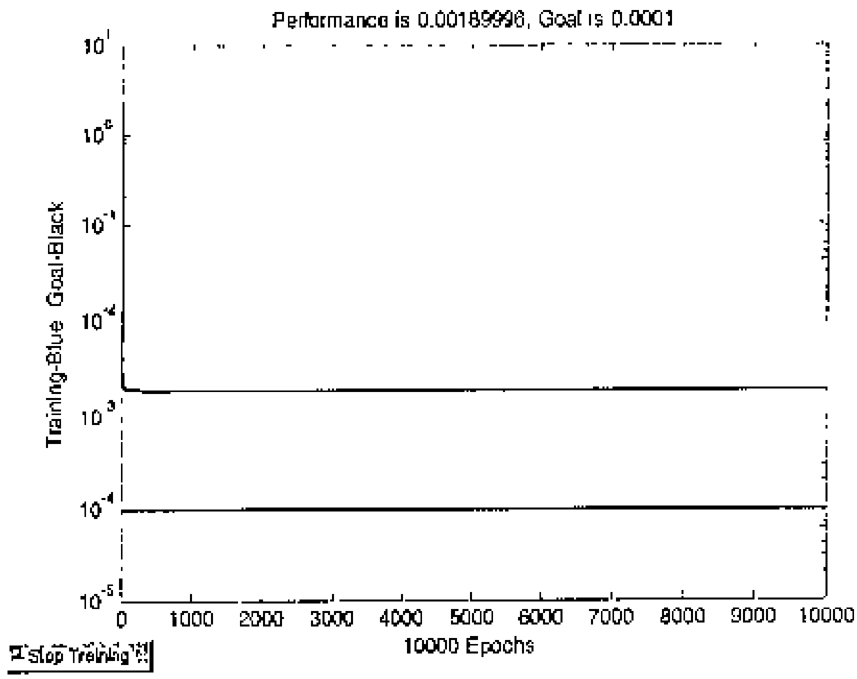


Fig.3.2 ANN training performance (Network architecture: 4-5-4)

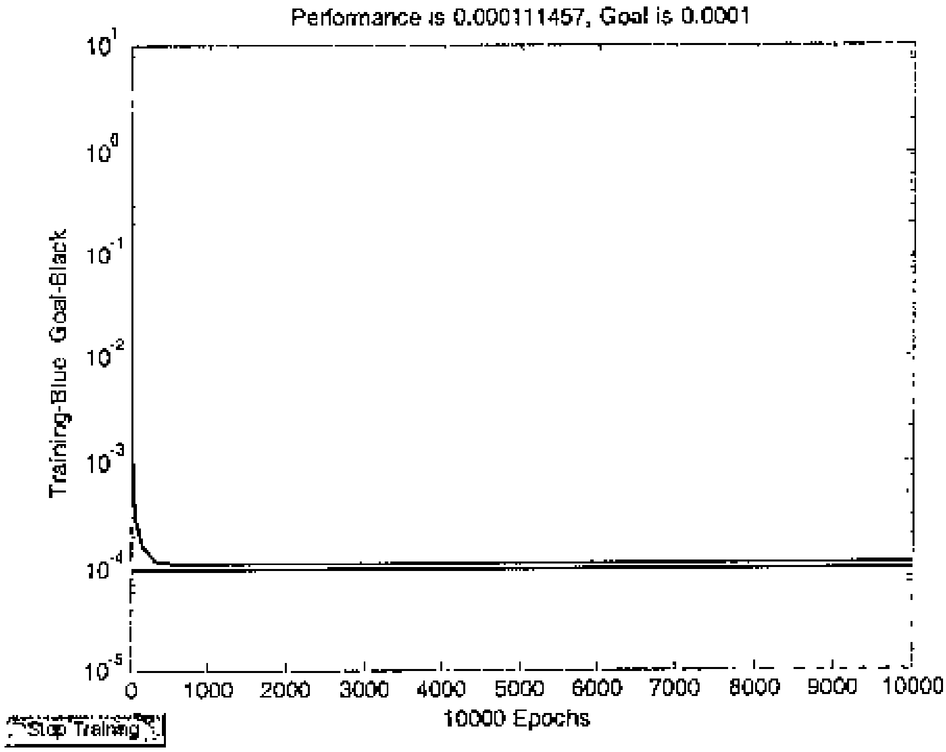


Fig.3.3 ANN training performance (Network architecture: 4-10-4)

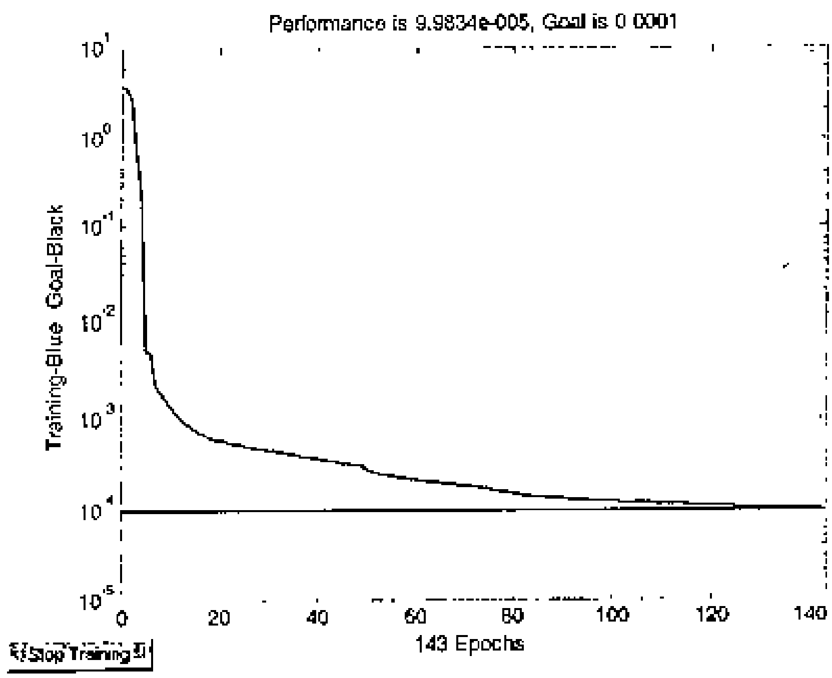


Fig.3.4 ANN training performance (Network architecture: 4-15-4)

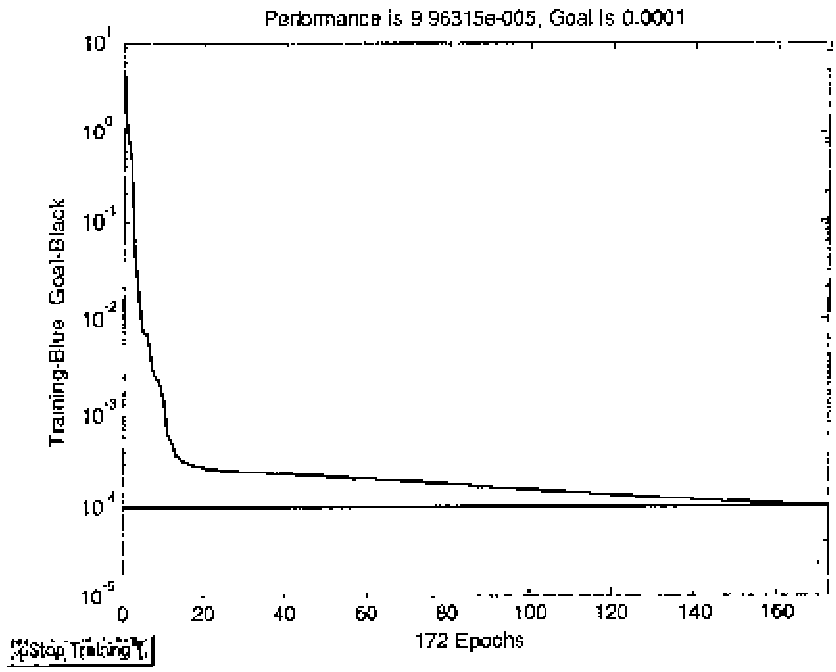


Fig.3.5 ANN training performance (Network architecture : 4-20-4)

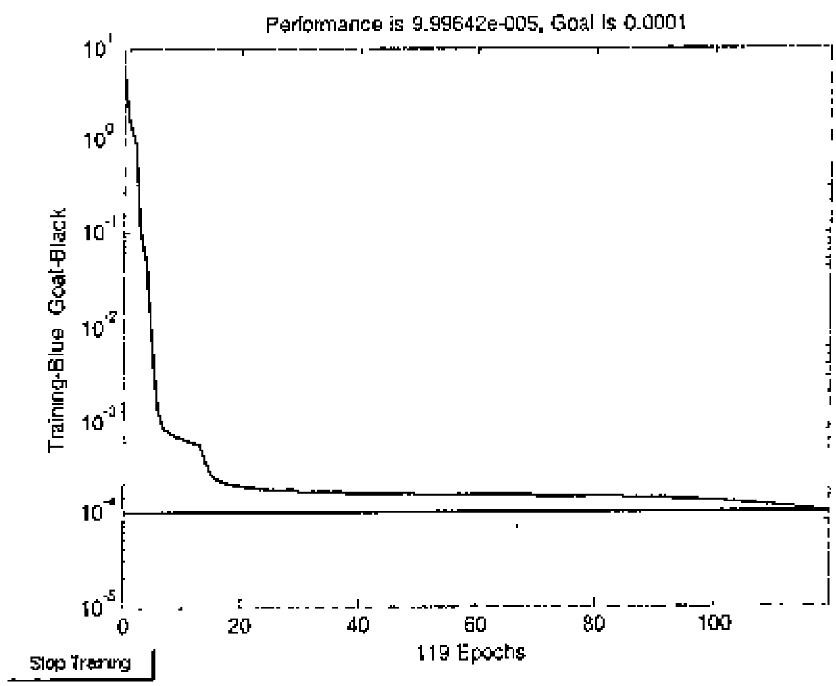


Fig.3.6 ANN training performance (Network architecture : 4-25-4)

MATLAB 7.1 has been used for training the network architecture which has been developed for prediction of tool wear and surface roughness. A computer program was performed under this MATLAB version. The input-output dataset consisting of 38 patterns was divided randomly into two categories: training dataset 75% of the data and test data set which consists 25% the data. There are 28 training patterns considered for prediction of tool wear and surface roughness. After the training, the weights are frozen and the model is tested for validation. For this purpose, the input parameters to the network are sets of values (in this case 10 pairs of dataset) that have not been used for training the network (raw untrained data) but are in the same range as those used for training. This enables to test the network with regard to its capability for interpolation. When we create a feed-forward network under MATLAB, it generates initial weight and bias values for a layer with the help of Nguyen-Widrow algorithm. This reduces training time by setting the initial weights in such a way that the active region of the layers neuron will be distributed approximately evenly over the input space. The advantage of this over completely random initialization is that once the training starts the weights movements are smaller and settle quickly, since the majority of weight movements were eliminated by the method of initialization [138].

Each neuron is a processing element, which performs a weighed sum of all input variables that feed it. Depending on the value of weighted sum of the variables, the neuron gives a signal to the neurons in the adjacent layer through a non-linear transfer function (sigmoid function in this case). The tool wear and surface roughness values of training samples are treated as the desired and target output. The algorithm used for the neural network learning is 'the backward propagation algorithm' with Levenberg-Marquardt

(LM) version This training algorithm (LM) was chosen due to its high accuracy in similar function approximation [139] .So, the learning has an adaptive nature that means vector pairs from the training model are mapped, respectively, to reinforce the weights until deviation between the training output and the desired output of each training vector sample converges to a negligible error of 0.0001 in this application. .

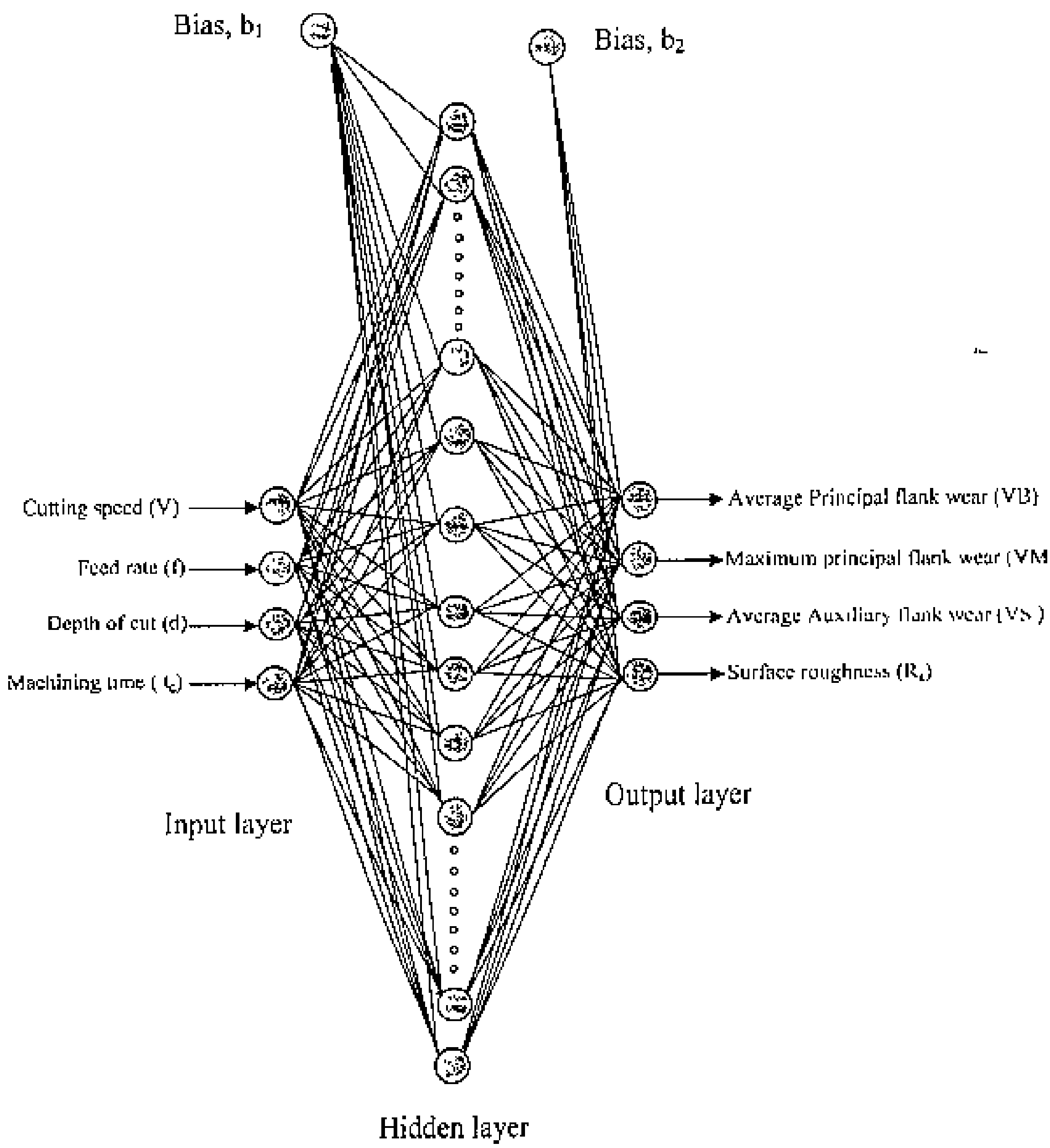


Fig. 3.7 Proposed ANN model (Network architecture: 4-25-4)

The optimum ANN architecture is shown in Fig. 3.7. For clarity, not all of the connections between input-hidden neurons and hidden-output neurons are shown in Fig. 3.7. The momentum constant and learning rate used in this model is 0.5 and 0.1 respectively. The maximum number of training epochs set was 10,000 and the training error goal was 0.0001. After the training is completed, the actual weight values are stored in a separate file. The Value of R^2 and MAPE values between the network predictions and the experimental values using training and test dataset for different network architecture have been shown in table 3.1 and table 3.2. The weight and bias values for the proposed ANN model have been shown in table 3.3 and table 3.4. The summary of the proposed model (Fig. 3.7) is given in table 3.5.

3.4.4 Testing and Performance of the Designed Network

Training and testing performance of the optimum network topology can be evaluated by the following measures:

$$\mathrm{RMSE} = \left(\left(\frac{1}{p} \right) \sum_j \left| t_j - o_j \right|^2 \right)^{1/2} \qquad \text{..............................[3.4]}$$

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \qquad \text{..............................[3.5]}$$

$$\mathrm{MEP} = \frac{\sum_j \left(\left((t_j - o_j)/t_j \right) \times 100 \right)}{p} \qquad \text{..............................[3.6]}$$

$$APE(\%) = \left|\frac{\text{Model prediction values} - \text{Experimental values}}{\text{Experimental values}}\right| \times 100\% \qquad \text{.............................[3.7]}$$

Where,

t	:	Target value
O	:	Output value
RMSE	:	Root mean squared error
MEP	:	Mean error percentage
APE	:	Absolute percentage of error
R^2	:	Coefficient of determination/ Absolute fraction of variance
P	:	Number of patterns
j	:	Processing elements

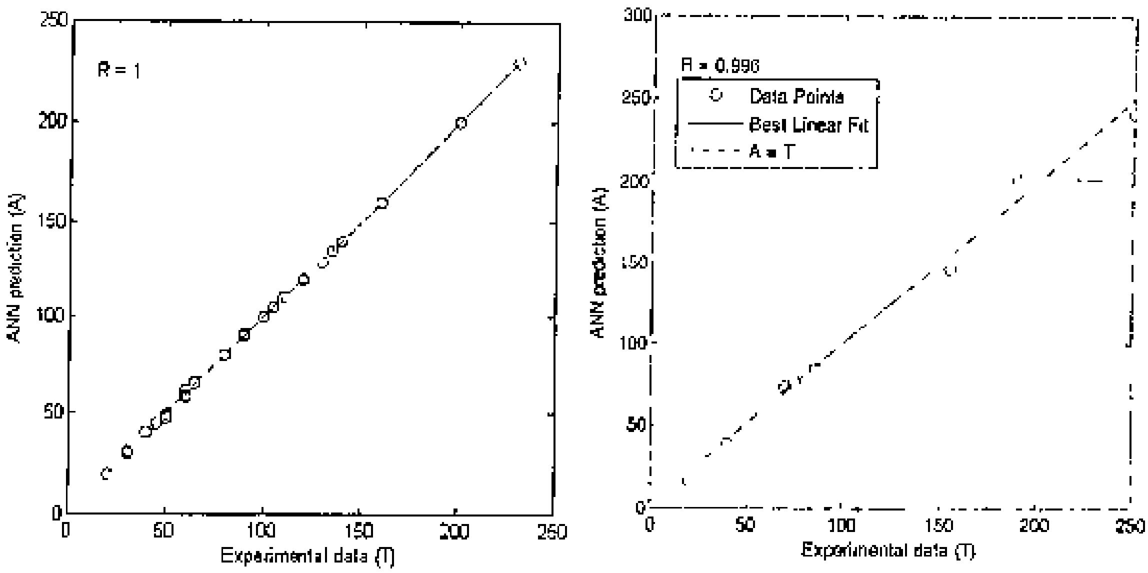
After post processing the predicted values by using the MATLAB command '**postmnmx**', regression analysis was adopted to find the coefficient of determination value (R^2) for both training and testing phases to judge the network performance. The performance capability of each network was examined based on the coefficient of determination value (R^2) between the network predictions and the experimental values using the training and test data set. Another index named mean absolute percentage of error (MAPE) is also used in this analysis to judge the training and testing performance. It is shown from the table 3.1 that network with 1 hidden layer and 25 neurons in the hidden layer with 'tansigmoid' and 'purelin' transfer function in the hidden and output layer respectively and trained with Levenberg-Marquardt algorithm provides the best result. It can also been seen from table 3.1 and table 3.2 that increasing the number of neurons from 25 to 35 has no significant improvement on the performance of the network. So, 4-25-4 network architecture was selected as the optimum ANN model.

Table 3.1 R^2 and MAPE values between the network predictions and the experimental values using training and test dataset (n=5-20)

Training algorithm	Levenberg-Marquardt algorithm							
Activation function	tansigmoid/ linear transfer function in hidden and output layer respectively							
	Training performance				Testing performance			
Hidden layers	1	1	1	1	1	1	1	1
neurons in the layer	5	10	15	20	5	10	15	20
VB (Average principal flank wear)								
R^2	0.9883	0.9996	0.9998	0.9998	0.9873	0.9935	0.9914	0.9643
MAPE	0.2879	0.0091	0.0083	0.0029	3.4613	7.5779	3.6315	2.4635
VM (Maximum principal flank wear)								
R^2	0.9887	0.9995	0.9999	0.9999	0.9882	0.4797	0.9728	0.9815
MAPE	0.3618	0.0149	0.0055	0.0044	0.5026	35.151	1.2000	0.0348
VS (Average auxiliary flank wear)								
R^2	0.9945	0.9993	0.9994	0.9994	0.9480	0.9402	0.9482	0.9528
MAPE	0.1083	0.0130	0.0126	0.0118	3.8217	20.732	0.4882	2.5265
R_a (Average surface roughness)								
R^2	0.9979	0.9998	0.9997	0.9996	0.9852	0.1108	0.8144	0.8901
MAPE	0.0175	0.0018	0.0047	0.0044	0.4560	22.701	3 2681	4.3964

Table3.2 R^2 and MAPE values between the network predictions and the experimental values using training and test dataset (n=25-35)

Training algorithm		Levenberg-Marquardt algorithm					
Activation function		tansigmoid/ linear transfer function in hidden and output layer respectively					
		Training performance			Testing performance		
Hidden layers		1	1	1	1	1	1
neurons in the layer		25	30	35	25	30	35
VB (Average principal flank wear)							
	R^2	0.9998	0.9998	0.9998	0.9915	0.9783	0.9957
	MAPE	0.0061	0.0138	0.0043	0.3633	1.2481	4.7226
VM (Maximum principal flank wear)							
	R^2	0.9999	0.9999	0.9999	0.9906	0.9772	0.9855
	MAPE	0.0051	0.0036	0.0095	0.3812	0.7553	3.5843
VS (Average auxiliary flank wear)							
	R^2	0.9995	0.9994	0.9994	0.9761	0.9435	0.9845
	MAPE	0.0096	0.0087	0.0143	1.6331	2.4674	1.9135
R_a (Average surface roughness)							
	R^2	0.9996	0.9996	0.9996	0.9627	0.9211	0.8691
	MAPE	0.0037	0.0082	0.0072	4.8069	0.8052	3.6261



(a) Training dataset (b) Testing dataset

Fig.3.8 Correlation between ANN prediction and experimental values of average principal flank wear, VB (for 4-25-4 ANN architecture)

From Fig. 3.8 we see that the correlation coefficient of 1 and 0.996 was obtained for training dataset and the model predictions respectively for average principal flank wear (VB) for the network topography (4-25-4) where the number of hidden neurons used is equal to 25. The correlation coefficients for other parameters are also realized from the table 3.1 and table 3.2. The percentage error of the model prediction was also calculated as the percentage difference between the experimental predicted values relative to the experimental value. Table 3.1 and table 3.2 clearly depicts the coefficient of determination (R^2) and mean absolute percentage of error (MAPE) for different network architecture for the four response variables VB, VM, VS and R_a. As shown in table 3.1 and table 3.2, 25 neurons gives the best values with respect to both training performance and testing performance or generalization capability of the ANN architecture. It is shown that the model can predict values within error ranging from 0.3633 to 4.8069. So, it can be concluded that the model suggested in this work have high accuracy for predicting the desired parameter in turning medium carbon steel under a MQL environment.

Fig. 3.9, Fig. 3.10, Fig.3.11 and Fig. 3.12 shows the ANN prediction values and observed values for four response variables namely average principal flank wear (VB), maximum principal flank wear (VM), average auxiliary flank wear (VS), and average surface roughness (R_a) respectively. From the graphs, it is clear that the proposed model can predict values which are nearly very close to experimental observations for each of the output parameters. The results show that the ANN can be used easily for prediction of tool wear and surface roughness and hence help in optimum selection of cutting parameters (VC, f, d, t_c) for the purpose of manufacturing process planning.

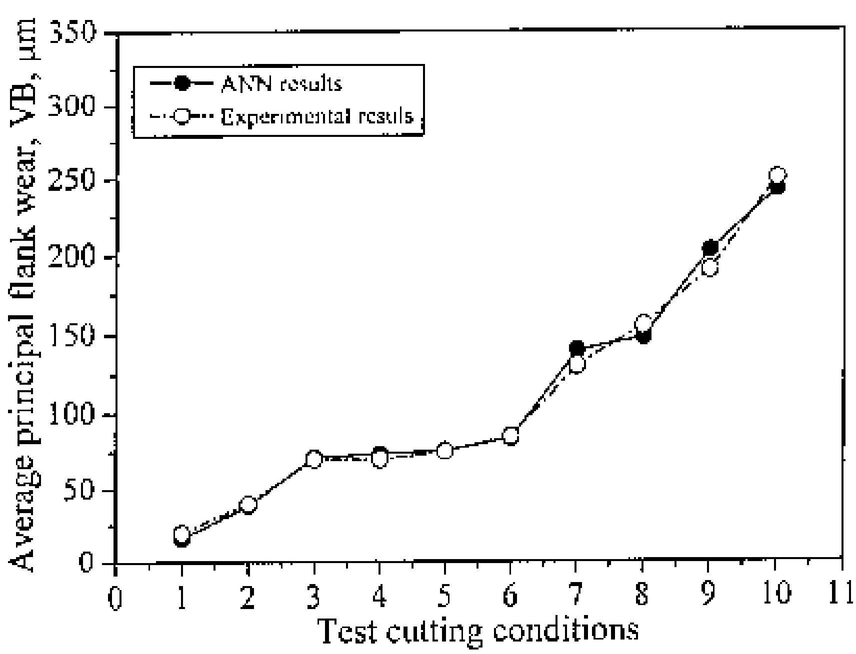


Fig.3.9 Experimental Vs. ANN prediction of average principal flank wear (VB) for 10 testing cases

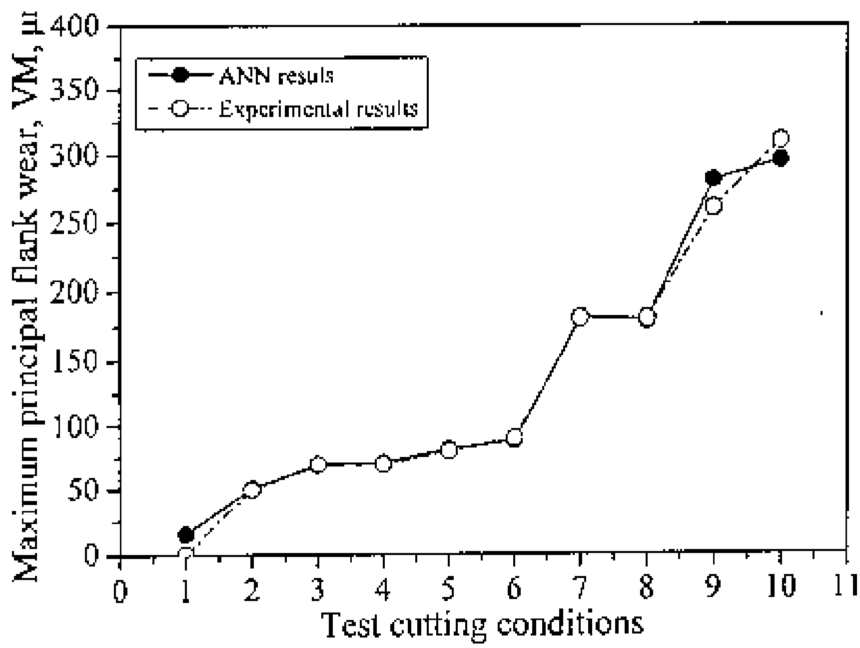


Fig.3.10 Experimental Vs. ANN prediction of Maximum principal flank wear (VM) for 10 testing cases

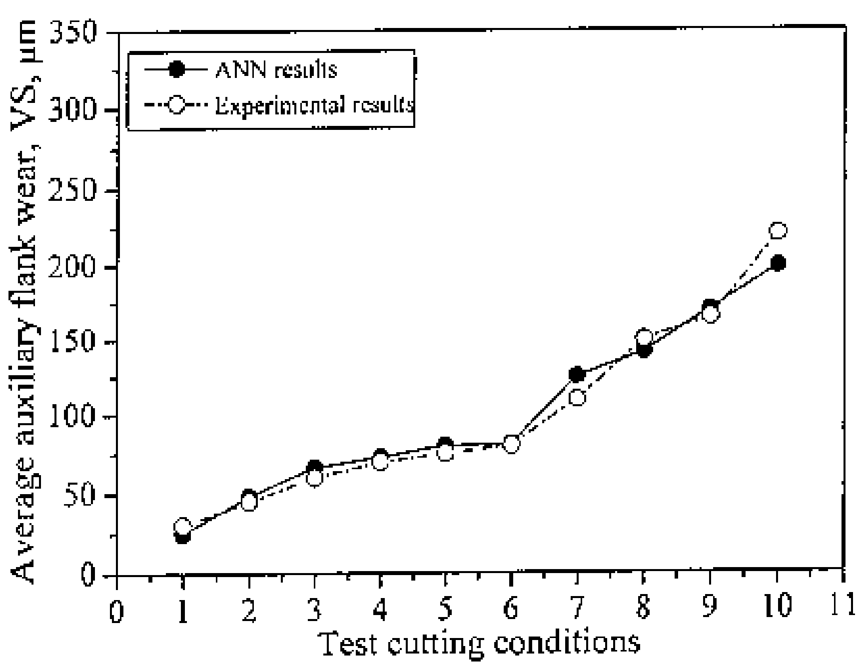


Fig.3.11 Experimental Vs. ANN prediction of Average auxiliary flank wear (VS) for 10 testing cases

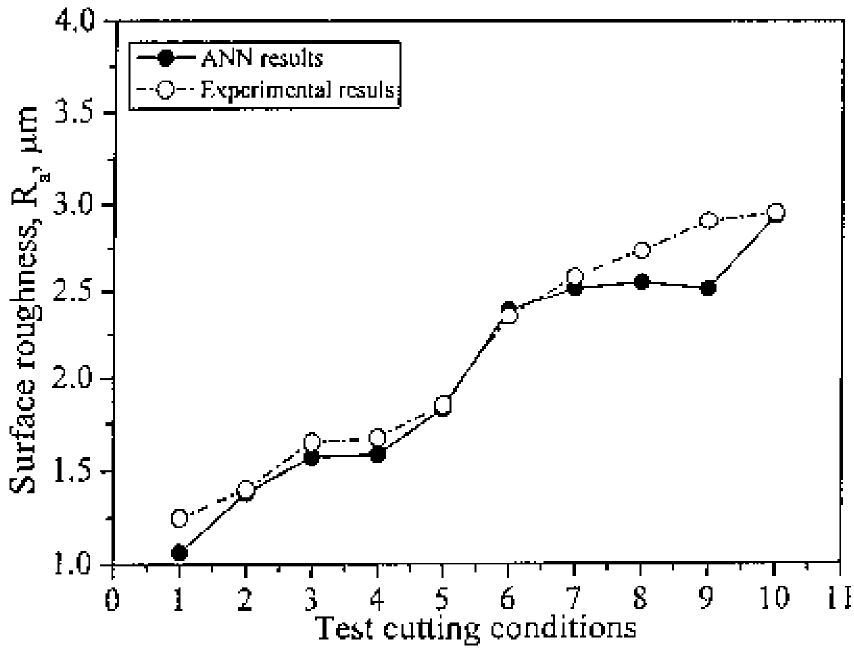


Fig.3.12 Experimental Vs. ANN prediction of average surface roughness (R_a) for 10 testing cases

Table 3.3 Weight corresponding to the input layer and hidden layer

i	w_1	w_2	w_3	w_4	b_i
1	2.3367	-1.2477	-1.3473	1.0588	-3.2414
2	-1.5410	-1.7688	1.5745	3.7736	3.5839
3	0.8811	0.8434	-2.8459	-0.0048	-2.9204
4	-0.0374	-2.2477	0.9248	1.8901	1.7723
5	1.9431	-1.5716	-1.7561	0.0070	-2.0942
6	1.0633	-2.5031	0.8945	1.7140	-1.4506
7	-0.2499	1.4486	-0.5402	0.4152	0.9697
8	-2.5066	-0.2961	1.8545	0.6299	1.4303
9	1.6626	2.1248	1.9478	2.2369	-1.4400
10	-0.2213	-0.0289	0.6696	-2.5884	0.2008
11	0.4683	-0.7635	-1.2912	2.3561	0.5310
12	1.4609	1.7240	1.8930	-0 6584	-0.3589
13	2.4854	0.3662	1.3494	-0.8430	-0.0455
14	1.9633	-1.0609	-0.8738	1.7251	1.1014
15	-2.2329	0.6405	1.1004	0.4554	-1.3378
16	-1.4225	1.1311	-0.2629	0.2341	-1.1534
17	1.9540	-1.5133	0.2614	-2.7172	0.8671
18	2.6101	1.4525	-1.1289	2.0836	0.2139
19	-0.9782	-1.2374	-0.8669	-2.6392	-1.2769
20	2.3221	1.9725	0.5233	-1.1875	1.7290
21	-2.3238	0.3414	0.9462	1.5883	-2.4303
22	-1.3512	1.5469	0.2624	-5.1658	-5.6020
23	1.4431	-1.1295	1.8299	-1.0938	3.0607
24	-2.1792	-0.8368	0.6297	-2.0089	-2.8066
25	-1.5625	-1.3336	-0.2595	2.1165	-3.1967

Table 3.4 Weight corresponding to the hidden layer and output layer

Wj				
w_1	0.8932	-0.0765	0.7734	0.1281
w_2	0.1990	0.0568	-0.0460	1.7590
w_3	0.0287	0.1783	0.0246	-0.2905
w_4	1.1713	0.4956	1.3498	-1.9564
w_5	0.9245	-0.4853	-0.0364	-0.4831
w_6	0.5741	-0.2269	-0.0135	-0.1710
w_7	0.8468	1.4655	1.1085	1.1063
w_8	0.0938	-0.1836	-0.6548	-0.5477
w_9	0.2711	0.3884	0.1293	0.6477
w_{10}	-0.2478	-0.6560	-0.4602	1.0947
w_{11}	0.0831	-0.1651	-0.2358	1.4362
w_{12}	-0.0473	-0.3442	1.3556	-0.2991
w_{13}	-0.4015	0.5747	0.1503	-0.9327
w_{14}	-0.4226	0.3094	0.0994	-1.3687
w_{15}	0.5203	0.4197	0.1737	1.2396
w_{16}	-0.2743	0.1871	-0.1559	-1.3713
w_{17}	0.9147	0.0043	-0.5004	-0.1232
w_{18}	0.2086	-0.2066	-2.1270	1.9041
w_{19}	-0.3849	-0.0643	-0.4436	1.8059
w_{20}	0.6455	0.2472	0.0521	-0.2237
w_{21}	-0.7966	0.4084	0.3586	1.1901
w_{22}	-0.7125	-0.4912	-0.9036	-1.7232
w_{23}	0.7443	0.1047	-0.2423	-0.7506
w_{24}	-0.4378	0.9725	-0.3147	-1.0994
w_{25}	0.5636	-0.1093	-1.6730	0.5414
b_j	**-0.7810**	**-0.6446**	**-1.0057**	**-0.7123**

Table 3.5 - **Summary of the ANN model**

Object model	**Input neuron**	**Output neuron**
Tool wear and Surface roughness	V, f, d, t_c	VB, VM, VS, R_a
Network structure		
Network type :	Feed-forward Back-propagation (BP) Network	
	o BP transfer function :	Tansig/Purelin
	o BP training function :	Trainlm
	o BP weight/bias learning function :	Leargdm
	o Network Performance function :	MSE
Learning conditions		
Learning scheme	: Supervised learning	
Learning rule	: Gradient descent rule	
Input neuron	: Four	
Output neuron	: Four	
Sample pattern vector	: 28 (for training), 10 (for testing)	
Number of hidden layer	: 1 (one)	
Neurons in hidden layer	: 25	
Learning rate, α	: 0.1	
Momentum constant, β	: 0.5	
Performance goal/Error goal	: 0.0001	
Maximum epochs (cycles) set	: 10,000	
Number of epochs required for	: 119	
MSE at the end of training	: 9.99642E-05	

Chapter 4

Discussion on Results

4.1 Chip Thickness Ratio

During any Machining process chips are produced. The chips produced forecast the interaction characteristics at chip-tool interface. To asses the performance of the machining, it is sometimes desirable to inspect the machining chips. Chip properties largely depend on the hardness of the work material, tool geometry-especially the rake angle and the cutting parameters i.e. cutting speed, feed rate and depth of cut. They are also somewhat dependant on the cutting environment and the nature of the chip-tool interaction.

In this study, the chip samples were collected while turning the medium carbon steel by uncoated SNMG-120408 insert at different V-f combinations under both dry and MQL conditions. Then the thicknesses of the chips were measured with the help of digital slide caliper. After that the chip thickness ratio (r_c) which is the ratio of the uncut chip thickness to chip thickness after cut was calculated.

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

$$r_c = \frac{a_1}{a_2} = \frac{f \sin \varphi}{a_2} \qquad [4.1]$$

Where,

r_c = Chip thickness ratio

a_1 = Chip thickness before cut = f sinφ

a_2 = Chip thickness

f = Feed rate

φ = Principal cutting edge angle

During the machining of the metals and alloys, continuous chips are produced and the value of r_c is generally less than 1.0 because chip thickness after cut (a_2) becomes greater than chip thickness before cut (a_1) due to almost all sided compression and friction at the chip-tool interface. Smaller value of r_c means larger cutting forces and friction and hence is undesirable. For given tool geometry and cutting conditions, the value of r_c depends upon the nature of chip-tool interaction, chip contact length and chip form, all of which are expected to be influenced by MQL in addition to the levels of V and f. All parameters in machining are directly or indirectly linked with the chip thickness ratio. If there is excessive heat generated at the cutting zone, there will be high friction between the tool and the work material. This frictional force will cause high energy consumption hence higher cutting force. These will lead to a low chip thickness ratio which is not desirable.

The variation in value of r_c with change in cutting velocity, V and feed rate, f and as well as machining environment evaluated for medium carbon steel for the depth of cuts of 1.0 and 1.5 mm have been plotted and shown in the fig. 2.4 and 2.5 respectively.

From Fig.2.4 and Fig.2.5 it has been shown that application of MQL jet has improved the value of chip thickness ratio for all V-f combinations due to reduction in friction at the chip-tool interface, reduction in built-up-edge formation and wear at the cutting edges. In all V-f combinations MQL by cutting oil shows more effectiveness than machining in a dry environment. The MQL jet, with both its lubricating and cooling effect, minimized the shrinkage of shear zone and plasticization and reduced the formation of built-up-edge.

The figures.2.4 and 2.5 clearly represents that throughout the present experimental domain the value of r_c gradually increased with the increase in V and f in different degree under both dry and MQL conditions. . This is due to the higher energy utilization associated with higher material removal rate.

4.2 Cutting Temperature

Generation of heat at the cutting zone is of prime concern in any machining process and this heat needs to be controlled to an optimum level in order to achieve better machining performance. During machining, shearing of work material, friction between the flowing chips and rake face of the tool and friction of auxiliary flank with finished surface are the principal sources of heat generation. Cutting temperature increases with the increase in specific energy consumption and material removal rate i.e. with the increase of cutting velocity, feed and depth of cut, as a result, high production machining is constrained by the ascend in temperature. The high temperature generated adversely affects, directly or indirectly, chip formation, cutting forces, tool life, dimensional accuracy and surface integrity of the machined components. Therefore, application of

MQL at chip-tool interface is expected to improve upon the aforesaid machinability characteristics that play vital role on productivity, product quality and overall economy in addition to environment-friendliness in machining particularly when chip-tool or work-tool interface temperature is high.

In this research work, a tool-work thermocouple with proper calibration [126] was used to determine the average chip-tool interface temperature during turning of medium carbon steel at different cutting velocities and feeds and the values were plotted against different cutting speed under both dry and minimum quantity lubrication (MQL) condition by uncoated SNMG insert. It was expected that the application of MQL jet would be much more effective at low speed and feed as well as high speed-feed condition in reducing the average chip-tool interface temperature which plays an imperative role on productivity, dimensional accuracy, surface integrity and overall economy in turning medium carbon steel. The evaluated role of MQL on average chip-tool interface temperature in turning medium carbon steel by uncoated carbide insert (SNMG-120408) at different V–f combinations for the depth of cuts of 1.0 and 1.5 mm under both dry and MQL condition have been shown in Fig.2.6 and Fig.2.7. The figure 2.6 and 2.7 clearly depicts in what extent tool-chip interface temperature, θ^0C has been decreased due to minimum quantity lubrication (MQL) under different experimental conditions. With the increase in cutting speed and feed rate, tool-chip interface temperature has been increased as usual, even under MQL due to increase in energy input.

It was expected to reduce tool-chip interface temperature to a great extent under MQL environment than it has been observed in this investigation. But practically, it has not been occurred due to the fact that the MQL jet has been employed in the form of a thin jet along the cutting edge and towards. Also the jets, like any cutting fluid could not reach deeply in the chip-tool interface for plastic or bulk contact, particularly when cutting speed and feed rate are large.

The effects of variation of process parameters on reduction of average tool-chip interface temperature due to MQL have not been uniform. This may be due to variation in the chip forms particularly chip-tool contact length, C_N which for a given tool widely varies with the mechanical properties and behavior of the work material under the cutting conditions. The value of C_N not only affects the cutting forces but also the cutting temperature.

4.3 Cutting Forces

The cutting forces generated during the machining process bears a significant effect on the quality of any machined component. High cutting forces may result in premature tool failure, tool vibration, high temperature generation, large tool deflections and significant mechanical loads on the workpiece surface. Large tool deflections can lead to form errors because the tool tip position deviates from the expected position. Large mechanical loads on the workpiece surface can affect the topography and integrity of a machined surface. For these reasons, it is obviously important to understand how changing process conditions affect cutting forces. In these investigations, two components of cutting force (main cutting force, F_c and feed force, F_f) were recorded during machining under dry and minimum quantity lubrication (MQL) conditions while turning medium carbon steel by uncoated SNMG insert at regular intervals. The force components were measured with a strain-gauge type force dynamometer and recorded with a PC-based data acquisition system for the combination of cutting velocities, feeds, depth of cuts and environments undertaken.

The effect of MQL on F_c and F_f that have been observed while turning medium carbon steel specimen by the uncoated carbide inserts SNMG-120408 under different V and f with depth of cuts of 1.0 and 1.5 mm have been graphically shown in Fig. 2.8, Fig. 2.9, Fig. 2.10, and Fig. 2.11.

Figure 2.8 to Fig. 2.11 clearly shows that the MQL jet has been quite successful in reducing the main cutting force and feed force. This is attributed to mainly the reduction of friction accomplished by the lubricating effect of the MQL jet. The MQL jet, with its and velocity, was able to reach the tool tip where it performed its lubricating and cooling effects and minimized friction to a remarkable amount. Reason acting behind reduction of cutting forces may be the reduction in chip load. The high velocity MQL jet impinged on the rake face uplifted the chip and reduced chip load which eventually helped to reduce the cutting forces significantly. From the figures, it has also been seen that main cutting forces and feed forces decreases with the increase of cutting speed and the force component increases with the increase of feed rate.

4.4 Cutting Tool Wear

The cutting tools in conventional machining, particularly in continuous chip formation process like turning, generally subjected to gradual wear by abrasion, adhesion, and diffusion depending upon the tool-work materials and machining conditions. Tool wear initially stars with a faster rate due to what is called break-in wear caused by attrition and micro –chipping at the sharp cutting edge. Cutting tools may often may fail prematurely, randomly and catastrophically by mechanical breakage and plastic deformation under adverse machining conditions caused by intensive pressure and temperature and/or dynamic loading at the tool tips particularly if the tool material lacks strength, hot-hardness and fracture toughness.

In this research work, the uncoated carbide insert (SNMG 120408) selected and used which attained flank wear progressively in varying pattern and magnitude while machining medium carbon steel under both dry and MQL conditions. Premature and catastrophic type of tool failure by plastic deformation or micro fracture was not found to occur within the present experimental domain.

It is already mentioned that wear of cutting tools are generally quantitatively assessed by the magnitudes of VB, VS, VM, VSM etc. shown in Fig.2.12, out of which VB is considered to be the most significant parameter at least in R&D work. It was reported earlier that application of conventional cutting fluid does not help in reducing tool wear in machining steels by carbides rather may aggravate wear[**127, 140**].

The growth of principal flank wear, VB with progress of machining time recorded while turning the medium carbon steel by uncoated SNMG insert at lower speed and feed (V=66m/min, f=0.10 mm/rev) and higher speed and feed (V=258 m/min, f=0.20 mm/rev) with two depth of cut (d=1.0mm and 1.5 mm) under dry and MQL (cutting oil) conditions have been shown in Fig.2.13, Fig.2.14, Fig.2.15 and Fig.2.16. Fig.2.13, Fig.2.14, Fig.2.15 and Fig.2.16 show the growth of average flank wear (VB) with time observed while turning medium carbon steel by SNMG insert at a particular V, f and d combination under dry and MQL (cutting oil) environments. The gradual growth of VB, the predominant parameter to ascertain expiry of tool life, observed under dry and MQL environments indicates steady machining without any premature tool failure by chipping, fracturing etc. establishing proper choice of domain of process parameters.

It has already been reported [141] that the application of MQL jet along the auxiliary cutting edge substantially changes chip formation and controls the cutting temperature. These enabled reduced rate of tool wear to a great extent and hence improved tool life as revealed in those graphs. Such improvements by MQL jets can be attributed mainly to retention of hardness and sharpness of the cutting edge for their steady and intensive cooling, protection from oxidation and corrosion and absence of built-up edge formation, which accelerates both crater and flank wear by flaking and chipping.

Another important tool wear criteria is average auxiliary flank wear which governs the surface finish on the job as well as dimensional accuracy. The growth of auxiliary flank wear, VS with progress of machining time recorded while turning the medium carbon steel by uncoated SNMG insert at lower speed and feed (V=66m/min, f=0.10 mm/rev) and higher speed and feed (V=258 m/min, f=0.20 mm/rev) with two depth of cut (d=1.0mm and 1.5 mm) under dry and MQL (cutting oil) conditions have been shown in Fig.2.17, Fig.2.18, Fig.2.19 and Fig.2.20. Irregular and higher auxiliary flank wear leads to poor surface finish and dimensional inaccuracy [3]. In the figures, the nature of growth of VS matches with that of VB expectedly. It is shown from the graphs that MQL cooling permit quick reduction in VS with the progress of machining time. So, it can be concluded that MQL can be successfully applied to have better surface finish and dimensional accuracy.

4.5 Surface Roughness

The quality of any machined product of given material is generally assessed by dimensional accuracy and surface integrity, which govern the performance and service life of that product. For the present study, only surface roughness has been considered for assessment of quality of product machined in dry and minimum quantity lubrication environment.

Surface finish is an important index of machinability because performance and service life of the machined component are often affected by its surface finish, nature and extent of residual stresses and presence of surface or subsurface micro-cracks, if any, particularly when that component is to be used under dynamic loading or in conjugation with some other mating parts. Generally good surface finish, if essential is achieved by finishing processes like grinding but sometimes it is left to machining. Even if it is to be finally finished by grinding, machining prior to that needs to be done with surface roughness as low as possible to facilitate and economize the grinding operation and reduce initial surface defects as far as possible. It is evident that MQL improves surface finish depending upon the work-tool materials and mainly through controlling the deterioration of the auxiliary cutting edge by abrasion, chipping and built-up edge formation. In our research work, surface roughness has been measured at two stages; first, after an interval of 45 seconds of machining with sharp tool while recording the chip-tool interface temperature and second, with the progress of machining while monitoring the growth of tool wear with machining time. In both stages, the surface roughness values under MQL condition shows better results as compared to dry condition.

The variation in surface roughness observed during machining of the medium carbon steel bar by the SNMG insert at variable V-f combinations and with two different depth of cut (1.0mm and 1.5 mm) under dry and MQL conditions have been shown in. Fig.2.33 and in Fig.2.34 respectively. It is apparent from the figures that surface roughness increases with the increase of feed rate and decreases with the increase of cutting speed. Reduction in roughness with the increase in cutting speed may be attributed to smoother chip-tool interface with lesser chance of built up edge formation in addition to possible truncation of the feed marks and slight flattening of the tool-tip. Increase in cutting speed may also cause slight smoothing of the abraded auxiliary cutting edge by adhesion and diffusion type wear and thus reduced surface roughness. It is clear from the Fig. 2.34 and 2.35 that MQL could provide improvement in surface finish to some extent._ This improvement might be due to reduction in wear and also to the fact of prevention of built-up-edge formation. It is also seen that increase in depth of cut might result in improvement of surface finish to a slight amount sometimes but that is insignificant.

Variation of surface roughness with progress of machining time at lower speed and feed (V=66m/min, f=0.10 mm/rev) and higher speed and feed (V=258 m/min, f=0.20 mm/rev) with two depth of cut (d=1.0mm and 1.5 mm) under dry and MQL (cutting oil) conditions have been shown in Fig.2.35, Fig.2.36, Fig.2.37 and Fig.2.38. In the graphs it is seen that surface roughness is increasing with machining time both for dry and MQL environment. It appears from those figures that surface roughness grows quite fast under dry machining due to more intensive temperature and stresses at the tool-tips, MQL appeared to be effective in reducing surface roughness. However it is crystal clear that MQL improves surface finish depending upon the work-tool materials and mainly through controlling the deterioration of the auxiliary cutting edge by abrasion, chipping and built-up-edge formation.

4.6 SEM Micrographs

The SEM views of the worn out inserts after machining of medium carbon steel at different V-f-d combinations under both dry and MQL environments for different time spans. shown in Fig.2.25, Fig.2.26, Fig.2.27, Fig 2.28, Fig.2.29, Fig.2 30, Fig.2.31 and Fig.2.32 quantitatively indicate that MQL has provided remarkable reduction in overall wear of the insert. After 24 min of machining the steel at low speed-feed condition with depth of cut 1.0 mm and 1.5 mm respectively, SEM views of worn out tips are shown in Fig.2.25, Fig.2.26, Fig.2.29 and Fig.2.30. Figures show that principal and auxiliary flank wears are reduced due to effective cooling and lubrication by MQL. MQL also eliminates the notch wear found in dry cutting. Auxiliary flank wears are almost uniform with out any built-up edge under low speed-feed condition for both the cases. Under high speed-feed for both the depth of cut temperature increase enormously that wear out the insert rapidly under dry condition. On the other hand MQL retarded the wear significantly by its cooling and lubrication shown in Fig.2.27, Fig.2.28, Fig.2.31 and Fig.2.32.

4.7 Artificial Neural Network (ANN) Model

Artificial neural networks are one of the most widely used computer modeling techniques to develop robust approach for prediction of tool wear and surface roughness in machining steel for different combinations of material properties, cutting tool geometries and cutting conditions. The generalization ability of an ANN depends on appropriate selection of input/output parameters, distribution of the dataset and format of the presentation of the dataset to the network. The schematic diagram of artificial neural network for the prediction of tool wear and surface roughness is shown in Fig.3.1. The figure reflects the input and output of the network that is going be developed. The selection of the neuron number, hidden layers, activation function and training algorithm play much significant roles in obtaining the best result. In this study, an artificial neural network (ANN) with feed-forward back-propagation algorithm was trained and the training epoch (cycles) set for each network is 10,000. The purpose of the training is to minimize the mean squared error (MSE). The training performance of different network architecture has been shown in Fig.3.2, Fig.3.3, Fig.3.4, Fig.3.5 and Fig.3.6. The proposed network architecture is shown in Fig.3.7. The performance of the ANN model has been highlighted in Fig.3.9, Fig.3.10, Fig.3.11 and Fig.3.12 for four response variables namely average principal flank wear (VB), maximum principal flank wear (VM), average auxiliary flank wear (VS), and average surface roughness (R_a) respectively. As shown in the figures, it is clear that the values predicted by ANN are very close to experimental values. To find the best network, different training algorithms were tested. Transfer functions in the hidden and output layer have also been changed and tested during design phase of the network. Finally, 'tansigmoid' function and 'purelin' function were used as the transfer function in the hidden and output layer respectively. The numbers of neurons in the hidden layer were found by trial and error method and finally 25 hidden neurons were chosen for the suggested network. The proposed network can be represented as 4-25-4. It was observed that, from network structure 4-15-4 to 4-35-4, every network meets the designed error goal of 0.0001. But, the interpolation or generalization capability of every network is not satisfactory. To find the optimal network architecture, coefficient of determination (R^2) and mean absolute percentage of error (MAPE) between the network prediction and experimental values were calculated for every network for both training and testing phases. The coefficient of determination (R^2) represents the percent of data that is closest to the line of best fit. The value of R^2 varies between 0 to 1. If correlation coefficient, R=0.922 then R^2=0.850, which means that 85% of the total variation in network prediction can be explained by the linear relationship between experimental values and network predicted values. The other 15% of the total variation in network prediction remains unexplained. The coefficient of determination (R^2) and mean absolute percentage of error (MAPE) for different network topography have been shown in table 3.1 and table 3.2. From the table it is shown that the value of R^2 increases up to hidden neuron 25. Then it starts to decrease. The network architecture consisting of 1 hidden layer and 25 hidden neurons shows best values of R^2 for both training and testing stages of the network. So, the network consisting of 25 hidden neurons was selected as the optimum one in this research work. The weights corresponding to input layer-hidden layer and hidden layer-output layer have been shown in the table 3.3 and 3.4 respectively. The summary of the proposed network architecture has been presented in table 3.5. As, the input and output vectors were supplied to the network, it was a supervised learning scheme. The back-propagation learning algorithm with LM versions was used at the training stage of the network. Gradient decent learning rule is used in this study. The learning rate and momentum constant used here are 0.1 and 0.5 respectively. The co-efficient of determination (R^2) obtained corresponding to VB, VM, VS and R_a is 0.9915, 0.9906, 0.9761 and 0.9627 respectively for testing. Regarding training, these values become 0.9998, 0.9999, 0.9995 and 0.9996. The MAPEs between the experimental and the predicted values are 0.3633% for VB, 0.3812% for VM, 1.6331% for VS and 4.8069% for R_a. The result shows that, the model can be successfully used to forecast tool wear and surface roughness in response to the process parameters for which the model has been constructed.

Chapter 5

Conclusions and Recommendations

5.1 Conclusions

Based on the analytical and experimental investigation, the following conclusions can be made

i. One of the primary objectives in machining operation is to produce product with low cost and high quality. In order to achieve such an objective, machining economics can be a significant consideration. Machining economics involves the optimum selection of machining parameters, e.g. cutting speed, feed rate, depth of cut and machining time. The machining parameters directly affect the cost, productivity and quality of products. A better prediction model can help as to choose the optimum machining parameters before performing machining operations. The objectives of this research work were to examine the effect of minimum quantity lubrication on the machining performance in terms of cutting forces, chip-tool interface temperature, tool wear and surface finish and also to develop an artificial neural network (ANN) model to predict tool wear and surface roughness while machining medium carbon steel in a MQL environment.

ii. An ANN model has been developed for prediction of tool wear and surface roughness as a function of cutting parameters. The model has been proved to be successful in terms of agreement with experimental results. The proposed model can be used in optimization of cutting process for efficient and economic production by forecasting the tool wear and surface roughness in turning operations. A computer program was performed under MATLAB 7.1 software to perform simulation by changing network parameters of the different network architectures considered in this research work. The best network architecture was selected after performing several simulation trials by the MATLAB 7.1 software.

iii. The multilayer feed forward network consisting of four inputs, 25 hidden neurons (tangent sigmoid neurons) and four outputs (network architecture represented as 4-25-4) was found to be the optimum network for the model developed in this study. The back propagation learning algorithm has been used in the developed feed forward single hidden layer network. Training of the network was performed using Levenberg-Marquardt (LM) feed forward back propagation algorithm. Tansigmoid function (TSF) and purelin function (PF) were used as the transfer function in the hidden and output layer respectively. A good performance of the neural network was achieved with coefficient of determination (R^2) between the model prediction and experimental values are 0.9915, 0.9906, 0.9761, and 0.9627 in terms of VB, VM, VS and R_a respectively The MAPE values for those variables are 0.3633, 0.3812, 1.6331 and 4.8069 respectively. These results show that the ANN model can be used easily for the prediction of tool wear and surface roughness in turning medium carbon steel by SNMG insert under minimum quantity lubrication environment.

iv. ANN models have emerged as a new promising method for estimating tool wear and surface roughness in an intelligent manufacturing system (IMS). These techniques can easily capture the complex relationship between various process parameters and can be easily integrated into an existing manufacturing environment. These techniques has opened up new avenues for parameter estimation, optimization and on-line control of manufacturing system and can assist a lot in computer aided process planning (CAPP).

v. The present MQL system has been proved to be successful in reduction of average chip tool interface temperature depending upon the work materials, tool geometry and cutting conditions. It is true that this small reduction has enabled significant improvement in machinability indices.

vi. MQL has reduced the cutting force. MQL provided effective cooling at the shear zone which reduced the chip-tool interface temperature. It also provided proper lubrication that minimizes the friction resulting in retention of tool sharpness for a longer period. Favorable change in the chip tool interaction and retention of cutting edge sharpness due to reduction of cutting zone temperature seemed to be the main reason behind reduction of cutting forces by the MQL.

vii. The application of MQL jet in machining medium carbon steel by the uncoated insert SNMG-120408 has enabled reduction in flank wear which could contribute in the improvement of tool life or enhancement of productivity at higher cutting velocity and feed rate. Such reduction in tool wear might have been possible for retardation of abrasion and notching, decrease or prevention of adhesion and diffusion type thermal sensitivity wear at the flanks and reduction of built np edge formation which accelerates wear at the cutting edges by chipping and flaking. Minimum quantity lnbrication reduces deep notching and grooving, which are very detrimental and may cause premature and catastrophic failure of the cutting tools.

viii. Dimensional accuracy and surface finish has been substantially improved mainly due to reduction of wear and damage at the tool tip and also due to reduction in the average chip tool interface temperature by the application of MQL

ix. After adopting the Artificial Neural Network (ANN) model, the MQL system can enable significant improvement in productivity, product quality and overall machining economy even after covering the additional cost of designing and implementing MQL system.

5.2 Recommendations

i. In this research work, input parameters considered to develop the ANN model are cutting speed, feed rate, depth of cut and machining time. The work can be further extended considering more input parameters such as tool-chip interface temperature, machine vibration, cutting tool geometry, workpiece composition, workpiece hardness etc. Then the ANN model to predict tool wear and surface roughness will be more robust and universally applicable.

ii. In this work, only feed-forward neural network has been considered. The work can also be analyzed by recurrent neural network or radial basis functional neural network and then compared the prediction accuracy or generalization capability of different types of neural network.

iii. In this research work, only tool wear and surface roughness model have been constructed. The work can be also extended to model cutting force, chip thickness ratio and chip-tool interface temperature, as those are also significant machinability indices in any machining process to control or optimize quality, productivity and overall machining economy under a MQL environment.

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Appendix

Chip Thickness Ratio (r_c)

V, m/min	Depth of cut, d, mm																			
	1.00 mm										1.50 mm									
	Environment																			
	Dry					MQL					Dry					MQL				
	Feed rate, f, mm/rev					Feed rate. f, mm/rev					Feed rate, f, mm/rev					Feed rate, f, mm/rev				
	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20
68	0.28	0.31	0.38	0.4	0.43	0.35	0.37	0.41	0.47	0.49	0.28	0.32	0.36	0.38	0.39	0.31	0.35	0.41	0.43	0.44
95	0.33	0.35	0.42	0.45	0.47	0.39	0.4	0.44	0.49	0.51	0.31	0.35	0.39	0.42	0.44	0.35	0.37	0.44	0.46	0.49
133	0.37	0.4	0.46	0.49	0.51	0.43	0.45	0.47	0.52	0.55	0.35	0.39	0.43	0.46	0.48	0.39	0.42	0.47	0.49	0.53
190	0.42	0.45	0.54	0.57	0.59	0.49	0.52	0.56	0.6	0.63	0.4	0.44	0.48	0.49	0.51	0.45	0.46	0.52	0.54	0.56
266	0.49	0.53	0.58	0.64	0.66	0.57	0.59	0.62	0.68	0.71	0.44	0.49	0.52	0.55	0.57	0.51	0.53	0.56	0.58	0.60

Chip-tool Interface Temperature (θ)

V, m/min	Depth of cut, d, mm																			
	1.00 mm										1.50 mm									
	Environment																			
	Dry					MQL					Dry					MQL				
	Feed rate, f, mm/rev					Feed rate, f, mm/rev					Feed rate, f, mm/rev					Feed rate, f, mm/rev				
	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20
68	410	419	431	442	454	396	405	419	431	442	448	459	471	485	494	416	431	445	459	474
95	448	459	474	488	497	428	442	457	474	485	474	485	506	529	537	462	471	494	517	526
133	485	494	517	543	549	468	483	500	514	523	526	540	555	569	578	511	529	546	558	566
190	529	543	555	575	586	506	517	526	537	546	558	569	589	610	621	540	558	578	592	604
266	575	589	612	633	638	540	555	572	586	595	595	618	633	647	656	581	604	618	630	641

Main Cutting Force (F_c)

V, m/min	Depth of cut, d, mm																			
	1.00 mm										1.50 mm									
	Environment																			
	Dry					MQL					Dry					MQL				
	Feed rate, f, mm/rev					Feed rate, f, mm/rev					Feed rate, f, mm/rev					Feed rate, f, mm/rev				
	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20
68	387	441	525	615	625	311	352	416	511	553	538	629	690	774	817	457	525	650	722	773
95	379	422	500	586	623	299	332	400	466	529	522	582	665	753	805	456	517	620	711	766
133	367	378	459	534	576	299	325	375	434	476	488	568	654	724	757	430	492	612	699	743
190	321	360	448	531	565	277	311	366	429	469	481	532	619	676	717	422	479	568	657	715
266	299	341	401	489	536	271	303	336	425	470	450	500	561	639	698	401	463	544	644	690

Feed Force (F_f)

V, m/min	Depth of cut, d, mm																			
	1.00 mm										1.50 mm									
	Environment																			
	Dry					MQL					Dry					MQL				
	Feed rate, f, mm/rev					Feed rate, f, mm/rev					Feed rate, f, mm/rev					Feed rate, f, mm/rev				
	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20
68	214	229	236	246	270	149	162	175	190	201	300	305	327	347	372	238	252	273	285	312
95	189	202	206	226	238	132	143	157	164	178	271	278	292	310	332	218	228	240	253	289
133	158	163	173	185	202	114	125	132	142	148	233	250	263	273	292	189	201	214	223	264
190	132	138	147	154	168	91	102	110	115	122	207	210	222	238	252	164	179	186	195	222
266	104	109	114	118	132	75	84	90	92	101	177	176	184	196	209	134	148	160	173	194

Surface Roughness (R_a)

V, m/min	Depth of cut, d, mm																			
	1.00 mm										1.50 mm									
	Environment																			
	Dry					MQL					Dry					MQL				
	Feed rate, f, mm/rev					Feed rate, f, mm/rev					Feed rate, f, mm/rev					Feed rate, f, mm/rev				
	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20	0.10	0.12	0.14	0.18	0.20
68	1.80	1.90	1.98	2.12	2.40	1.18	1.36	1.56	1.75	2.24	1.6	1.68	2.10	2.19	2.24	1.10	1.29	1.45	1.84	1.96
95	1.62	1.76	1.86	1.98	2.24	1.10	1.30	1.43	1.51	2.1	1.48	1.56	1.90	2.00	2.12	0.98	1.11	1.34	1.72	1.81
133	1.42	1.48	1.56	1.68	1.88	0.88	1.01	1.17	1.28	1.79	1.34	1.40	1.74	1.84	1.96	0.94	1.11	1.24	1.49	1.69
190	1.26	1.32	1.40	1.54	1.68	0.84	0.98	1.02	1.12	1.5	1.14	1.20	1.38	1.64	1.72	0.85	0.93	1.00	1.30	1.56
266	1.10	1.18	1.26	1.38	1.55	0.72	0.84	0.94	1.02	1.32	1.00	0.98	1.13	1.48	1.54	0.70	0.79	0.88	1.04	1.36

Tool Wear and Surface Roughness (ANN Training Dataset)

Training Dataset									
Input condition vector	Input Parameter				Target condition vector	Output Parameter			
	V	f	d	t_c		VB	VM	VS	R_a
P1	66	0.1	1	0.5	T1	20	30	30	1.2
P2	66	0.1	1	1	T2	30	40	40	1.35
P4	66	0.1	1	2	T4	45	60	55	1.75
P5	66	0.1	1	5	T5	65	80	70	2.2
P7	66	0.1	1	11	T7	105	100	90	2.5
P8	66	0.1	1	14	T8	110	120	95	2.64
P9	66	0.1	1	18	T9	120	145	105	2.71
P11	66	0.1	1	24	T11	140	200	115	2.83
P13	66	0.1	1.5	1	T13	30	30	40	1.38
P14	66	0.1	1.5	1.5	T14	40	40	50	1.65
P15	66	0.1	1.5	2	T15	50	50	60	1.85
P17	66	0.1	1.5	8	T17	80	85	90	2.84
P18	66	0.1	1.5	11	T18	90	100	100	2.92
P19	66	0.1	1.5	14	T19	100	110	110	2.84
P20	66	0.1	1.5	18	T20	110	130	120	2.86
P21	66	0.1	1.5	22	T21	135	160	135	2.86
P23	258	0.2	1	0.5	T23	30	30	30	1.2
P24	258	0.2	1	1	T24	50	50	50	1.3
P25	258	0.2	1	1.5	T25	60	60	60	1.35
P27	258	0.2	1	5	T27	120	110	105	1.44
P28	258	0.2	1	8	T28	160	180	130	1.55
P30	258	0.2	1	14	T30	230	360	220	1.96
P31	258	0.2	1.5	0.5	T31	40	40	40	1.3
P32	258	0.2	1.5	1	T32	60	60	50	1.56
P34	258	0.2	1.5	2	T34	90	100	80	2.05
P35	258	0.2	1.5	4	T35	130	155	110	2.39
P36	258	0.2	1.5	6	T36	160	200	130	2.63
P37	258	0.2	1.5	8	T37	200	245	160	2.78

Tool Wear and Surface Roughness (ANN Testing Dataset)

Testing Dataset									
Input condition vector	Input Parameter				Target condition vector	Output Parameter			
	V	f	d	t_c		VB	VM	VS	R_a
P3	66	0.1	1	1.5	T3	40	50	45	1.65
P6	66	0.1	1	8	T6	85	90	80	2.35
P10	66	0.1	1	22	T10	130	180	110	2.73
P12	66	0.1	1.5	0.5	T12	20	0	30	1.25
P16	66	0.1	1.5	5	T16	70	70	75	2.58
P22	66	0.1	1.5	24	T22	155	180	150	2.95
P26	258	0.2	1	2	T26	70	70	70	1.4
P29	258	0.2	1	11	T29	190	260	165	1.67
P33	258	0.2	1.5	1.5	T33	75	80	60	1.85
P38	258	0.2	1.5	10	T38	250	310	220	2.9

Experimental and ANN Predicted Values of VB

Test cutting conditions*	V	f	d	t_c	VB (Exp)	VB (ANN)
1	66	0.1	1.5	0.5	20	15.7493
2	66	0.1	1	1.5	40	38.5753
3	66	0.1	1.5	5	70	71.6073
4	258	0.2	1	2	70	73.5195
5	258	0.2	1.5	1.5	75	75.9082
6	66	0.1	1	8	85	83.8691
7	66	0.1	1	22	130	139.4062
8	66	0.1	1.5	24	155	147.3347
9	258	0.2	1	11	190	202.3814
10	258	0.2	1.5	10	250	242.082

* Test cutting conditions for average principal flank wear, VB (Fig.3.9)

Experimental and ANN Predicted Values of VM

Test cutting conditions*	V	f	d	t_c	VM (Exp)	VM (ANN)
1	66	0.1	1.5	0.5	0	15.5852
2	66	0.1	1	1.5	50	50.903
3	66	0.1	1.5	5	70	69.9255
4	258	0.2	1	2	70	71.3545
5	258	0.2	1.5	1.5	80	81.6185
6	66	0.1	1	8	90	88.2417
7	66	0.1	1	22	180	178.7381
8	66	0.1	1.5	24	180	181.0299
9	258	0.2	1	11	260	280.9479
10	258	0.2	1.5	10	310	295.3626

* Test cutting conditions for maximum principal flank wear, VM (Fig.3.10)

Experimental and ANN Predicted Values of VS

Test cutting conditions*	V	f	d	t_c	VS (Exp)	VS (ANN)
1	66	0.1	1.5	0.5	30	24.6452
2	66	0.1	1	1.5	45	48.3019
3	66	0.1	1.5	5	60	66.7315
4	258	0.2	1	2	70	72.8378
5	258	0.2	1.5	1.5	75	80.3461
6	66	0.1	1	8	80	80.7794
7	66	0.1	1	22	110	125.3759
8	66	0.1	1.5	24	150	141.9225
9	258	0.2	1	11	165	170.6635
10	258	0.2	1.5	10	220	198.859

* Test cutting conditions for average auxiliary flank wear, VS (Fig.3.11)

Experimental and ANN Predicted Values of R_a

Test cutting conditions*	V	f	d	t_c	R_a (Exp)	R_a (ANN)
1	66	0.1	1.5	0.5	1.25	1.0656
2	66	0.1	1	1.5	1.4	1.3801
3	66	0.1	1.5	5	1.65	1.5702
4	258	0.2	1	2	1.67	1.5785
5	258	0.2	1.5	1.5	1.85	1.8274
6	66	0.1	1	8	2.35	2.3893
7	66	0.1	1	22	2.58	2.5105
8	66	0.1	1.5	24	2.73	2.547
9	258	0.2	1	11	2.9	2.5086
10	258	0.2	1.5	10	2.95	2.9301

* Test cutting conditions for surface roughness, R_a (Fig.3.12)

Matlab Code of ANN Model

```
clear all
close all;
clc;
p=[66,66,66,66,66,66,66,66,66,66,66,66,66,66,66,66,258,258,258,258,258,258,258,258,25
8,258,258,258;0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.2,0.2,0.2,0.2.
0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2;1,1,1,1,1,1,1,1,1.5,1.5,1.5,1.5,1.5,1.5,1.5,1.5,1,1,1,1,1,1,1.5.
1.5,1.5,1.5,1.5,1.5;0.5,1,2,5,11,14,18,24,1,1.5,2,8,11,14,18,22,0.5,1,1.5,5,8,14,0.5,1,2,4,6,
8]; %input
%.................................................................................................
t=[20,30,45,65,105,110,120,140,30,40,50,80,90,100,110,135,30,50,60,120,160,230,40,60.
90,130,160,200;30,40,60,80,100,120,145,200,30,40,50,85.100,110,130,160,30,50,60,110,
180,360,40,60,100,155,200,245;30,40,55,70,90,95,105,115,40,50,60.90,100,110,120,135,
30,50,60,105,130,220,40,50,80,110,130,160;1.2,1.35,1.75,2.2,2.5,2.64,2.71,2.83,1.38,1.65
,1.85,2.84,2.92,2.84,2.86,2.86,1.2,1.3,1.35,1.44,1.55,1.96,1.3,1.56,2.05,2.39.2.63,2.78];
%.................................................................................................
%Taking target data-set (4 Output Neurons:vb,vm,vs,Ra)
%plot of original data and untrained output
%figure(1);
%plot(p,t,'b+-')
%title('plot of original data and untrained Network output')
%.................................................................................................
[pn,minp,maxp,tn,mint,maxt]=premnmx(p,t); %Normalization of the data;pn = 2*(p-
minp)/(maxp-minp) - 1;
%.................................................................................................

net=newff(minmax(pn),[25,4],{'tansig','purelin'},'trainlm','learngdm','mse');
% Define Network Architecture
% To give better training results, Initialize the weights and biases, these values should be
small).
% net.LW{2,1}=net.LW{2,1}*0.01;
```

```
% net.b{2}=net.b{2}*0.01;
%Train the network and plot the Result
net.trainparam.goal=0.0001;          % sum-squarred error goal/performance goal;
net.trainparam.show=20;              % Frequency of progress display (in epochs);
net.trainparam.epochs=10000;         % Maximum number of epochs to train;
net.trainparam.lr=0.1;               % Network learning rate;
net.trainparam.mc=0.5;               % Momentum constant;
net=train(net,pn,tn);                % Training of the Network;
yn=sim(net,pn);                      % To see response to training data
[y]=postmnmx(yn,mint,maxt);          %p = 0.5(pn+1)*(maxp-minp) + minp;
%.....................................................................................

sz1=size(t);
for i=1:sz1(1)
   figure
   plot(t(i,:),y(i,:))
   [m(i),b(i),r(i)]=postreg(y(i,:),t(i,:))
   d(i,:)=[t(i,:)-y(i,:)]/t(i,:)*100;
   APE(i)=mean(abs(d(i,:)))
end
r_sqr1=r.*r
%.....................................................................................

% net=init(net);
% net=train(net,pn,tn);
% [y1]=postmnmx(yn,mint,maxt);
%[m,b,r]=postreg(y,t)                        % Judge by regression Analysis.
%d=t-y.^2;                                   % Error calculation
%mse=mean(d)
%figure(2);
%plot(p,t,p,y,'cd-')
%xlabel('Input Vector');
%ylabel('output');
```

```
%legend({'Input Vector','Desired output','test output'})
%title('Comparison between Actual Target and Predictions')
%.................................................................................................................................

% Testing of the Network

pnew=[66,66,66,66,66,66,258,258,258,258;0.1,0.1,0.1,0.1,0.1,0.1,0.2,0.2,0.2,0.2;1,1,1,1.5,
1.5,1.5,1,1,1.5,1.5;1.5,8,22,0.5,5,24,2,11,1.5,10];   % Test Input

tnew=[40,85,130,20,70,155,70,190,75,250;50,90,180,0.0,70,180,70,260,80,310;45,80,110,
30,75,150,70,165,60,220;1.65,2.35,2.73,1.25,2.58,2.95,1.4,1.67,1.85,2.9]          % Actual
Target
%.................................................................................................................................

pnewn=tramnmx(pnew,minp,maxp);
ynewn=sim(net,pnewn);            %Network is simulated to see its output
[ynew1]=postmnmx(ynewn,mint,maxt);
ynew=abs(ynew1)
sz=size(tnew);
for i=1:sz(1)
   figure
   plot(tnew(i,:),ynew(i,:))
   [m(i),b(i),r(i)]=postreg(ynew(i,:),tnew(i,:))
   d(i,:)=(tnew(i,:)-ynew(i,:))/tnew(i,:)*100;
   APE(i)=mean(abs(d(i,:)))
   %d(i,:)=d(i,:).*d(i,:);
   %mse(i)=mean(d(i,:));
end
r_sqr =r.*r
%.................................................................................................................................

%figure(3);
%plot(p,t,pnew,ynew,'bd--')
%title('Testing MLP Network');
```

```
%xlabel('Input Vector');
%ylabel('output');
%legend({'Input Vector','Desired output','test output'})
%title('Comparison between Actual Target and Predictions')
% An Alternative way to test training:post training Analysis
% [m,b,r]=postreg(ynew,tnew)    % Judge by regression Analysis.
% To calculate mse between actual and predicted values use:
% d=tnew-ynew.^2; % Error calculation
% mse=mean(d)
% for i=1:4
%    figure
%    plot(pnew(4,:),ynew(i,:),'--s','MarkerEdgeColor','k','MarkerFaceColor','g')
%      if i==1
%       hold
%    end
%    %d(i,:)=d(i,:).*d(i,:);
%    %mse(i)=mean(d(i,:));
% end
```