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Prediction of Tool Wear in Milling Process Using Artificial Neural Network Technique and Modal Analysis

A Project Report

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ABSTRACT

Milling is the process of cutting away material by feeding a work piece past a rotating multiple tooth cutter. This work deals a methodology of continuously and indirectly monitoring tool wear in milling operations. Tool wear influences of cutting conditions on tool life and surface finish in the milling process. In this work, Regression and Artificial Neural Network models have been developed to predict tool wear and surface roughness in the milling process. There are many parameters affect tool wear such as cutting speed, feed rate and depth of cut. By controlling these machining parameters, the tool wear can be minimized and the surface finish can be improved.

Experiments have been conducted in CNC vertical machining center based on Design of Experiment (Three Factors – Five Level design matrix). The co-efficient values of regression model are derived using DOE PCIV Six sigma software. With the help of the measured values of tool wear and surface roughness, the ANN model feed forward back propagation network type has been trained. The simulated user interface is used to predict the tool wear and surface roughness.

The percentage of error in tool wear is found to be 0.875 % in ANN model and 2.217 % in regression model. Also the percentage of error in surface roughness is 0.956 % in ANN model and 2.011 % in regression model .It is found that Neural Network model is more accurate and faster in predicting tool wear and surface roughness than the regression model. Modal analysis has been developed to determine the frequency of the milling cutter assembly. It is used to select the operating frequency of cutter in order to reduce the deflection of cutter.

ஆய்வு சுருக்கம்

Work Piece – ஐ சுழலும் Multiple cutter எதிராக உட்செலுத்தும் போது Material –ஐ வெட்டும் செயல் முறை Milling எனப்படும். இந்த திட்ட பணியானது Milling operation –ல் தொழிற்கருவி தேய்மானத்தை தொடர்ச்சியான மற்றும் மறைமுகமாக கண்காணிக்கும் முறையை ஆராய்கிறது. Milling செயல்முறையில் கருவி தேய்மானமானது கருவி காலம் மற்றும் (சர்வேல் ∴ப்னிஷ்) வெட்டு காரணங்களில் வினைவை ஏற்படுத்துகிறது. இந்த பணியில் , மில்லிங் செய்முறையில் கருவி தேய்மானம் மற்றும் surface roughness யை முன்பே அறிய , மின்னடைவு மற்றும் செயற்கை நரம்புச்சார்ப ஒருங்கிணைவு மாதிரியானது. உருவாக்கப்பட்டது , கருவி தேய்மானத்தை பாதிக்கும் காரணிகனாவன வெட்டும் வேகம் , உட்செலுத்தும் வீதம் , மற்றும் வெட்டும் ஆழம் இந்த காரணிகளை கட்டுப்படுத்துவதன் மூலமாக கருவி தேய்மானம் குறைகிறது மற்றும் Surface finish மேம்படுத்தப்படுகிறது.

செய்முறை வரைபட மென்பொருளை உபயோகித்து , (கணினி மயமாகப்பட்ட இயந்திரத்தில் செய்முறையானது கட்டுப்படுத்தப்பட்டது. **DOE PCIV** Six – Sigma மென் பொருளை பயன்படுத்தி பின்னடைவு மாதிரியின் குனக மதிப்புகனானது பெறப்பட்டது. கருவி தேய்மானம் மற்றும் surface roughness –ன் எடுக்கப்பட்ட மதிப்புகளை பயன்படுத்தி செயற்கை நரம்புச்சார்ப ஒருங்கிணைவு மாதிரிக்கு பயிற்சி அளிக்கப்பட்டது. கருவி தேய்மானம் மற்றும் surface roughness – யை முன்பே அறிய , simulated user interface பயன்படுத்தப்பட்டது. செயற்கை நரம்புச்சார்ப ஒருங்கிணைவு மாதிரியில் கண்டறியப்பட்ட கருவி தேய்மானத்தின் பிழைவீதம் 0.875% மற்றும் பின்னடைவுமாதிரியில் கண்டறியப்பட்ட கருவி தேய்மானத்தின் பிழைவீதம் 2.217% . இதை போல் செயற்கை நரம்புச்சார்ப ஒருங்கிணைவு மாதிரியில் கண்டறியப்பட்ட surface roughness –ன் பிழைவீதம் 0.956% மற்றும் பின்னடைவு மாதிரியில் கண்டறியப்பட்ட surface roughness –ன் பிழைவீதம் 2.011% இதிலிருந்து கருவி தேய்மானம் மற்றும் surface roughness மதிப்பானது. பின்னடைவு மாதிரிரய விட செயற்கை நரம்புச்சார்ப ஒருங்கிணைவு மாதிரியில் துல்லியமாக இருக்கும் . மில்லிங் கட்டர் அசம்பினி –ன் அதிர்வை கண்டறிய மாதிரி ஆராய்ச்சியானது. உருவாக்கப்பட்டது cutter –ன் வியக்கத்தை குறைக்க பொருத்தமான அதிர்வை தேர்ந்தெடுக்க மாதிரி ஆராய்ச்சியானது உபயோக்கப்பட்டது.

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LIST OF ABBREVATIONS

ANN	-	Artificial Neural Network
DOE	-	Design of Experiments
MLP	-	Multi Layer Perception
ANOVA	-	Analysis of Variance
LMS	-	Least Mean Square
IGES	-	Initial Graphics Exchange Specification
DOC	-	Depth of Cut

Chapter 1

Introduction

1.1 BASIC CONSIDERATION OF TOOL WEAR

In machining of parts, good surface finish is one of the most specified customer requirements, and less tool wear is one of the ways for an industry to reduce its manufacturing cost. Hence these factors have to be controlled and should be kept within the desired limits for any machining process. So if the input machining parameters are controlled, simultaneously the output variables like tool wear and surface finish would be controlled within the desired limit. It is always desirable to know these output process variables in advance for a specific combination of input process variables, so that appropriate combination of machining parameters can be chosen for the process to get the most efficient output responses. But it is very difficult to know the process responses for a specific combination of selected machining parameters. There is the process models play an important role and can be used to address these issues. In order to maximize the manufacturers gains from utilizing the manufacturing process, an accurate model must be constructed of the process. The same has been developed in this project work for the milling process with speed, feed and depth of cut as input machining parameters and tool flank wear and surface roughness as output variables.

1.2 MILLING PROCESS

Milling is the process of cutting away material by feeding a work piece past a rotating multiple tooth cutter. The cutting action of the many teeth around the milling cutter provides a fast method of machining. The machined surface may be flat, angular, or curved. The surface may also be milled to any combination of shapes. The machine for holding the work piece, rotating the cutter, and feeding it is known as the Milling machine.

Milling is used in the metal work industry and defined as the process of cutting, shaping, and finishing a piece of metal. It is one of several metalworking processes that include turning, welding, and fringing. Milling is used when more complex metal shapes are desired. The process is used to create a number of metal parts and structures on everything from rings and bracelets to bridges and freight ships. Typically, milling involves cutting away pieces of metal to create dovetails, threads, bevels, slots, and ridges. The grooved edges of coins are a simple example of the milling process.

Milling operation is performed in milling machine, which consist of a cutter that rotates on an axis similar to a drill bit and an adjustable worktable upon which the metal is placed. Accessory parts include a vise or clamping kit that attaches the metal to the worktable, a digital scale, and a point master. The cutter is fixed into position and can only move up and down, while the worktable is able to move up and down as well as side-to-side and front to back. In most cases a single cutter is used; however, it is possible to simultaneously use several cutters at the during the milling process.

The rotating cutter is used to cut the metal. There are several types of cutters or mills including end mills, facing mills, and form mills - each serving a different purpose. For example, end mills cut slots and pockets; face mills cut flat surfaces; form mills are used for milling dovetails and bevels in metal. The three most important factors in the milling process are rotation speed, the cutting depth and the sending speed, or the rate at which metal is fed to the cutter.

There are three different types of milling machines: vertical, horizontal, and a combination of the two. Vertical and horizontal milling machines are most commonly used. In a vertical milling machine, the cutter is mounted on a vertical axis; on a horizontal milling machine, it is mounted on the horizontal axis.

Milling machines are either manually operated or numerically controlled by computer numerical control in a process referred to as CNC. CNC milling machines are most often associated with vertical milling machines. They are more precise, yet able to maintain a slow speed, which makes them a cost effective alternative to hand engraving also.

1.3 PROCESS MODELS

Process models are the one, which can predict the output (responses of a process) for a specific combination of input variables used in the machining process. Reliable processes are extremely important in different fields of computer-integrated manufacturing. They are required for selecting optimal process parameters during process planning, for designing and implementing adaptive control systems or model based monitoring algorithms. A number of reasons back the required models like optimization of processes, control of processes, simulation of processes and design of processes, and design of experiment etc

The following two techniques have been used to develop the process model:

1. Design of Experiments and

2. Artificial Neural Network

The design of experiments is one of the statistical analysis technique widely used to develop the statistical mathematical models. This work has dealt with regression based mathematical models development. Another technique used was artificial neural network technique, which is one of the popularly used artificial intelligence method to develop models.

Because of their model free estimation, uncertainty handling and learning abilities, artificial neural networks (ANNs) are frequently used for modeling of machining parameters. Hence it is used in this work for modeling of machining parameters in milling process and is compared with the regression based mathematical model developed based on design of experiments technique.

1.3.1 Design of Experiments

An experiment is a series of trials or tests produces quantifiable outcomes. The experiment may be random or deterministic. A scientific approach to planning of experiments must be incorporated in order to perform an experiment efficiently. The statistical design of experiments or experimental design suits this need.

Design of experiments is a powerful technique, which involves the process of planning and designing an experiment so that appropriate data can be collected and then analyzed by statistical methods, resulting in objective and valid conclusions. It is an alternative to a one factor – at – a – time approach to experimentation, where an experimenter generally varies one factor or process parameter at a time keeping all other factors at a constant level. In one-at-a-time design, numerous experiments are performed at many different values of that factor, while all other factors are held constant at some reasonable values. This process is then repeated for each of the other factors, in turn. It is a time consuming strategy and costly and also results in a less than optimal solution to a problem, despite the extra work and consequent expense. Here the statistical design of experiments comes as a perfect replacement for the classical one-at-a-time experimental method. One of the most important characteristics of the statistical design of experimentation is that it would take into account if there were any interactions between the factors (i.e.) if the effect of one factor depends on the

level of one or more of the other factors. But for these the one-at-a-time experiments would lead to wrong conclusions. The merit of the statistical design is that the total number of experiments is reduced resulting in less cost for experimentation.

The statistical design of experiments is employed to fulfill the following requirements:

1. To get the uniformly distributed over the whole range of controllable factors to be investigated.
2. To establish a relationship between different input variables and the output parameters accurately within the selected range of investigation
3. To reduce the total number of experiments resulting in less time consumption and the cost of experimentation.

1.3.2 Artificial Neural Network (ANN)

Work on artificial neural networks, commonly referred to, as "Neural Network" has been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, non-linear and parallel computer. It has the capability to organize its structural constituents, known as neurons, to perform certain computations many times faster then the fastest digital computer in existence today. In its most general from, a neural network is a machine that is designed to model the way in which the brain performs a particular task or functions of interest; the network is usually implemented by using electronic components or is simulated in software on a digital computer. The neural network performs useful computations through a process of learning. To achieve good performance, neural networks employ a massive interconnection of simple computing cells referred to as "neurons" or "processing units".

A neural network is a massively parallel-distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network, from its environment through a learning process.
2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights, of the network in an orderly fashion to attain a desired design objective. The modification of synaptic weights provides the traditional method for the design of neural networks.

1.3.3 Benefits of Neural Networks

It is apparent that a neural network derives its computing power through, first, its massively parallel distributed structure and second, its ability to learn and therefore generalize. Generalization refers to the neural network producing reasonable outputs for inputs not encountered during training or learning. These two information-processing capabilities make it possible for neural networks to solve complex problems that are currently intractable.

The use of neural networks offers the following useful properties and capabilities:

1. Nonlinearly
2. Input-Output Mapping
3. Adaptively
4. Evidential Response
5. Contextual Information
6. Fault Tolerance.
7. Uniformity of Analysis and Design.
8. Neurobiological Analogy.

1.4 TOOL WEAR MECHANISMS

The tool wear are of different types and they occur due to a lot of reasons during the machining process. The tool wear mechanisms describe about the tool wear phenomenon, region of occurrence in the tool and the reasons associated with the specific wear. The types of tool wear mechanisms are as follows:

1. Adhesive wear associated with shear plane deformation,
2. Abrasive wear resulting from hard particles cutting action,
3. Diffusion wear occurring at high temperature, and
4. Fracture wear such as chipping due to fatigue.

The two major predominant wear mechanisms are

1. Flank wear
2. Crater wear.

1.4.1 Flank Wear

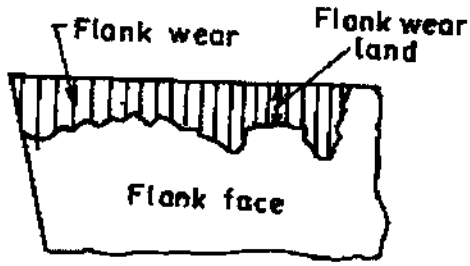

FIGURE 1.1 FLANK WEAR

Flank wear occurs on the relief face of the tool as shown in Figure 1.1 and is mainly attributed to the rubbing action of the tool on the machined surface. Flank wear is determined by measuring the maximum distance (termed V_{Bmax}) between the top of the tool edge and the bottom of the worn surface.

1.4.2 Crater wear

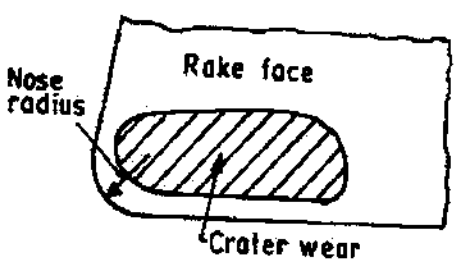

FIGURE 1.2 CRATER WEAR

Crater wear occurs on the rake face of the tool as shown in Figure 1.2 and changes the chip-tool interface, thus affecting the cutting process.

1.4.3 Role Of Flank Wear In Tool Life Evaluation

The flank wear is a predominantly occurs in multiple point cutting tool, so the tool life of a particular tool used in machining process depends upon the

amount of flank wear occurred at the time of measurement, but the crater wear is prevalent only under certain cutting condition (i.e.,) higher cutting speeds and feeds leads to more crater wear, in this case tool life is evaluated by means of crater wear, as the flank face of the cutting tool having a rubbing action against the work piece materials. The surface finish of the work piece machined mostly depends upon the amount of flank wear (i.e.,) if the amount of flank wear increases that leads to reduction in nose radius of the cutting tool, which in turn reduces the surface finish. In this thesis the flank wear only considered to evaluate the tool condition during the machining process.

1.5 SURFACE ROUGHNESS

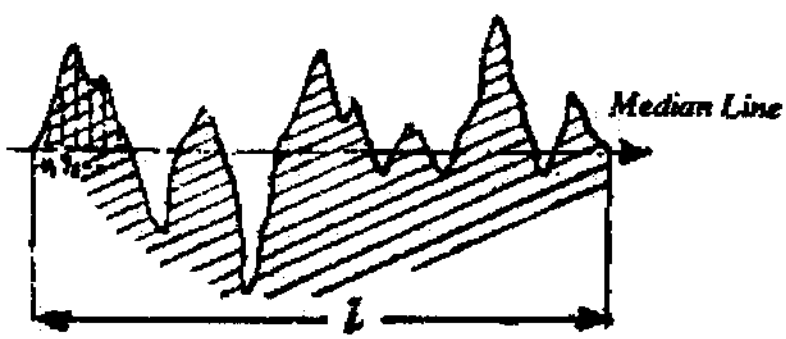

FIGURE 1.3 SURFACE ROUGHNESS

The accurate characterization of surface texture involves the definition of parameters that quantify be surface topographical or geometrical features. It includes several features present in a part's surface profile; roughness, waviness, lay and flaws as shown in Figure 1.4. Roughness is comprised of the randomly distributed surface irregularities, extending over the whole area, on a microscope scale. It is mainly attributed to the action of the machining process. Waviness, characterized by height variations at a given spatial frequency, is the more widely spaced component of surface texture. It results from such factors as machine or work deflections, vibrations, and tool chatter. The lay of a surface is the direction of the predominant surface pattern and is usually determined by the machining method used. Flaws are mentionable irregularities, which occur at one location or at relatively infrequent intervals on the surface, arising from accidental damage either during or the surface generation.

Spatial parameters derived directly from the surface profile, are commonly used to characterize textural properties of various machined surface. Amplitude parameters R_a (centre-line average) and R_q (RMS average) are the most widely used and are essentially the same.

Frequency parameters, derived by decomposing the surface profile into a number of periodic components of different wavelengths and amplitudes are used to reveal more information about the machining process. Using a discrete Fourier transformation commonly carries out the decomposition procedure.

The stylus profilometer has traditionally been used the surface roughness measurement in an industrial clean room. All the national and international standards are defined in terms of the measurements produced by this instrument. However, due to the direct physical contact required to produce the surface profile, it damages the surface (particularly soft materials). Also, line sampling of the data limits its repeatability and ability to accurately describe the surface characteristics.

1.6 MODAL ANALYSIS

Modal analysis to determine the vibration characteristics (natural frequencies and mode shapes) of a structure or a machine component while it is being designed. It also can be a starting point for another, more detailed, dynamic analysis, such as a transient dynamic analysis, a harmonic response analysis, or a spectrum analysis.

1.6.1 Model Generation

The ultimate purpose of a finite element analysis is to recreate mathematically the behavior of an actual engineering system. In other words, the analysis must be an accurate mathematical model of a physical prototype. In the broadest sense, this model comprises all the nodes, elements, material properties, real constants, boundary conditions, and other features that are used to represent the physical system.

The term model generation usually takes on the narrower meaning of generating the nodes and elements that represent the spatial volume and connectivity of the actual system. Model generation in this discussion will mean

the process of defining the geometric configuration of the model's nodes and elements.

1.6.2 Expand the Modes

The term "expansion" to mean writing mode shapes to the results file. That is, "expanding the modes" applies not just to reduce mode shapes from the reduced mode-extraction method, but to full mode shapes from the other mode-extraction methods as well. Thus, if you want to review mode shapes in the postprocessor, you must expand them to the results file.

1.6.3 Review the Result

Post processing means reviewing the results of an analysis. It is probably the most important step in the analysis, because you are trying to understand how the applied loads affect your design, how good your finite element mesh is, and so on.

Chapter 2

Literature Review

Chattopadhyay (1996) has used neural network for evaluation of wear in carbide inserts. He has taken speed, feed, and depth of cut as input parameters to develop the model. The feed forward back propagation artificial neural network has been used and the model results come closer to the actual values. He has suggested that the accuracy of the model can be improved by increasing the number of nodes in the hidden layer.

Choudhary (1999) predicted tool wear using neural network and design of experiments. He analyzed the role of temperature in tool wear. He used the experimental data from the conducted experiments as per design of experiments methodology and developed a regression model and neural network model. In his work, he has considered temperature along with other machining parameters like feed and cutting speed as input parameters and tool wear as the output parameter. His results prove that the neural network model is the better model. But one limitation in his work is that he has not considered tool geometry as a input parameter.

Viktor (2003) has selected a tool life criterion to determine the diametric accuracy of machining, its stability and reliability. Flank wear of cutting tool is to contact conditions at tool flank – work piece interface and to evaluate the physical process of wear. To analyze through the experimental assessment of different characteristic of flank wear in contact stresses. He conformed the minimum tool wear occurs at the optimum cutting speed. But one limitation is limiting amount of energy that can be transmitted through the cutting wedge until it fails.

Prabhakaran et al (2000) have developed multiple regression models and group method data handling model (GMDH) for predicting tool wear in milling process. They utilized cutting temperature, cutting force, rack angle along with cutting speed and feed as process variables to develop the models. Experiments were conducted on mild steel specimens using carbide inserts. They have suggested that the tool wear values could be predicted with the help of cutting conditions and tool geometry to a reasonable accuracy using different modeling techniques.

Zuperl (2000) has proposed a methodology for modeling of cutting conditions during machining by using artificial neural network. He has also devised device a method for the optimization of the cutting conditions by an algorithm. He has described how the neural network can be trained with the data and also elaborated on the training procedure. He has recommended an algorithm for searching the optimum parameters. His paper deals with a multiple objective optimization of cutting parameters. His procedure could be used for the fast approximate determination of optimum cutting conditions on the machine, when there is not enough time for deep analysis.

Nadgir (2002) `developed a back propagation neural network model to predict tool wear on chamfered and honed Carbide cutting tools for a range of cutting conditions. He found that the developed neural network model results were satisfactory and correlate well with the experimental results.

Filho (2002) has to study the influence of cutting conditions – cutting speed, feed velocity and feed per tooth – on tool life and surface finish of the work piece in the milling of flat surfaces. Several milling experiments were carried out with different cutting speeds, feed velocities and feeds per tooth. Tool flank wear and surface roughness of work piece were measured as cutting time elapsed. Cutting speed has a strong influence on tool life whether feed velocity or feed per tooth vary and increase in surface roughness of work piece is not closely related to an increase in wear of cutting edge

Wang (2002) suggested an exponential model for surface roughness including cutting time, work piece hardness, cutting tool point angle, feed, and cutting speed and depth of cut. He conducted testing and used regression analysis to develop a complete empirical model of surface roughness for traditional milling.

Feng (2003) has compared regression models with back propagation feed forward neural network model by using sparse experimental data obtained for traditional milling of aluminum 6061 and ANSI 8620 steel. His results indicate that back propagation neural network model provides better predictions for all of

the cutting conditions. However, he concluded that regression model might perform better when experimental data generated from experimental design.

Ozel (2003) has developed exponential regression model and neural network model to predict surface roughness and tool wear in finish hard turning using Carbide tools. In the work, material hardness, Carbide content in tool material, cutting speed, feed and cutting time have been considered as the process parameters and has found their influence on tool wear and surface finish. He has compared the neural network model with regression model and found that the ANN model provided better prediction capabilities because they generally offer the ability to model more complex non-linearity's and interactions than linear and exponential models.

Chapter 3

Design of Experiments

3.1 INTRODUCTION

The design of experiments is one of the statistical analysis technique widely used to develop the statistical mathematical models. This work has dealt with regression based mathematical models development.

3.2 SELECTION OF PROCESS PARAMETERS FOR EXPERIMENTATION

This is the first step in process of developing the mathematical model. This step deals with the selection of the input parameters that has to be used during the experimentation. These input parameters would vary depending upon the problem that is handled. The input variables have to be chosen depending upon the output responses that is to be considered. The process parameters are those, which affect the output variables to some considerable extent. Normally there would be a lot of process variables that might affect the output variables. But only a limited number of parameters which substantially influence the responses of the process have to be chosen so as to avoid the state of considering many input parameters which marginally affect the output and not useful thus resulting in more experimental cost and more time consumption without leading into profitable results. Usually "screening of experiments "is a strategy used for this purpose. Screening experiments are extremely useful for separating out the "vital few" factors from the "trivial many". The idea of performing such an experiment is to reduce the number of factors or key variables to a manageable number in a limited number of experimental trials.

It is not a good practice to conduct a large experiment involving many factors or process variables. If none of the factors or process variables is significant, the experiment would then be a waste of time and money. Screening experiments are widely accepted in industries for screening out the key factors, which influence the quality characteristic of a product from a large number of factors. For example, one may be able to study seven factors using just eight experimental trials.

Usually the process of identifying the important process variables is also done by the experimenter's previous experience in that particular field. It reduces the cost and time consumption. It is advisable not to invest more than 25 percent

of the experimental budget in the first phase of experimentation such as screening. By this experimental scheme, one may be able to develop the regression based mathematical model that depicts the relationship between the key process variables and the process response. This model can then be used to predict the values of the responses at different variable settings.

In this work, the selected machining process, input parameters and responses were as follows:

Machining process : CNC milling process.

Input parameters : Cutting speed (m/min), Feed (mm/rev), Depth of cut (mm),

Responses : Tool wear (mm) and Surface finish (Microns)

3.3 FINDING THE RANGES AND LEVELS OF PROCESS VARIABLES

The limits of the process variable have to be found out after finding the important process variables that are to be used for experimentation. The limits are known as the working range of the experimentation. The upper and lower limits of the process variables have to be found out within which the experiment has to take place. The selection of the limits of the process variables follows with the choosing of the number of levels within the limits of the variables. Normally the levels of the variables chosen vary from two to five within the experimental region. Choosing two levels would be appropriate if the experimental region is short and if the response of the process is a linear function. It is not advisable to choose two levels if the response would be a curvilinear function and if the experimental region is large. Five levels have always to be selected if the vast experimental region has to be covered and to get accurate results. Usually the upper limits and the number of levels of the process variables are chosen by conducting trial runs by changing one of the process variables and keeping the constant. The process variable values considered have to be converted into coded values to form the design matrix table and to conduct the experiment as per the design.

3.3.1 Machine specification

Type	: CNC machining center (BMV 45 AGNI)
Axis	: Vertical axis machine
Power	: 5.5/7.5 Kw
Speed	: 6000 rpm
Table clamping Area	: 450 mm X 900 mm
Maximum Load	: 500 Kg
Feed rates	: 1-1000 mm/min
Type of control	: Servo motor
Spindle bore	: 80 mm

In the present work, the following are the working ranges of the process variables:

Cutting speed, V = 280 - 920 m/min.

Feed rate, F = 0.12 - 0.25 mm/rev.

Depth of cut, D = 0.7 - 2.3 mm.

After selecting the working range of the experimentation, the intermediate process variables are selected and all the actual variables are converted into the coded variables.

3.3.2 Equation for finding coded variables

The equation for finding the coded variables of the actual variables is as in Equation (3.1) and Equation (3.2)

$$\text{Coded Value} = \frac{\text{Value under consider} - \text{Average Value}}{(\text{Upper Limit} - \text{Lower Limit})/2} \qquad (3.1)$$

The above equation is written as follows

$$X_i = \frac{2[2X - (X_{max} + X_{min})]}{X_{max} - X_{min}} \qquad (3.2)$$

Where,

X_i = required coded value of a variable X,

X = any value of the variable from X_{min} to X_{max},

X_{min} = lower limit of the variable,

X_{max} = upper limit of the variable.

Five levels were chosen and the upper limit is coded as +1.682 and the lower limit is coded as -1.682. The coded level for the intermediate values is determined as +2, ,0 and -2 as in Table 3.1.

TABLE 3.1 THREE MACHINING PARAMETERS AND FIVE LEVELS

Level	Cutting Speed m/min	Feed rate mm/rev	Depth of Cut mm
-1.682	280	0.12	0.7
-1	400	0.14	1.0
0	600	0.18	1.5
+1	800	0.22	2.0
+1.682	920	0.25	2.3

3.4 DEVELOPMENT OF DESIGN MATRIX

The next step in the methodology is to select a design matrix. The design matrix is a table, which contains the coded values, which corresponds to the actual variables. The design matrix shows the combination of input parameters to be used for each experimental run. The design matrix plays an important role in experimentation for it decides the number of experiments to be conducted and the best suitable combination of experiments so that sufficient results are obtained in less number of experiments for analyzing it to get valid conclusions.

Factorial design is a standard statistical tool to conduct the experiment in an optimal way. The most important advantage of this design is that the number of parameters is simultaneously studied for a deeper insight into the combined effects of the parameter on the response. In addition to that the interaction between two or more parameters can also be evaluated which is not possible with the conventional experimental approach since in that approach all parameters, other than the one investigated is held constant.

The experimental plan is to first choose fixed number of levels for each of the parameters and then experiments are conducted with all possible combination

of the factors. The simplest and the most economical factorial design is a two level factorial experiment consisting of 2^k experimental runs in which every factor is fixed at two levels and all the combinations of k factors are used. It can be suitably augmented to form composite designs if a more thorough local exploration is needed and the interpretation of the results produced by the design can proceed largely by common sense and elementary arithmetic.

However, the number of runs required by a full 2^k factorial design increases geometrically as k is increased. This factorial experiment has a great surplus number of trials involving wastage of time and money. Under such conditions it is possible to use only part of the full factorial design for achieving reductions in experimental runs i.e. fractional factorial design and the concept of confounding. This would be at the expense of information such as the effect of the combined interaction of all factors that is not very significant in constructing linear models. Apart from two level factorial designs, response surface designs are employed in the empirical study of relationships between one or more measured response variables and a number of independent or controllable variables of a process.

The relationship between response and control variables is almost always polynomial of the second order because the second order designs are well devised. Besides, second order responses lend themselves to detect optimum conditions with ease. To describe second order polynomials, the factors in experimental design should take at least three different values. A three level factorial experiment in which possible combinations of k factors at all levels are used is called a 3^k full factorial design. Such designs involve large observations even when k is greater than S, and the coefficient of the squared terms are estimated relatively with low precision.

Wilson had developed new designs specially for fitting second order response surfaces called central composite rotatable designs which are constructed by adding further treatment combinations to those obtained from a 2^k factorial. The total number of observations is reduced significantly by employing these designs. Each design consists of a two level factorial box 2^k augmented by replicated experiments at the center point and symmetrically located star points. For 2 through 4 factors, the central box I a full factorial design. For 5 or more factors it becomes a half factorial designs. The center point is replicated to provide a measure of experimental error and hence in using second order rotatable design

no replications is needed in order to find error mean square. Rotatable design means that the standard error of the experimental response at any point on the fitted response is the same for all points that are at the same distance from the center of the region.

The Central composite design is constructed as per the following procedure:

Step 1: Construct a complete or factorial 2^k factorial layout, describing on the need for efficiency and the ability to ignore interaction effects.

Step 2: Add 2^k axial or star points along the coordinate axes. Each pair of star points is denoted using coded levels as follows:

$(\pm a, \quad 0, \quad 0)$

$(\ 0, \quad \pm a, \quad 0)$

$(\ 0, \quad 0, \quad \pm a)$

Where "a" is a constant, which can be chosen to make the design rotatable or to satisfy some other desirable property.

Step 3: Add "m" repeat observations at the deign center:

(0, 0.... 0)

Step 4: Randomize the assignment of factor level combinations to the experimental units or to the run sequence, whichever is appropriate.

The total number of test runs in a central composite design based on a complete 2^k factorial is $n = 2^k + 2k + m$. Most central composite designs would require five levels of each factor $(0, \pm 1, \pm a)$.

The selected design matrix for experiments in Table 3.2 is a three factors five levels central composite rotatable design consisting of 20 sets of coded conditions. The design for the above said model comprises a fill replication of 2^3 (=8) factorial design plus 6 center points and 6 star points

TABLE 3.2 DESIGN MATRIX

Ex no	Cutting speed	Feed rate	Depth of cut
1	-1	-1	-1
2	-1	-1	1
3	-1	1	-1
4	-1	1	1
5	1	-1	-1
6	1	-1	1
7	1	1	-1
8	1	1	1
9	-1.682	0	0
10	+1.682	0	0
11	0	-1.682	0
12	0	+1.682	0
13	0	0	-1.682
14	0	0	+1.682
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
20	0	0	0

3.5 EXPERIMENTAL DETAILS

The experiments have to be conducted as per the design matrix table. The combination of process parameters in each experimental run and the number of experiments to be conducted corresponds to the design matrix table. The responses of the experiments for each combination of process parameters have to be recorded for analyzing it and for developing the mathematical model.

In this work, the experiments were conducted in the vertical axis CNC milling machine. The milling operations were carried out on rectangular slab work pieces made of EN 28 steel. Tungsten coated carbide inserts were used as the tool material for machining the work pieces. The experimental details are as given below:

3.5.1 Work piece specification

Work piece material : AISI 4340 steel (or) EN 24 steel

Length of the work piece : 100 mm

Width of the work piece : 100 mm

Height of the work piece : 60 mm

3.5.2 Composition of the work piece material:

The chemical composition of the work piece as shown in table 3.3

TABLE 3.3 WORK PIECE COMPOSITIONS

C	Mn	Si	Ni	Mo	Cr
0.35/0.45	0.45/0.75	0.10/0.35	1.3/1.8	0.25/0.35	0.90/1.40

3.5.3 Cutting tool specification

Tool material : Tungsten coated carbide

Make : Sandvik

Type : CNMG

Tool holder Make : WIDAX-LS Tool holder

Type : PCLNR

The experiments were performed for different combination of machining parameters as per the central composite design matrix. Apart from the 20 experiments as in the design matrix and addition of 5 more experiments were performed for using those to validate the mathematical model and train the artificial neural network. The experiments were performed under wet cutting conditions using coolants to aggravate tool wear. The milling processes were conducted on the work piece over a length of 100 mm by width of 100 mm and the height of 50 mm is machined. A simple contour section to 75 X 75 X 10 mm in each work piece.

3.6 CALIBARATION

The responses tool flank wear and surface roughness of the experiments were recorded. The tool flank wear is calibrated using tool makers

microscope and the Surface roughness is measured by profilometer. The surface roughness values were recorded at eight equally spaced locations around the circumference every 25 mm distance from the edge of the specimen.

3.6.1 Tool maker's microscope specification

Type	:	Digital microscope.
Magnification factor	:	Maximum of 150 X
Least count	:	0.001 mm
Field of view	:	8 mm diameter
Working distance	:	80 mm (approx)
Image	:	Errect image
Observation tube	:	Monocular inclined at 30 degrees.
Measuring stage	:	150 * 150 mm size travel up to 50 mm in each direction.
Eye piece protractor	:	Graduated 0 to 360 degree with adjustable Vernier
Illumination	:	Build in base transmitted from halogen lamp and incident light from two lamps
Stand	:	Large and heavy base provide extra over all rigidity.

3.6.2 Profilometer specification

Profilometer make	: Taylor habson surtonic 3+ profilometer
Surface analyzer make	: Mitutoyo sj surface analyzer
Type	: Digital analyzer
Type of filter	: M1 band pass filter.
Trace length	: 4.8 mm
Cut off length	: 0.8 mm

TABLE 3.4 RESPONSES MEASURED

Ex.no	Cutting speed	Feed	Depth of cut	Tool wear (mm)	Surface roughness (microns)
1	-1	-1	-1	0.152	2.08
2	-1	-1	1	0.157	2.11
3	-1	1	-1	0.172	2.32
4	-1	1	1	0.199	2.42
5	1	-1	-1	0.155	1.76
6	1	-1	1	0.182	2.42
7	1	1	-1	0.172	1.85
8	1	1	1	0.222	1.93
9	-1.682	0	0	0.144	2.45
10	+1.682	0	0	0.194	1.51
11	0	-1.682	0	0.131	2.36
12	0	+1.682	0	0.217	2.46
13	0	0	-1.682	0.155	1.51
14	0	0	+1.682	0.198	1.74
15	0	0	0	0.16	1.94
16	0	0	0	0.159	1.96
17	0	0	0	0.157	1.95
18	0	0	0	0.159	1.93
19	0	0	0	0.158	1.95
20	0	0	0	0.158	1.96

Chapter 4

Regression Based Mathematical Model

4.1 CALCULATION OF THE COEFFICIENTS OF THE POLYNOMIAL

This step deals with the development of mathematical models. A mathematical model is the one which shows the relationship between the input and output variables. In the process models it relates the input process variables to the response variables of the process. Hence it is able to predict the response of the process for the input variables considered.

In many problems there are two or more variables that are related, and it's important to model and explore this relationship. In general, if there is a single dependent variable or response 'Y' which depends on 'K' independent variables such as x_1, x_2.....x_k, the relationship between these variables are characterized by a mathematical model called regression equation. The regression model is obtained using a set of experimental data. In some instances, the experimenter knows that exact form of true relationship between y and x_1, x_2.....x_k, i.e. $y=f(x_1, x_2.....x_k)$ but in most cases the true functional relationships is unknown and the experimenter chooses an appropriate function. Polynomial models are widely used as approximating functions and normally second order polynomial is used to form mathematical models.

The second order model for four selected factors is as in Equation (4.1) and (4.2)

$$Y = B_0 + \sum_{i=1}^{3} B_i X_i + \sum_{i=1}^{3} B_{ii} X_i^2 + \sum \sum_{i<j} B_{ij} X_i X_j . \qquad (4.1)$$

$$Y = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + + B_{11}X_1^2 + B_{22}X_2^2 + B_{33}X_3^2 + B_{12}X_1X_2 + B_{13}X_1X_3 + B_{23}X_2X_3 \qquad (4.2)$$

Where,

Y	- represents the response,
X_1, X_2, X_3	- represents the coded values of the process parameters
B_0, B_1, B_2, etc	- represents the regression co-efficient to be determined.

In this work the input process variables were cutting speed, feed, depth of cut and nose radius. The responses were tool flank wear and surface roughness.

Hence the relationship between these input and response variables were to be found out by developing a regression based mathematical model.

Hence, X_1, X_2, X_3 – Coded values of cutting speed, feed, and depth of cut respectively.

Y_1, Y_2 – Tool wear and surface roughness respectively.

The coefficients of the polynomials such as B_0, B_1, B_2, etc have to be determined for the development of the regression based mathematical model. Substitution of the determined coefficients in the polynomial Equation 4.3 to Equation 4.6 gives the required model for the process. Once the model is formed, the coded values of the actual process variables have to be substituted in the equation to get the predicted response of the process.

The values of the coefficients of the polynomial equation are as follows:

$$B_0 = 0.142857 \sum Y - 0.035714 \sum \sum (X_{ii} Y) \quad (4.3)$$

$$B_1 = 0.041667 \sum (X_i Y) \quad (4.4)$$

$$B_2 = 0.03125 \sum (X_{ii} Y) + 0.035714 \sum \sum (X_{ii} Y) - 0.035715 \sum Y \quad (4.5)$$

$$B_3 = 0.0625 \sum (X_{ij} Y) \quad (4.6)$$

In this work the values of the regression coefficients are calculated using six sigma software. It is statistical analysis software that can be used to create statistical mathematical models. The coefficient values for tool wear and surface finish from the six sigma software are shown in Table 4.1

4.1.1 Coefficient values for models

TABLE 4.1 COEFFICIENT VALUES

Coefficients	Tool wear model values	Surface roughness model values
B_0	0.171	1.774
B_1	0.016	-0.177
B_2	0.023	0.267
B_3	0.010	0.078
B_{11}	-0.001	0.035
B_{12}	-0.001	0.000
B_{13}	0.001	-0.001
B_{22}	0.001	0.033

4.2 CHECKING THE ADEQUACY OF THE MODEL

The adequacy of the mathematical model has to be tested as per analysis of the variance (ANOVA) technique. As per this technique:

1) The calculated value of the F - ratio of the model developed should not exceed the standard tabulated value of F – ratio for a desired level of confidence (say 95%).

2) The calculated value of the R- ratio of the model developed should exceed the standard tabulated value of the R- ratio for a desired level of confidence (say 95%).

If the above conditions are satisfied then the model is considered as adequate within the confidence limit.

4.2.1 Adequacy of developed models

The following are the F- ratio and R- ratio values in developing the tool wear and surface roughness models:

Model F - ratio value = 2.21

Table F- ratio value for (8, 5, 0.05) = 4.82

Model R - ratio value =9.42

Table R- ratio value for (20, 5, 0.05) =4.56

Here the calculated tool wear model F- ratio value (2.21) is less than the table F-ratio value (11.24) and the calculated R- ratio value (9.42) is more than the table R- ratio value (4.56)

These results are as per the rules of the ANOVA technique. Hence the tool wear model can be considered as adequate.

4.3 DEVELOPMENT OF THE REGRESSION MODELS AND CHECKING THE CORRELATION

This step deals with the development of the final mathematical model. The value of the regression coefficients gives an idea as what extent the control variables affect the responses quantitatively. The less significant coefficients can be eliminated along with their responses with which they are associated, without affecting much of the accuracy of the model. To achieve these students t-test was used. As per this test, when the calculated value of t corresponding to a coefficient exceeds the standard tabulated value for the desired level of confidence limit, the coefficient becomes significant. The elimination of the insignificant coefficients is known as backward elimination criteria. After finding the significant coefficients, the final model is to be developed using only these significant coefficients.

In this work the mathematical models were developed for tool wear and surface roughness by substituting the values of the determined coefficients in the second order polynomial equation. Then the backward elimination was used to find the significant parameters and to develop the final mathematical model.

4.3.1 Mathematical model for tool wear

The regression mathematical model for tool flank wear is as in Equation (4.7)

$$\text{Tool wear (mm)} = 0.171 + 0.017A + 0.025B + 0.01C + 0.001A*A + 0.001C*C - 0.002\,A*B + 0.002B*C \quad (4.7)$$

Where,

A – Coded value of cutting speed in m/min

B – Coded value of feed in mm/rev

C – Coded value of depth of cut in mm

The mathematical model developed as per the regression coefficients were then analyzed for most significant coefficients. The backward elimination of 0.75

criterions was used for determining the significant coefficients. Six sigma software was used for this technique.

The final mathematical model after backward elimination of 0.75 probability criterions is as in Equation (4.9)

Tool wear equation in (mm)

$$Y = 0.171 + 0.017A + 0.025B + 0.01C + 0.001A*A + 0.001C*C - 0.002A*B + 0.002B*C \quad (4.8)$$

4.3.2 Mathematical model for surface roughness

The regression mathematical model for surface roughness is as in Equation (4.9):

Surface roughness (microns) = $1.774 - 0.177\ A + 0.267\ B + 0.078\ C + 0.035\ A^2 + 0.033\ B^2 + 0.014\ C^2 - 0.001\ A * C - 0.001\ B * C$ (4.9)

The final mathematical model after backward elimination of 0.75 probability criterion is as in Equation (4.10):

Surface roughness (microns) = $1.774 - 0.177\ A + 0.267\ B + 0.078\ C + 0.035\ A^2 + 0.033\ B^2 + 0.014\ C^2 - 0.001B*C$ (4.10)

4.3.3 Finding the Coefficient Of Correlation of the Regression Models

The coefficient of correlation "r" which is used to find how close the expected and observed value lies can be calculated by Equation (4.11):

$$R^2 = \frac{\sum (P - \acute{Y})}{\sum (O - \acute{Y})} \quad (4.11)$$

Where,

R = Coefficient of correlation.

P = Predicted value from the developed model.

O = Observed value of the response variable from the experiments.

Ý = Average experimental value.

The coefficient of correlation of the tool wear model is as follows:

Average experimental value Ý=0.152

Observed value of response from experiments O =0.147

Predicted value from the developed model P =0.150

Hence, Coefficient of correlation of the tool wear model R = 96.3

The Coefficient of correlation of the surface roughness model is as follows:

Average experimental value $\acute{Y}$=1.32

Observed value of response from experiments O =1.27

Predicted value from the developed model P =1.24

Hence, Coefficient of correlation of the surface roughness model R = 98.2

Finally the developed mathematical model can be checked by substituting the input process parameters to find the output of the model The models predicted value have to be compared with the actual experimental value to find the error percentage. Normally the validation of the mathematical model is done by substituting the input variables of the experiments, which were not used to develop the mathematical model, and verifying the model results with the actual results. The actual variables have to be converted into coded variables if they are to be used in the mathematical models.

The percentage of error of the model value can be found by Equation (4.12)

$$\%Error = \frac{ActualValue - \Pr edictedValue}{ActualValue} X100 \qquad (4.12)$$

The predicted values by the regression model were compared with the actual values and their % of error was calculated. They are shown in Table 4.2 and Table 4.3

TABLE 4.2 COMPARISON OF ACTUAL AND MODEL TOOL WEAR VALUES

Ex no	Actual tool wear (mm)	Predicted tool wear using Regression model (mm)	% of error
1	0.152	0.148	2.631
2	0.173	0.171	1.156
3	0.201	0.195	2.985
4	0.155	0.159	2.580
5	0.180	0.175	2.777
6	0.222	0.225	1.351
7	0.144	0.145	0.861
8	0.132	0.128	2.310
9	0.155	0.157	1.296
10	0.168	0.171	1.785
11	0.165	0.171	3.636
12	0.17	0.171	0.588
13	0.169	0.171	1.183
14	0.168	0.171	1.785
15	0.167	0.171	2.395

TABLE 4.3 COMPARISON OF ACTUAL AND MODEL SURFACE ROUGHNESS VALUES

Ex no	Actual surface roughness (microns)	Predicted surface roughness using Regression model (microns)	% of error
1	1.99	1.95	2.010
2	2.03	1.99	1.971
3	2.46	2.38	3.252
4	1.57	1.52	3.184
5	1.82	1.86	2.197
6	2.44	2.40	1.639
7	1.24	1.20	3.225
8	2.42	2.48	2.479
9	2.45	2.42	1.224
10	1.26	1.22	3.174
11	1.55	1.51	3.205
12	1.82	1.77	2.527
13	1.80	1.77	1.444
14	1.84	1.77	3.586
15	1.82	1.77	2.527

4.4 VALIDATION OF REGRESSION MODELS

The developed regression models have to be validated for their performance. The validation has to be done by testing the model for the experimental values, which were not used to develop the mathematical model. Hence, in this work the developed model was tested for the additional experiments as shown in Table 4.4 and Table 4.5

4.4.1 Validation of tool wear model

TABLE 4.4 TOOL WEAR MODEL VALIDATION

Ex no	Actual tool wear (mm)	Model tool wear (mm) using Regression model	% of error
1	0.156	0.151	3.204
2	0.170	0.165	2.941
3	0.192	0.186	3.125
4	0.219	0.213	2.716
5	0.197	0.191	3.045

The coefficient of correlation of the tool wear model for the validation values are

Average experimental value $\acute{Y}$=0.187

Observed value of response from experiments O =0.192

Predicted value from the developed model P =0.186

Hence, Coefficient of correlation of the tool wear model R = 91.32

4.4.2 Validation of surface roughness model

TABLE 4.5 SURFACE ROUGHNESS MODEL VALIDATION

Ex no	Actual surface roughness (microns)	Model surface roughness using Regression model (microns)	% of error
1	2.32	2.26	2.586
2	2.46	2.41	2.032
3	1.72	1.76	2.325
4	1.84	1.77	3.586
5	1.82	1.77	2.527

The coefficient of correlation of the surface roughness model for the validation values are

Average experimental value $\acute{Y}$= 2.03

Observed value of response from experiments O =1.84

Predicted value from the developed model P =1.77

Hence, Coefficient of correlation of the surface roughness model R = 94.25

The validation results show that the predicted values of the regression model come close to the actual experimental values. The adequacy of the model is also as per the ANOVA rule and the coefficient of correlation is found to be satisfactory. Hence the developed model can be used to predict the tool wear and surface roughness.

Chapter 5

Prediction of tool wear using ANN

5.1 INTRODUCTION

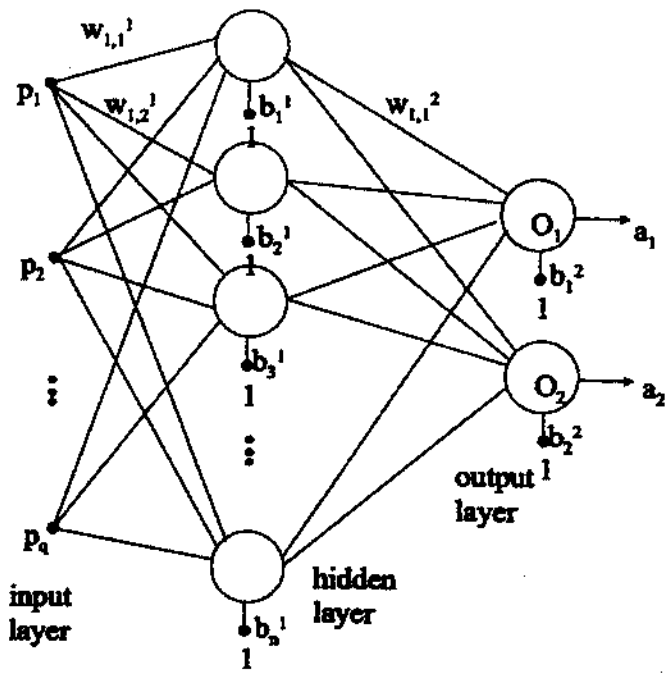

FIGURE 5.1 ANN GENERAL STRUCTURES

Neural Networks are non-linear mapping systems that consist of simple processors, which are called neurons, linked by weighted connections. Each neuron has inputs and generates an output that can be seen as their reflection of local information that is stored in connections. The output signal of a neuron is fed to other neurons has input signals via interconnections. Since the capability of a single neuron is limited, complex functions can be realized by connecting many processing elements. Network structure, representation of data, normalization of inputs and outputs and appropriate selection of activation functions etc. are the factors that have strong influence on the performance of the Network. They are biologically inspired, as they are composed of elements that perform in a manner that is analogous to the most elementary functions of the biological neurons.

An artificial neural network generally consists of three layers namely

(1)Input layer

(2)Hidden layer and

(3)Output layer.

A multilayer perception (MLP) consisting of three layers is as shown in Figure 5.1. Inputs are applied at the first layer (input layer) as p_i and outputs are obtained at the last layer (output layer) as a_i. Learning is achieved when the associations between a specified set of input-output (training examples) pairs $\{(p_1,t_1), (p_2, t_2), \ldots\ldots (p_Q, t_Q,)\}$ are established. Internal layers are called hidden layers there may be more than one hidden layer. A multilayer perception trained with the back propagation algorithm may be viewed as a practical way of performing a non linear input – output mapping of a general nature.

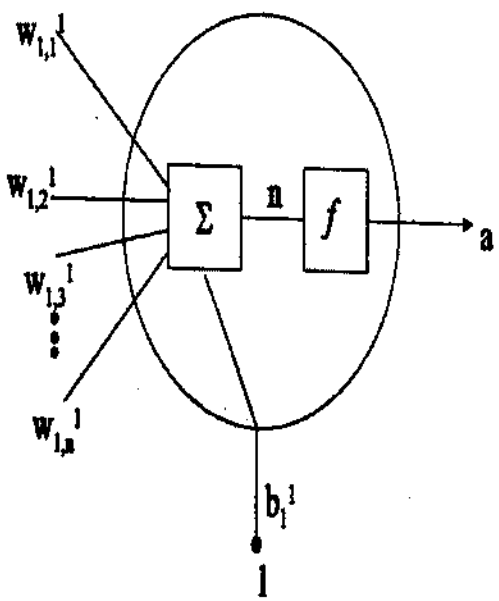

FIGURE 5.2 MODEL OF A NEURON

A neuron is an information-processing unit that is fundamental to the operation of a neural network. The block diagram as showed in figure 5.2 shows the model of a neuron, which forms the basis for designing neural networks. Here we identify three basic elements of the neuronal model:

A set of synapses or connecting links, each of which is characterized by a weight or strength of its own. Specifically, a signal x_j at the input of synapse j connected to neuron k is multiplied by the synaptic weight w_{kj}.

An adder for summing the input signals, weighted by the respective synapses of the neuron; the operations described here constitutes a linear combiner.

An activation function for limiting the amplitude of the output of a neuron. The model also includes an externally applied bias, denoted by b.

5.2 TRAINING OR LEARNING METHOD

All learning methods used for adaptive neural networks can be classified into two major types as supervised and unsupervised learning.

5.2.1 Supervised learning

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

5.2.2 Unsupervised learning

This learning uses no external teacher and is based on local information. Paradigms of unsupervised learning are Hebbian learning and competitive learning. The neural network learns offline if the learning phase and the operation phase are distinct. A neural network learns online if it learns and operates at the same time. Usually, supervised learning is performed offline, whereas unsupervised learning is performed online. There is no teacher use to check the error associated with the actual outputs of the neural network. The neural network itself does the determination and comparison, not by the teacher, to guide whether the learning process has been accomplished.

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

By knowing some topology and the learning properties of a neural network, one can determine whether a specific neural network, one can determine whether specific neural network architecture is appropriate for a problem. Using

the back-propagation learning procedure for GT, the initial weights of connections are generated at random, and an input vector representing the shape or envelope of a standard part propagates forward through the entire network to compute the output of each neuron in the hidden and output layer.

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

5.3 BACK PROPAGATION ALGORITHM

The term back propagation is used to imply a backward pass of error to each internal node within the network, which is then used to calculate weight gradients for that node. Learning progresses by alternately propagating forward the activations and propagating backward the instantaneous errors.

Back propagation is a supervised error-correcting learning algorithm. It realizes a gradient descent in error. A simpler version of propagation the simple delta rule or the perception convergence layer can be proven to find a solution for all input-output mappings which are realizable in that simple architecture.

A back propagation network consists of at least three layers of units namely, an input layer, at least one intermediate hidden layer, and a output layer. Typically units are connected in a feed forward fashion with input units fully connected to the units in output layer. When a backdrop network is cycled, an input pattern is propagated forward to the output units through the intervening input to hidden and hidden to output units. Back drop networks can adapt their weights to acquire knowledge. With back prop networks, learning occurs during a training phase in which the each input pattern in a training set is applied to the

input units and then propagated forward. The pattern of activation arriving the output layer is then compared with the correct output pattern to calculate an error signal. The error signal for each such target output pattern is then back propagated from the outputs to the inputs in order to approximately adjust the weights in each layer of the network. After back prop has learned the correct classification for the set of inputs, it can be tested on a second set of inputs to see how well it classifies untrained patterns, thus an important consideration in applying back prop learning is how well the network generalizes.

5.3.1 Feed forward dynamics

When a back propagation network is cycled, the activations units are propagated forward to the output layer through the connecting weights. It is as per Equation (5.1) and Equation (5.2).

$$net_j = {}_I w_{ji} a_i \qquad (5.1)$$

Where, a_i is the input activation from I and w_{ji} is the weight connecting unit I to j. However, instead of calculating the binary output, the net input is added to the units bias and the resulting value is passed through a sigmoid function:

$$f(net_j) = 1 / (1+e^{-net_{jj}^{+}}) \qquad (5.2)$$

The bias term plays the same role as the threshold in the perceptron. But unlike binary output of the perceptron, the output of a sigmoid is a continuous real value between 0 and 1, the sigmoid function is sometimes called squashing function because it maps its inputs onto a fixed range.

5.3.2 Gradient descent

Learning in a back propagation network is in two steps. First each pattern I_P is presented to the network and propagated forward to the output. Second, a method called gradient descent is used to minimize the total error on the patterns in the training set. In gradient descent , weights are changed in propagation to the negative of the error derivative with respect to each weight.

Weight move in the direction of steepest descent on the error surface defined by the total error as in Equation (5.3)

$$E = \tfrac{1}{2} {}_{pj}(t_{pj} - o_{pj})^2 \qquad (5.3)$$

Where o_{pj} be the activation of output unit u_j in the response to pattern p and t_{pj} is the target output value for unit u_j.

After the error on each pattern is computed, each weight is adjusted in proportion to the calculated error gradient back propagated from the outputs to the inputs. The changes in the weight reduce the overall error in the network.

5.4. ANN MODEL DEVELOPMENT METHODOLOGY

The following steps describe the methodology in developing the ANN model:

Step 1 : Create network and input values of hidden neurons and desired output.

Step 2 : Initialize the weights and the bias term.

Step 3 : Calculate net input to hidden layer units.

Step 4 : Calculate the net input to each output unit.

Step 5 : Calculate the output , error term and RMS value.

Step 6 : If the RMS value is not equal to the desired value , update the weights between input and hidden layer and between hidden and output layer. Continue training until the desired accuracy is reached.

5.4.1 Creating the network

Creating the network is the first step in the development of the ANN. The function "newff" creates a feed forward network. The training function used was "traingd".

net = newff ([ ],{ 'tansig' , 'purelin', }, 'trainlm');

This command creates the network object and initializes the weights and biases of the network; therefore the network is ready for training.

5.4.2 Initializing weights

Before training the network, the weights and biases must be initialized. The newff command will automatically initialize the weights, but to reinitialize them the "init" command is used.

net = init (net):

This function takes a network object with all the weights and biases initialized.

5.4.3 Simulating the network

The function "sim" simulates the network. "sim" takes the network input 'P' and the network object net, and returns the network outputs 'a'.

a = sim (net, p).

5.4.4 ANN program

```
%creates new network
net1 = newff([ 0 inf; 0 inf; 0 inf; 0 inf], [30 2], {'tansig ', 'purelin'}, 'trainlm');
net2 = newff([ 0 inf; 0 inf; 0 inf; 0 inf], [10 2], {'tansig ', 'purelin'}, 'trainlm');
net3 = newff([ 0 inf; 0 inf; 0 inf; 0 inf], [40 2], {'tansig', 'purelin'}, 'trainlm');
%intialise weights to random values
net1 = init(net1);
net2 = init(net2);
net3 = init(net3);
%set training parameters
net1.trainParam.show = 20; %display after every 2 iteration
net1.trainParam.lr = 0.05; % learning rate 0.05
net1.trainParam.epochs = 1000; %number of iterations
net1.trainParam.goal = 1e-6;  %goal is net error
net2.trainParam.show = 20;  %display after every 2 iteration
net2.trainParam.lr = 0.05;   % learning rate 0.05
net2.trainParam.epochs = 1000; %number of iterations
net2.trainParam.goal = 1e-6;    %goal is net error
net3.trainParam.show = 20;    %display after every 2 iteration
net3.trainParam.lr = 0.05;   % learning rate 0.05
net3.trainParam.epochs = 1000; %number of iterations
net3.trainParam.goal = 1e-6;    %goal is net error
%train with given data
net1 = train(net1,fInp,fTrg);
net2 = train(net2,fInp,fTrg);
net3 = train(net3,fInp,fTrg);
```

5.4.5 Training the network

Once the network weights and biases have been initialized, the network is ready for training. During training the weights and biases of the network are iteratively adjusted to minimize the network performance "net.performfcn"

The structure of the developed ANN is shown in Figure 5.3 and the training parameters used are given below:

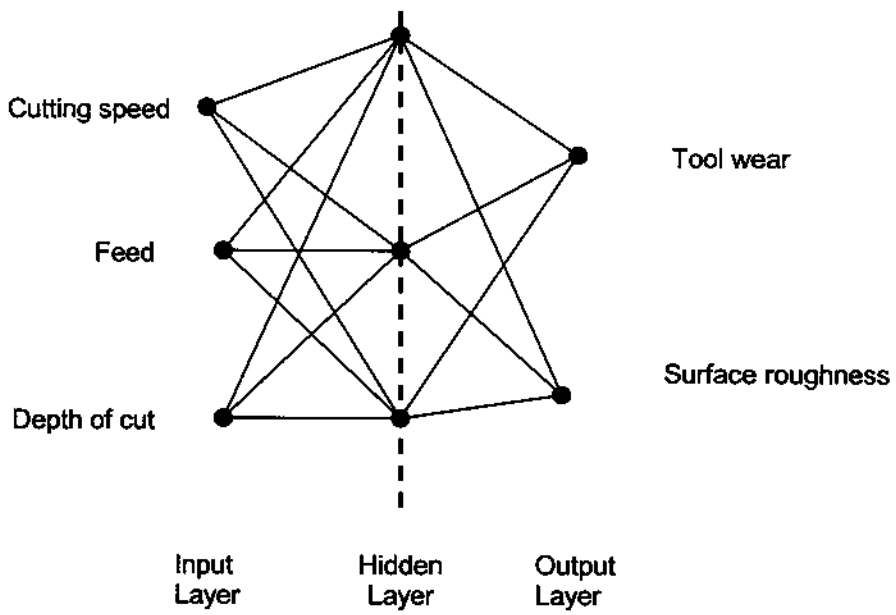

FIGURE 5.3 ANN MODEL STRUCTURE

Number of input nodes	: 3 nodes
Number of hidden nodes (Feed forward)	: 10, 20, and 30 nodes
Number of hidden nodes (Radial basis)	: 111(nodes)
Number of output nodes	: 2 nodes
Type of learning method	: Supervised learning.
Algorithm	: Back propagation
Learning rule	: Gradient descent rule.
Number of learning patterns used	: 20
The leaning parameter used	: 0.5
Number of epochs	: 1000

The number of input parameters in the work was three namely cutting speed, feed, and depth of cut. Hence they were the three input nodes used and the numbers of output nodes were two as tool wear and surface roughness were the two responses of the present work.

The number of hidden nodes depends upon the accuracy of the model. The accuracy of the model increases as the number of nodes in the hidden layer is increased. In the present work feed forward networks with 10, 20and 30 hidden layers were developed. Their performance is as in Figure 5.4 to Figure 5.6.

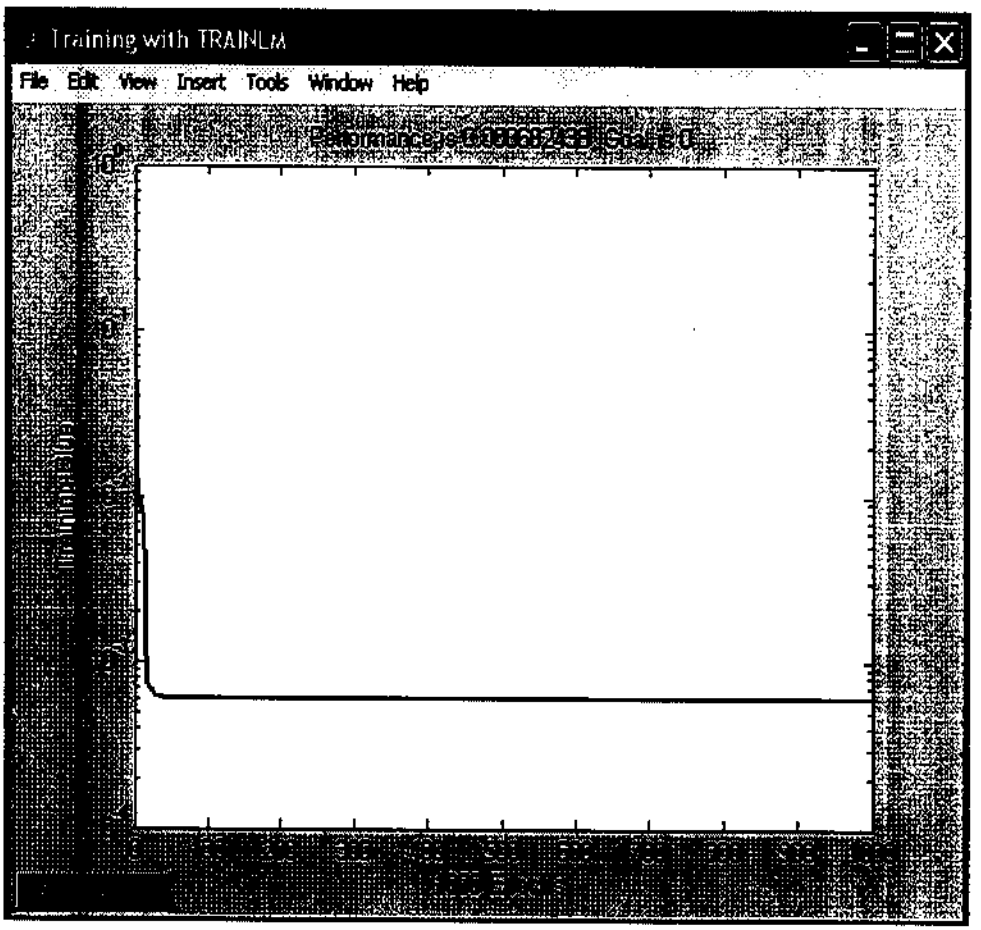

FIGURE 5.4 ANN TRAINING GRAPH (10 NODES)

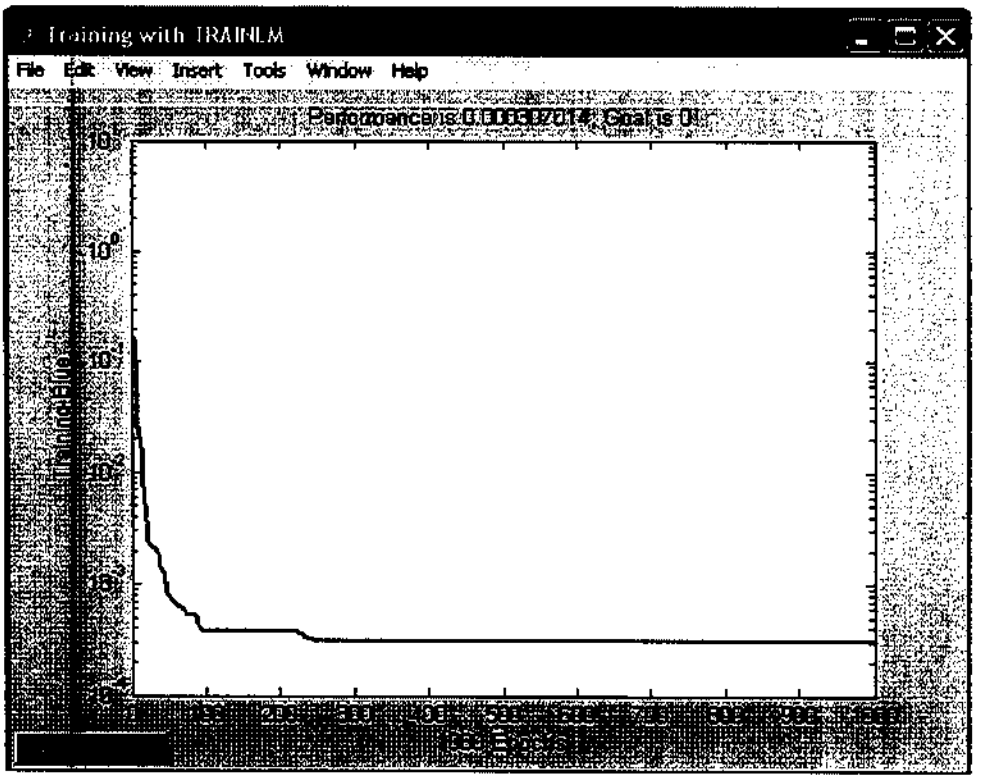

FIGURE 5.5 ANN TRAINING GRAPH (20 NODES)

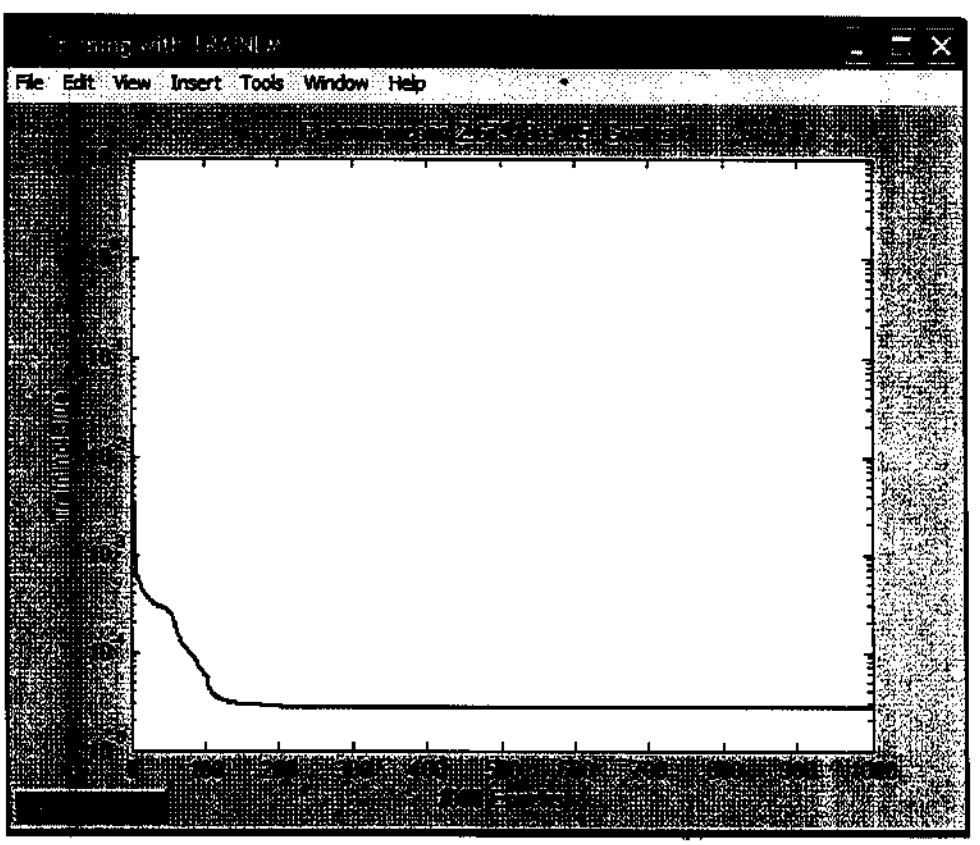

FIGURE 5.6 ANN TRAINING GRAPH (30 NODES)

5.5 ANN SIMULATION BY SIMULINK

The ANN simulation was done using simulink tool in the matlab software. Initially a user interface for the developed ANN model was developed. The ANN simulation can be done by entering the input variables in the developed user interface. Running the simulation gives the predicted results of he developed ANN model for the corresponding inputs entered.

The Figure 5.6 shows the developed ANN model with 30 nodes in the hidden layer. It shows the network connections from the nodes of the input layer to the nodes of the hidden layer and the weights associated with it.

The Figure 5.6 shows the user interface which is used to run the simulation of the developed ANN model. It shows the input and output variables associated with the model. A combination of input variables can be entered in the user interface to get their output by running the simulation. The Figure 5.6 shows the developed feed forward ANN models with 10, 20 and 30 nodes. A radial basis model was also developed as shown.

The prediction Values of each of the models can be obtained by running the simulation. The value of ANN modeled tool wear and surface finish in Table 5.1 & 5.2

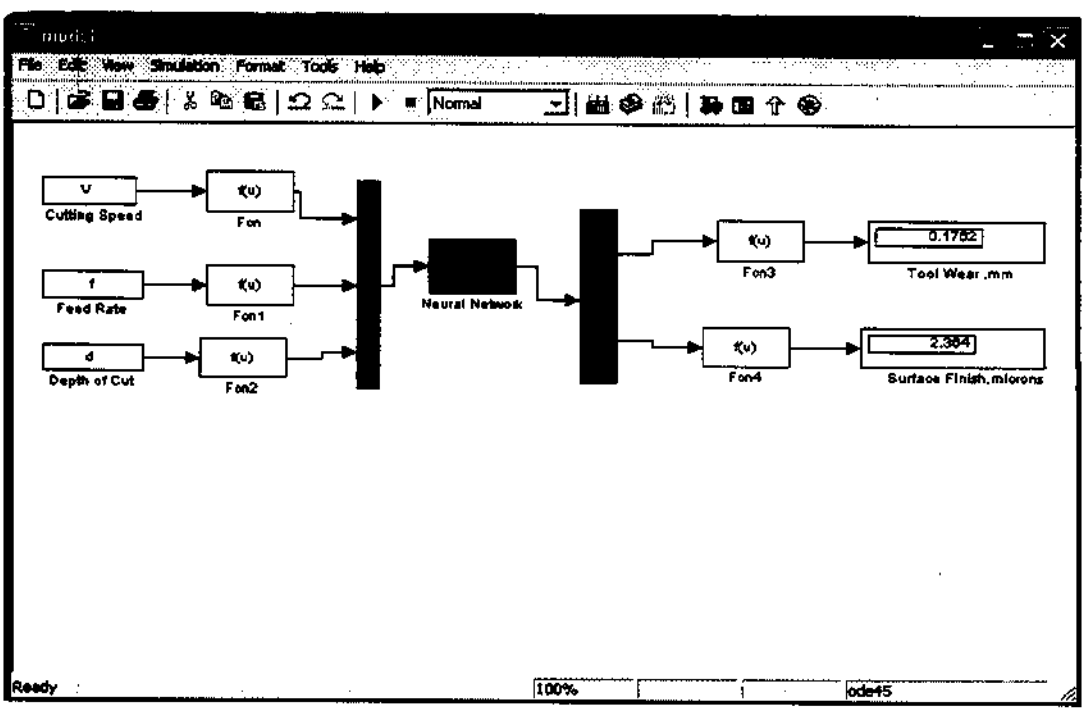

FIGURE 5.7 ANN USER INTERFACE

TABLE 5.1 COMPARISON OF ACTUAL AND MODEL TOOL WEAR VALUES

Ex no	Actual tool wear (mm)	Predicted tool wear using ANN model (mm)	% of error
1	0.152	0.149	1.973
2	0.173	0.172	0.578
3	0.201	0.199	0.995
4	0.155	0.153	1.290
5	0.180	0.182	1.111
6	0.170	0.172	1.17647
7	0.222	0.222	0
8	0.192	0.194	1.041
9	0.155	0.157	1.290
10	0.197	0.197	0
11	0.157	0.158	0.636
12	0.159	0.158	0.628
13	0.156	0.158	1.282
14	0.159	0.158	0.628
15	0.160	0.158	1.250

TABLE 5.2 COMPARISON OF ACTUAL AND MODEL SURFACE ROUGHNESS VALUES

Ex no	Actual surface roughness (microns)	Predicted surface roughness using ANN model (microns)	% of error
1	1.99	2.020	1.507
2	2.03	2.065	1.724
3	2.32	2.347	1.163
4	1.57	1.593	1.464
5	2.46	2.481	0.853
6	1.82	1.823	0.164
7	2.44	2.468	1.147
8	1.24	1.260	1.612
9	1.26	1.264	0.317
10	1.55	1.567	1.096
11	1.82	1.848	1.538
12	1.84	1.848	0.434
13	1.82	1.848	1.538
14	1.84	1.848	0.434
15	1.83	1.848	0.983

5.6 ANN MODEL VALIDATION

The validation of ANN developed model was done by testing the predicting accuracy of the model with the experimental values that were not used to train the model. In this work, feed forward ANN model with three different numbers of nodes in hidden layer and one radial basis network were used. It was found that as the number of nodes increase in the hidden layer, the accuracy of the model was improved. The feed forward ANN model with 20 and 30 hidden layer nodes were found accurate. The radial basis network model was also found satisfactory. Hence those models were taken for validation.

The Table 5.1 and Table 5.2 show the comparison of actual and ANN model values for tool wear and surface roughness respectively.

TABLE 5.3 VALIDATION OF ANN TOOL WEAR

Ex. No.	Actual value of Tool wear (mm)	ANN model value (mm)	% of Error
1	0.156	0.157	0.641
2	0.144	0.145	0.694
3	0.132	0.131	0.757
4	0.219	0.217	0.913
5	0.157	0.158	0.628

As shown in Table 5.3, five experimental values of tool wear which were not in the training set of data were used to validate the developed ANN model. The most accurate model with 30 nodes in the hidden layer was used for validation. The average error rate in validation was found as 0.726 %. Hence the developed model is accurate.

As shown in Table 5.4, five experimental values of surface roughness which were not in the training set of data were used to validate the developed ANN model. The most accurate model with 30 nodes in the hidden layer was used for validation. The average error rate in validation was found as 0.766%.

TABLE5.4 VALIDATION OF ANN SURFACE ROUGHNESS

Ex. No.	Actual value of surface roughness (microns)	ANN value of surface roughness (microns)(30 nodes)	% of Error (30 nodes)
1	2.460	2.480	0.813
2	1.720	1.717	0.853
3	2.420	2.400	0.826
4	2.450	2.467	0.693
5	1.860	1.848	0.645

This shows that the predicted value of surface roughness by the ANN model comes closer to the actual values. Hence the developed model is accurate.

Chapter 6

Results and discussion

6.1 COMPARISON OF ANN AND REGRESSION MODELS

TABLE 6.1COMPARISONS OF TOOL WEAR MODELS

Ex no	% of Error in Regression model	% of Error in ANN model
1	2.985	0.995
2	1.156	0.578
3	2.310	0.757
4	2.716	0.913
5	1.183	0.636

TABLE6.2 COMPARISONS OF SURFACE ROUGHNESS MODELS

Ex no	% of Error in Regression model	% of Error in ANN model
1	3.252	0.813
2	2.032	0.853
3	2.479	0.826
4	1.444	0.645
5	2.527	0.983

The developed ANN models and regression models were compared for their predicated capabilities .for comparison, the error percentage of the ANN models in predicting the validation values were compared with error percentage of the regression models for that value.

The table 6.1 & 6.2 shows the comparison of the models in predicting tool wear and surface roughness values. The predicted values of both the regression

and ANN models come close to the actual values .The predicted values of both the regression and ANN model was found more accurate of the two models.

The average percentage of error in predicting tool wear is found to be 2.07 % in the regression model and the average percentage of error in predicting tool wear is found to be 0.776 %in of the ANN model. Hence the ANN model is the best model for predicting the tool wear.

Similarly, the average percentage of error in predicting surface roughness is found to be 2.347 % in the regression model and the average percentage of error in predicting surface roughness is found to be 0.824 % in the ANN model. Hence the ANN model is the best model for predicting the surface roughness also.

The comparison of regression and ANN model prediction shows that the ANN model is the accurate of the two models. The accuracy of ANN model was increased by increasing the hidden layer nodes.

Chapter 7

Modal Analysis of Milling Cutter

7.1 3D MODEL OF MILLING CUTTER ASSEMBLY

The solid model of milling cutter with given dimension is modeled using the software Pro/E2001. The Pro/E2001 software is a one of the most commonly used software for modeling any parts. This model is created using protrusion and cut features. The 3D model was exported to the IGES format from the modeling software and 3D model as shown in figure7.1. The IGES format was imported for the analysis work in the ANSYS 8.1 software. Then the analysis of the milling cutter was carried out for the given conditions.

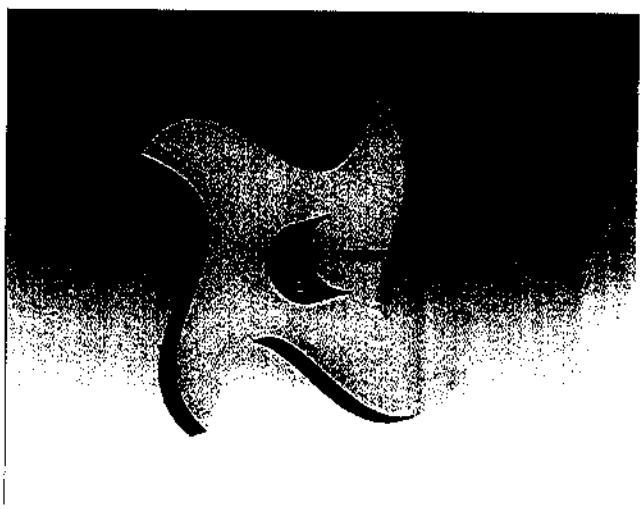

FIGURE 7.1 PROE 3DMODEL

7.2 MODAL ANALYSIS

Modal analysis is used to determine the vibration characteristics (natural frequencies and mode shapes) of a structure or machine component while it being designed. Modal analysis outputs are used as the input for the following analysis,

- Transient Dynamic analysis
- Harmonic response analysis, and
- Spectrum analysis

Steps in modal analysis

- Build the model,
- Apply loads and obtain the solution,
- Expands the modes, and
- Review the results

7.3 CUTTING FORCE NMODEL

Consider a milling cutter with two degrees of freedom and N number of teeth with a zero helix angle. The cutting forces excite the structure in feed direction X and normal direction Y, causing dynamic displacements X and Y, respectively. Cutting forces values are determine by conducting the experiment in CNC machining centre (Milling Tool Dynamometer) as shown in table 7.1

TABLE 7.1 LOAD PATTERN FOR MODAL ANALYSIS

Case	Depth of cut	Fx (N)	Fy (N)
1	0.5	120	190
2	1.0	150	235
3	1.5	190	290
4	2.0	250	360
5	2.5	300	450

7.3.1 Material properties of the cutter

Type of Material : Tungsten Coated Carbide Insert
Young's modulus Ex : $200*10^9$ N/m^3
Density : 8600 Kg/m^3
Poison ratio : 0.32

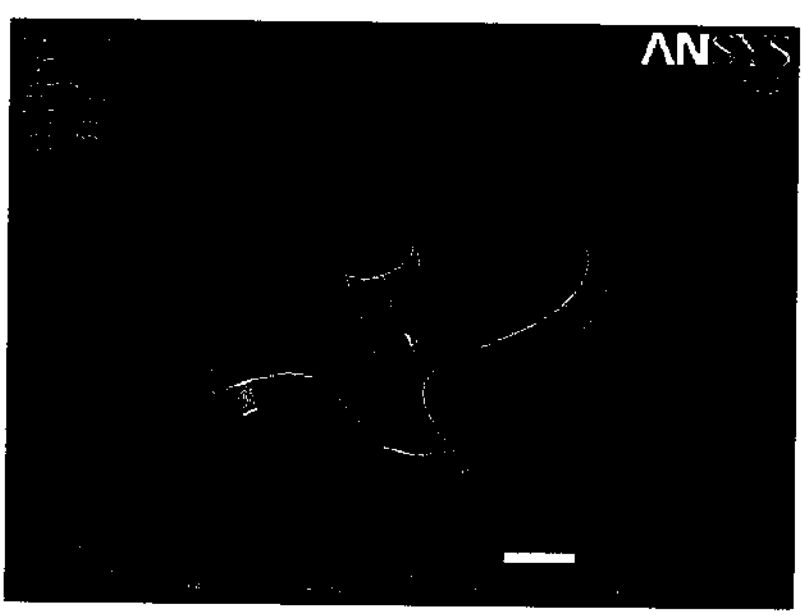

FIGURE 7.2 MODAL ANALYSIS OF CUTTER

7.4 RESULT OF MODAL ANALYSIS

To review results at one sub step over the entire model or selected portion of the model. We can obtain contour displays, deformed shapes, and tabular listings to review and interpret the results of the analysis. It offers many other capabilities, including error estimation, load case combinations, calculations among results data, and path operations and extracted modal analysis frequency in table 7.2 and corresponding result of stressed values in table 7.3. chart plotted between Depth of cut and Von misses equivalent stress in figure 7.3

TABLE 7.2 RESULTS OF MODAL ANALYSIS

Mode	Frequency (Hz)
1	07.38
2	67.29
3	98.07
4	160.52
5	323.78
6	471.68
7	476.22
8	743.97
9	864.50
10	1111.00
11	1282.00
12	1584.70
13	1594.20
14	1934.30
15	1981.00
16	2131.00
17	2241.60
18	2477.90
19	2648.20
20	2855.10

7.3 TABLE STRESS VALUES

S.no	Depth of cut in mm	Von misses stress (N/mm^2)
1	0.5	1527
2	1.0	1883
3	1.5	2380
4	2.0	2878
5	2.5	3845

From this analysis, totally twenty modes are extracted with a frequency range of 7.38 to 2855.10 Hz. the Maximum displacement of cutter assembly occurs at 1100 Hz with a value of 2.4 mm (irrespective of loads) and the stress value is maximum (i.e., 3845 N/mm^2) at the fifth case. The Chart plotted between Depth of cut and Von misses equivalent stress in figure 7.3

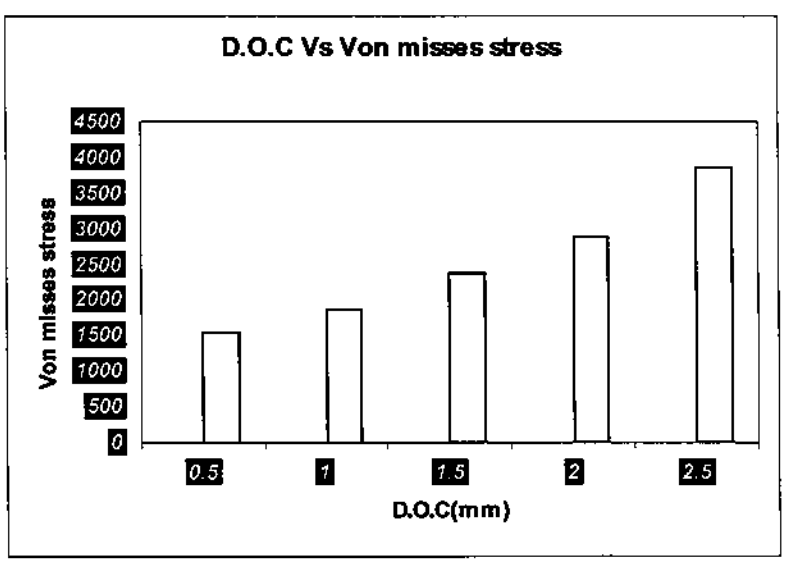

FIGURE 7 .3 RESULT PLOTS

According to the Vonmisses theory, the maximum stress should be less than the permissible yield stress. The maximum stress values and deflection value indicate it is far safe. The increase in the natural frequency values clearly indicates the dynamic stiffness values of the system. Frequency and Von misses stress indicates the importance of operating characteristics and 50 % increase of DOC causes a 27 % increase of the stress values. The stress values obtained are less than their yield stress values. The frequency of cutting edge into work piece, in which optimal deflection reducing tool wear and surface roughness for above condition.

Chapter 8

Conclusion

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