Tool Wear Prediction by Regression Analysis in Turning A356 With 10% SiC

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***Abstract*— In recent years, the utilization of metal matrix composites (MMC) materials in many engineering fields has increased predominantly. The need for accurate machining of these composites has also increased enormously. Despite the recent developments in the near net shape manufacture, composite parts often require post-mold machining to meet dimensional tolerances, surface quality and other functional requirements. In general 70% of the components need machining to attain the final shape. In the present work, the tool wear has been studied in this paper by turning the composite bars using HSS and Carbide tools. The paper presents the results of experimental investigation machinability properties of silicon carbide particle (SiC-p) reinforced aluminum metal matrix composite. The effect of machining parameters, e.g. cutting speed, feed rate and depth of cut on tool wear and surface roughness was studied. Machinability properties of the selected material were studied using HSS and Carbide tool material; surface roughness was generally affected by feed rate and cutting speed. Hence the tool wear were measured at different speed and feed conditions. Experimental data collected are tested with Multiple Regression Analysis. On completion of the experimental test, multiple regression analysis is used to predict the wear behavior of the system under any condition within the operating range.**

***Key words:* Tool wear, Machining, Surface finish, Regression Analysis.**

I. Introduction

Composite materials are continuously displacing traditional engineering materials because of their strength over homogeneous materials. Composites may have ceramic, metal or polymer matrices and may be reinforced with continuous fibres, whiskers or particles. The development of metal matrix composites has been one of the major innovations in the materials in the past two decades [1]. A metal matrix composite (MMC) is normally fabricated using a ductile metal (e.g., Al, Ti or Ni) as the base material, which is normally reinforced by a ceramic material (e.g., alumina, SiC or graphite). Combining the metallic properties such as good ductility and toughness of the matrix with properties such as high strength, hardness and elastic modulus of the ceramic reinforcement, the composites exhibiting high toughness, specific strength and stiffness and good wear resistance can be obtained. MMCs can also have low thermal and electrical conductivity and low sensitivity to temperature variation. Consequently, they have extensive interest from defense, aerospace and automotive industries and have become very promising materials for structural applications as well. Some of the examples of the applications of MMCs include fuselage of the space shuttle orbiter, vertical tail section of advanced fighter planes, sport equipments and automobile engine parts like pistons, cylinder liners, brake rotors, brake drums etc[2].

The need for new wear-resistant materials for high performance tribological applications has been one of the major incentives for the technological development of MMCs during the last two decades. A detailed understanding of the micromechanisms of wear is necessary to model the wear behaviour of composites and to set design guidelines for manufacturing of materials with optimum tribological properties [3].

While many engineering components, made from MMCs are produced by the near net shape forming and casting processes, they frequently require machining to achieve the desired dimensional accuracy and surface quality [4]. Since the composite material is non-homogeneous and anisotropic, the cutting behavior of this material is quite different from that of homogeneous material like steel. Also, a number of reinforcement materials are significantly harder and highly abrasive than the commonly used tool materials. Thus, machining of MMCs presents a significant challenge.

Despite the superior mechanical and thermal properties of MMCs, their poor machinability and high machining costs have been the main deterrent to their substitution of metal parts. With the advent of the excessive usage of MMCs, the study of their machinability aspects have become a prospective research area of significant interest. Considering the importance on use of MMC owing to its high strength, hardness and wear resistance, the present work aims at characterizing the tribological properties of

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Aluminium based Metal Matrix Composites and studying the machinability of such composites.

If tool wear take place in the cutting process, the information of tool wear will be shown in the signal of cutting process. Monitoring the tool wear and predicting the tool failure in the cutting process helps in eliminating the failure in the early period. Tool wear monitoring is always paid attention by the experts, and there have been researches to monitor the tool wear, failure prediction and recognition based on dynamic signals of the cutting forces and AE signals. Surface roughness measurement and the temperature between the tool and work piece interface. [5]

Tool wear is a complex phenomenon occurring in metal cutting process; generally worn tools adversely affect the surface finish of work piece. Hence many diagnostic systems attempt to monitor the tool failure. Sensor based monitoring and diagnostic systems have become increasingly useful in improving the efficiency of manufacturing systems [6]. Therefore there is a need to develop tool wear condition monitoring system which alerts the operator about the state of the tool. Tool wear condition monitoring can be done by following methods

- **Direct method** involves measurements of volumetric loss of tool material after machining. The loss of material can be done by the sensing method like optical, Radioactive, Electrical resistance method etc.

- **Indirect method** utilize measurement of parameters which are dependent on tool wear like cutting force, vibration, tool tip temperature, Acoustic Emission etc which can be operated online.

Tool-life estimation is an important factor in all machining operations. Tool-life equations were determined experimentally as early as 1906 by Taylor. Since then, numerous investigations have been carried out to determine the tool life as a function of cutting conditions, and the type of work piece materials. Aside from the problem of experimentally determining the parameters in these equations, there are inherent variations in tool life for a given set of machining conditions.
Tool life is defined as the length of time that a cutting tool can function properly before it fails. To be precise, tool life represents the essential life of a tool, expressed normally in time from the start of a cut to some end point defined as failure criteria. The tool failure is related to tool wear and condition of the finished products. The criterion can be surface finish of the work piece, dimensional accuracy, maximum material removal or tool wear. Various tool failure criteria like wear land measurement, crater depth, surface finish, etc., have been used to determine tool life. A common way of quantifying the end of a tool life is to put a limit on the maximum acceptable flank wear, VB or VBmax [7].

The study on tool wear in machining Sic particle reinforced aluminum matrix composites has a special attention on the effect of material structures on the tool wear mechanism. It is also found that, the volume fraction and the size of SiC particles played an important role on tool life. It was concluded that coarser SiC particle reinforcement and higher volume fractions required harder cutting tools. Edge and corner breakage of carbide and hard film coated tools are also reported [8].
Studies on various tooling systems for machining the MMCs have indicated that Carbides, either plain or coated, sustain significant levels of tool wear after a very short period of machining [9].

Lin et al [10] have selected homogenized 5% SiC-p aluminum MMC material for experimental investigation of tool wear and surface roughness at different cutting speeds (50, 100 and 150 m/min), feed rates (0.1, 0.2 and 0.3 mm/rev) and depths of cut (0.5, 1 and 1.5 mm). In dry turning condition, tool wear was found to be mainly affected by cutting speed, which increased with increasing cutting speed. Tool wear was lower when coated cutting tool was used in comparison to uncoated one. Surface roughness was found to be influenced by cutting speed and feed rate. Higher cutting speeds and lower feed rates produced better surface finish. He has also observed the flank wear as a primary mode of tool failure in machining Al-SiC MMC with two bodies and three-body abrasion between the tool and workpiece playing a dominant role in causing the flank wear land. In their experiments at high speed turning with PCD tools (cutting speeds 300 to 700 m/min) tool wear was found to increase with increasing cutting speed and feed.

D. Dornfeld, [11] in his paper has presented the applications of acoustic emission sensing techniques in manufacturing processes. This paper gives some background on the sensing needs in manufacturing for machine diagnostic as well as process monitoring. The paper also reviews the potential for AE application in manufacturing and illustrates some of the existing application. Special emphasis is given on machining and tool condition monitoring.

Ivankhnenko et al [12] used the algorithms of Group method of Data Handling for solving various problems of experimental data processing. The choice of an algorithm for particular use depends on the type of the problem, level of noise variance, sufficiency of sampling and the continuous variables. The algorithm data obtained will be used and the graphs will be drawn for the observed and estimated errors. The choice of best algorithm depends on accuracy and completeness of detailed experimental data and type of problem to be solved.

S. A. Dolenko et.al[13] have discussed in their paper the issues of practical implementation of Group Method of Data Handling (GMDH). The method was tested on wide range artificial and real –world problems. The method allows to find an analytical formula, which expresses the dependence of modeled system output on the values of most significant inputs of the system. GMDH proved to be most effective to solve small and medium-sized problems with continuous output

H.S.Liu et al [14] studied the polynomial networks for inprocess prediction of corner wear in drilling operations. Thrust force or the Torque in drilling operations has been related with the corner wear. The Thrust force is better than the Torque as the sensing signals for the inprocess prediction of corner wear. Corner wear will be predicted if cutting speed, feed rate, drill diameter and Thrust force/ Torques are given. The error between the measured corner wear and the predicted wear are considered for plotting the graphs.

Sudev.L.J [15] in his paper has carried the tool wear estimation in drilling using GMDH and Regression analysis. He quoted the estimation capability of the multiple regression analysis method was better at lower cutting conditions than at higher cutting conditions, due to the fact that the magnitude of the measured AE signals at lower cutting conditions is much lesser. The estimation results from the three GMDH criteria show that the regularity criterion function provides good estimation than the unbiased and combined functions. It was found that the least error of estimation and best-fit was found for 75% of data in the training set.

2. EXPERIMENTAL DETAILS

The experimental work consisted of turning Aluminum based Metal Matrix Composite (10%Sic) with HSS and Carbide tools. Initial experiments consisted of machining at different feeds and speeds using a fresh cutting edge and the depth of cut was kept constant. Further experiment was performed to obtain measurements with progressive wear. Depending upon the length of cut the machining was stopped and the width of the flank wear was measured. Force components, temperature at the interface of work piece and tool, Surface finish were recorded along with the Acoustic Emission signals. The Composition of work material is given in Table2.1.

Composition of work material				
Work material	Aluminium based Metal Matrix Composite A356 (10% SiC)			
Composition	Al	90.15-91.55	Mn	0.3
	Cu	0.2	Ni	0.1
	Fe	0.5	Si	6.50-7.50
	Pb	0.1	Sn	0.05
	Mg	0.20-0.60	Ti	0.05
	Other	0.15	Zn	0.1

Table 2.1 Composition of Work Material

3. Test procedure:

In the present investigation, machinability of the materials was assessed by considering *Tool wear, surface finish cutting forces and temperature* as the criterion. These machinability factors were measured for different cutting conditions viz., Cutting Speed, Feed rate and Depth of Cut (in Turning). Tool Wear and Acoustic Emission signals were measured using Tool Maker's Microscope and AE sensor and data acquisition system respectively. Infrared Heat Spy, handy surf and Dynamometers are used to measure Temperature, Surface finish and Cutting forces respectively. AE signals can be classified as continuous and burst type. Continuous type signals are associated with plastic deformation in ductile materials and the burst type signals are observed during crack growth within a material, impact and breakage. AE provides for the possibility of identifying, by means of signal changes between continuous and burst types, the tool wear state, which is essential for predicting tool life, and monitoring the status of the cutting process such as chip tangling, chatter vibrations and cutting edge breakage.

Turning operations was carried out along a fixed length of 55mm. Cutting forces, temperature and AE signal were monitored during the cutting operation. Tool wear was measured after each stage of turning, and the operation was repeated until the flank wear reached a value of 0.4microns. A new cutting edge was used for each subsequent 55 mm section with a different cutting condition. The turning tests were performed on an Enterprise 1330 precision lathe as per the cutting conditions mentioned in Table 3.1. During the process of operation, Cutting-force measurements were made with the aid of a lath tool dynamometer which provided information on the axial, radial and tangential cutting forces. Tool work piece interface temperature was measured using infrared heat spy and AE signals were recorded using the AE sensor and data acquisition system. After each test the worn cutting edge was measured with the aid of a tool maker's microscope to determine the degree of flank wear, surface finish was measured using surface measuring handy surf device.

Cutting speed in rpm	315 , 500, 775
Cutting speed in m/min	53, 81, 120
feed rate in mm/rev	0.150, 0.360, 0.451
Depth of cut in mm	0.5

Table 3.1 Cutting Conditions

The experiment was conducted using different tool material.viz, HSS tool and carbide tool (rhombic shaped tool insert) with 0.4 mm nose radius.

4. RESULTS AND DISCUSSION

4.1 Taylor's Tool Life Criteria.

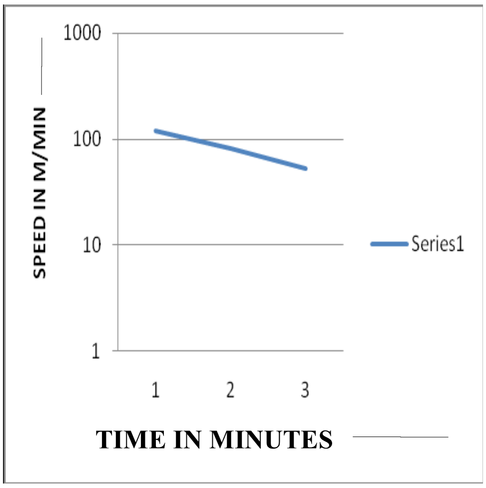

Fig: 4.1 (a) SPEED V/S TIME
(logarithmic scale)
feed 0.45 mm/rev, doc-0.5 mm for carbide tool

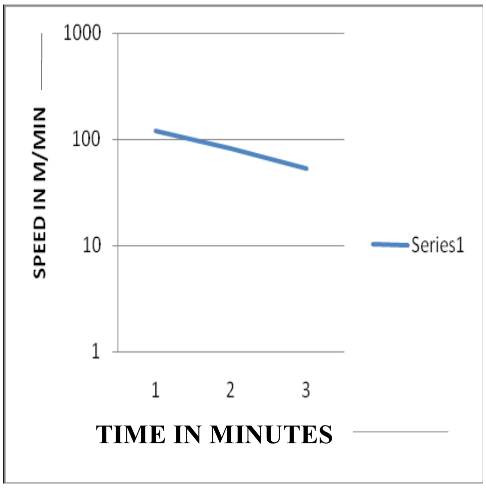

Fig: 4.2 (a) SPEED V/S TIME
(logarithmic scale)
feed 0.45 mm/rev, doc-0.5 mm for HSS tool

Taylor's tool life equation

$$VT^n=C$$

Where, V= Cutting speed in m/min, T= Tool life in seconds (at flank wear 0.4 mm), n and C are constant.

Fig 4.1(a) and Fig 4.1(b) represent a log-log plot, the tool life values for different cutting speeds, for HSS and Carbide tools. Based on the graph, the Taylor's tool life equation have been obtained for the two tools for the present experimental conditions. The equations obtained are

1. $VT^{-3.35841} = 8.68$ for Carbide tools.
2. $VT^{-4.00581} = 9.143$ for HSS tools.

4.2 Multiple Regression Analysis

Multiple Regression analysis method is used for the estimation of tool flank wear; both average and maximum width of flank wear are estimated. The objective of Multiple Regression Analysis is to construct a model that explains as much as possible, the variability in a dependent variable, using several independent variables. The model fit is usually a linear model, though some times non linear models such as log linear models are also constructed. Machining parameters like Speed, Feed and Depth of cut are considered as the dependent variable and Cutting time is considered as the independent parameter for constructing the Regression models. The variations of measured and estimated wear with time have been presented in the form of graphs for further discussion and comparison.

Making use of the experimental data, a mathematical model has been developed, using regression analysis. In this analysis, flank wear is considered as the dependent variable and machining conditions like cutting time, speed, and feed rate are considered as the independent variable. The first order polynomial model has been developed. The first-order polynomial model is given in the Equation

$$Y= a_0 + a_1X_1 + a_2X_2 + a_3X_3$$

After regression analysis the above equation is obtained as,

$Y = -0.0180 + 0.00039\ X_1 + 0.00119X_2 + 0.4155\ X_3$,
For carbide tool material.

$Y = -0.0620 + 0.0022\ X_1 + 0.00102\ X_2 + 0.4121\ X_3$,
For HSS tool material.

Where X_1=Cutting time in seconds, X_2= Cutting speed in m/min, and X3= feed rate in mm/rev are the variables. a_0, a_1, a_2, and a_3 are the co-efficient of X_1, X_2, and X_3.
Multiplicative model is given in Equation

$$Y= b_0\ X_1^{\ b1}X_2^{\ b2}X_3^{\ b3}$$

After regression analysis the above equation is obtained as,

$Y = -0.6044\ X_1^{0.2802}\ X_2^{0.2896}X_3^{\ 0.4090}$,
For carbide tool material.

$Y = -0.5203\ X_1^{0.3512}\ X_2^{0.1839}\ X_3^{\ 0.2282}$,
For HSS tool material.

Where X_1=Cutting time in seconds, X_2= Cutting speed in m/min, and X3= feed rate in mm/rev are the variables. b_0, b_1, b_2, and b_3 are the co-efficient of X_1, X_2, and X_3.

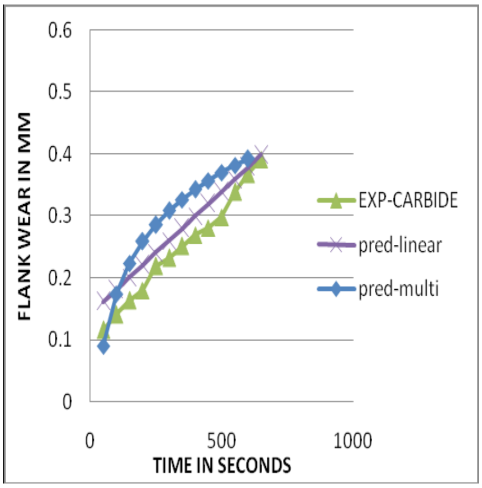

FIG: 4.2 (a)FLANK WEAR V/S TIME
Speed: 120m/min, feed 0.15 mm/rev, doc-0.5 mm

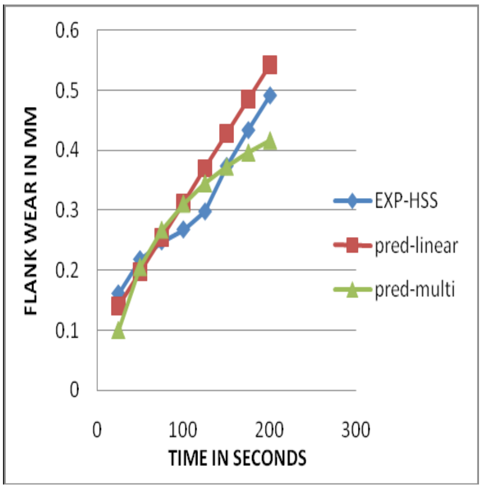

FIG: 4.2 (b)FLANK WEAR V/S TIME
Speed: 81m/min, feed 0.15 mm/rev, doc-0.5 mm

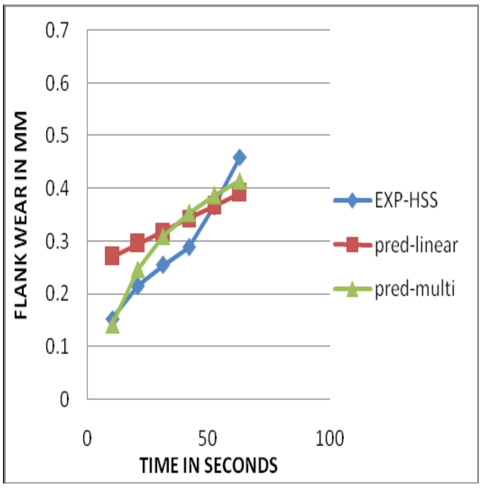

FIG: 4.2 (c)FLANK WEAR V/S TIME
Speed: 120m/min, feed 0.45 mm/rev, doc-0.5 mm

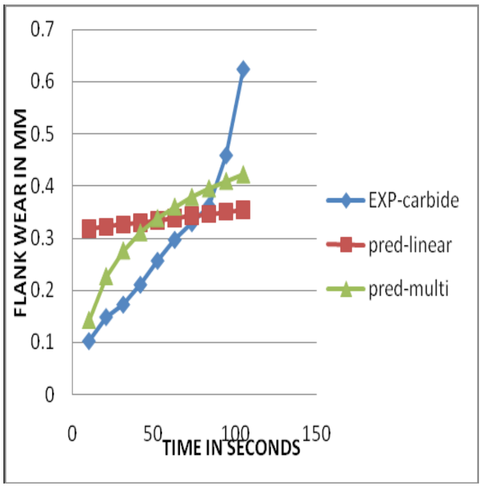

FIG: 4.2 (d)FLANK WEAR V/S TIME
Speed: 120m/min, feed 0.45 mm/rev, doc-0.5 mm

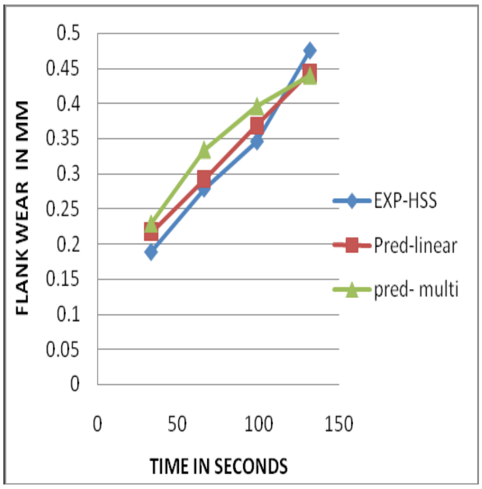

FIG: 4.2 (e)FLANK WEAR V/S TIME
Speed: 53m/min, feed 0.36 mm/rev, doc-0.5 mm

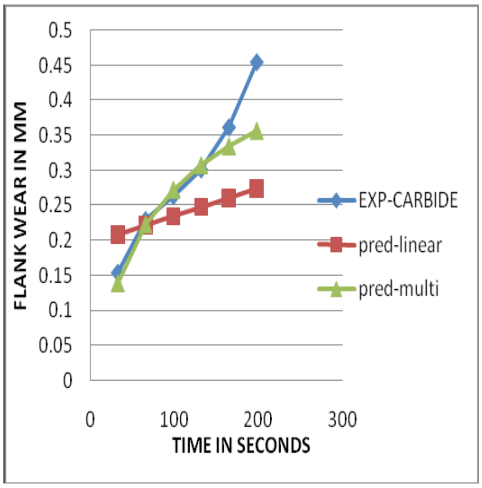

FIG: 4.2 (f)FLANK WEAR V/S TIME
Speed: 53 m/min, feed 0.36 mm/rev, doc-0.5 mm

Fig 4.2 (a)-4.2(f) illustrates the wear predictions by two regression models in comparison with the experimentally observed values of wear. Because of the non linear behavior of the wear pattern, the prediction of the wear by the multiplicative regression model appears to be much closer to the experimental values than those predicted by the linear model.

5. Conclusions:

Tool condition monitoring and diagnostic systems are important capabilities required to be incorporated in an unmanned machining system. Although a wide variety of tool wear sensing techniques have been developed over the years, it seems that a reliable and widely suitable quantitative in process monitoring method has not been evolved so far due to the difficulties in direct observation of worn zone, and hence there is a need for indirect methods.

Turning machine tool is one of the most versatile machine tool used in manufacturing industries. The quality of the finished products depends mainly on the condition of the cutting tool and stability and rigidity of different machine components of a Turning machine tool. It is required to collect more information about the condition of turning tool in terms of various sensor signals.

The experimental data were subjected to theoretical analysis to estimate tool flank wear. Measured parameters like cutting speed, feed are considered for estimations.

1. Multiple regression analysis method can be considered reliable for tool wear estimation based on the machining conditions, since the estimates of average and maximum wear correlated well with the measured average and maximum wear respectively.
2. The estimation capability of the multiple regression analysis method was better at lower cutting conditions than at higher cutting conditions, due to the fact that the magnitude of the measured AE signals at lower cutting conditions is much lesser. This implies that the data handling capability of this estimation method is less.

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