CHAPTER 2
LITERATURE REVIEW

2.1 INTRODUCTION

A machine component may vibrate over large or small distances, quickly or slowly, and with or without perceptible heat. Many vibration problems due to inadequate engineering design of a product have not considered the possible effect of vibration. Machine vibration can take various forms. Three different types of mechanical vibrations such as free vibrations, forced vibrations and self-excited vibrations that arise due to the lack of dynamic stiffness and the stability of the machine parts and vibrations generated under unsuitable cutting conditions is an extremely serious problem. The effect causes excessive tool wear, noise, tool breakage, and deterioration of the surface quality.

2.2 PREDICATION OF VIBRATION AMPLITUDE- REVIEW OF LITERATURE

Mechanical vibrations generally result from periodic wave motions. The nature of the vibration signal arising from the metal cutting process such that it incorporates facets of free, forced, periodic and random types of vibration, Dimla and Dimla (2000). Tate et al (2010) categorizes vibration during the metal cutting process into dependent and independent. Tool engagement conditions during machining play a notable role in the vibration produced. Coker and Shin (1996), Shather and Ibrheem (2008) demonstrated
that the influencing parameters can be divided into controlled and non-controlled parameters. The controlled parameters are the spindle speed, feed rate, and depth of cut. However, there are many non-controlled cutting parameters such as vibrations, tool wear, machine motion errors, and material non-homogeneity of both the tool and work piece, chip formation, etc., which are hard to reach and whose interactions cannot be exactly determined. Boothroyd and Knight, (1989) stated that the occurrence of vibrations of the machine tool, defects in the structure of the work material, wear of the tool, or irregularities of chip formation contribute to the surface damage in practice during machining.

Hartung et al (2006) demonstrated that the unwanted relative vibrations between the tool and the work piece represent significant challenges in high-speed milling. In order to avoid unwanted vibrations, the spindle speed, depth of cut for which the process is stable. Rashid and Nicolescu, (2006) have reported that due to the interaction between the workpiece and tool, the relative vibration of work piece and tool has been an inextricable part during a machining process and it has detrimental effects on machined surfaces. Ismail and Ziaei (2002) stated that the vibration in the cutting process is significantly affected by the amount of feed rate, Spindle speed, depth of cut, etc., so as to optimize and minimize the vibration. Abouelatta and Madl (2001), Sivasakthivel et al (2011) conducted an experiment by changing the helix angle of an end mill cutter, is a significant parameter, which reduces the vibration amplitude. By increasing the helix angle up to 45°, the vibration in the machine tool is almost lessened.

A vibration measurement is classified into relative, or absolute. A relative vibration measurement is one that is relative to a fixed point on the machine. Relative vibration measurements are generally limited to displacement measurements. An absolute vibration measurement is one that is
relative to free space. Absolute vibration measurements are made with seismic vibration transducers. Seismic vibration transducers are transducers and accelerometers. Yesilyurt and Ozturk (2007) demonstrated that the vibration analysis is widely accepted, reliable technique to monitor the operating conditions of a machine as it is a non-destructive and a continuous monitoring method. There are various testing techniques currently used to measure vibrations. The usual sensors used are accelerometers and dynamometers, Soliman and Ismael (1997). The accelerometers measure acceleration amplitude, which measures surface vibration and is also used to detect the tool condition. Huang and Wang (2010) developed an analytical model for the forced vibration in an end milling process. Based on this model, a pole/zero cancellation technique has been proposed and verified for selecting the cutting conditions to suppress the forced vibration. Chang and Chen (2009) conducted an experiment by using piezo transducer to test the spindle vibration.

Kim and Klamecki (1997) investigated to find the tool wear in end milling process using laser Doppler velocimeter method to measure spindle shaft torsion vibration. Orhan et al (2007) reported that the cutting conditions, cutter geometry, tool and work piece material, chip formation, tool wear and the vibration of the tool and work piece configuration as parameters that affected production performance significantly. Lacerda and Lima (2004) stated that the depth of cut is the significant parameter to reduce chatter vibrations, followed by considering the input parameters such as spindle speed and depth of cut.

It is observed that the various optimization techniques are employed to predict vibration amplitude; Statistical regression technique, Artificial Neural network, fuzzy logic, genetic algorithm, Tabu search, Simulated annealing, and response surface methodology are being applied
successfully in industrial applications for optimal selection of process variables in the area of end milling operations. Regression analysis has numerous areas of applications. Rahim et al. (2009) developed a vibration measuring unit using a micro electro mechanical system accelerometer, and experimental tests were carried out. A multiple regression model was used for detecting the tool breakage based on the resultant cutting forces in end milling operations. The feed rate and depth of cut are the most influencing parameter which reduces vibration amplitude. Toh (2004) derived the vibration analysis on the cutter path orientations employed in rough and finish milling via the use of fast Fourier transform (FFT) analysis.

Zhong et al (2010) proposed a method called little quantity lubrication (LQL) in machining and a comparative study on dry milling and LQL milling based on vibration signals. The vibration signals were acquired from the work piece surface in milling and were analyzed in time domain, frequency domain and time-frequency domain. The results show that vibration signals can be significantly affected by cutting fluid in milling process. Asfar and Akour (2005) derived a systematic approach based on a univariate search optimization method is used to determine the best design parameters for suppressing self-excited vibrations. A significant vibration between tool and work piece was observed. Zuperl et al (2006) proposed an Artificial neural network technique is used to predict the effect of machining variables (spindle speed, feed rate, axial/radial depth of cut, and number of flutes, tool geometry, flank wear) on the cutting forces. A neural network-based sensor fusion model has been developed for tool condition monitoring (TCM). Hino and Yoshimura (2000) proposed anew methodology, to predict chatter vibration in high-speed end milling using a fuzzy neural network model. The vibration data generated by an accelerometer were used to predict the surface roughness by using neural fuzzy optimize technique, Shin et al (1995). Based on Taguchi method and ANOVA, vibrating amplitude in feed
direction has a dominant effect of more than 40% in contribution ratio, while its associated frequency has some influence on slot-width accuracy of about 21% in contribution ratio, Chern and Chang (2006). The cutting forces exerted by the cutting tool on the workpiece during a machining action to be identified in order to control the tool wear and occurrence of vibration, thus to improve tool-life, Babu et al (2008).

2.3 PREDICATION OF SURFACE ROUGHNESS- REVIEW OF LITERATURE

With the increase of the demand for the high quality of surface finish, the effects of cutting vibration on surface generation attract a lot of attention. In this effort, one method accurately measuring the vibrational displacements of tool and workpiece is proposed and employed in signal acquisition. Based on the measured vibration displacement signals of tool and work piece, a geometric peripheral milling model and surface profile generation algorithm are presented. Since surface quality is greatly concerned in manufacturing industry, many attentions have been paid to the effects of cutting vibration on the surface finish. In the past efforts, the most researchers in this area are based on these two approaches. One uses virtual vibration signals to analyze the effects of cutting vibrations on the machined surface. Another one uses predicted vibrations which are determined by the cutting process dynamics. In the former approach, hypothesis on the properties of cutting vibration is required.

The previous research vividly indicates that the application of various methods for machining optimization to predict Surface roughness such as Statistical regression technique, ANN, fuzzy logic, Genetic Algorithm, Tabu search, Simulated annealing, and response surface methodology is being applied in manufacturing applications for best possible selection of process variables in the area of end milling operations. Okafor and Adetona (1995)
suggested that the multi-sensor signatures (acoustic emission, spindle vibration, cutting force components and machining time) acquired during circular end-milling of 4140 steel and the surface roughness and bore tolerance is measured to create the model of networks. Tsai et al (1999) demonstrated that the surface roughness could be effectively predicted by using spindle speed, feed rate, depth of cut, and the vibration per revolution (VAPR) by applying the input neurons through an ANN model. The surface recognition model was developed by ANN methodology.

Oktem et al (2006) suggested that the Artificial neural network and genetic algorithm have been used for determining optimum cutting parameters leading to minimum surface roughness during end milling operation. Sonbaty et al (2008) suggested that to achieve specific surface roughness profile geometry an Artificial neural network (ANNs) models were developed for the analysis and prediction of the relationship between the cutting conditions and the corresponding fractal parameters of machined surfaces in milling operation by considering the input parameters of rotational speed, feed, depth of cut, pre-tool flank wear and vibration level. Ship-Peng Lo (2003) suggested that the adaptive-network based fuzzy inference system (ANFIS) is used to predict the workpiece surface roughness of end milling process and to analyze the effect of milling parameters, including spindle speed, feed rate and depth of cut, on the surface roughness. Lou and Chen (1999) a new approach, neural fuzzy system were developed to predict surface roughness using in process surface roughness recognition (ISRR) systems to predict surface roughness (Ra) in-process using an accelerometer to measure vibration signals and cutting conditions while end-milling.

Ghani et al (2004) proposed that the surface roughness can be predicted with a 96% accuracy rate by ISRR using the neural fuzzy system. The use of high cutting speed, low feed rate and low depth of cut leads to
better surface finish and low cutting force. Tsao (2002) proposed that the taguchi method is used to analyze flank wear width and performance index of surface to study the optimization design of cutting parameters for milling 6061 aluminum alloy. John, Yang and Chen (2001) applied a multiple regression and artificial neural network (ANN) techniques to predict the surface roughness. Zhang, Chen and Kirby (2007) proposed that the systematic procedure can effectively and efficiently have been implemented to identify the optimum surface roughness by using Taguchi parameter design of an end milling machine. For the optimization of milling parameter to predict surface roughness by the combination of feed rate, spindle speed and depth of cut by using Taguchi design technique.

Alauddin et al (1995) developed a model for the mathematical model for the prediction of surface roughness in terms of cutting speed, feed and axial depth of cut. The effect of these cutting parameters on the surface roughness has been investigated using response surface methodology to predict vibration due to the, deflection of the work-tool system. Kadirgama et al (2008) suggested the most dominant variables which increase Ra are cutting speed, feed rate, axial depth and radial depth. RSM and Radian Basis Function Network (RBFN) model reveal that feed rate is the most significant design variable in determining surface roughness as compared to others. RBFN predict surface roughness more accurately compared to RSM. Surface roughness is the most influenced by the feed rate, whereas the vibrations increase the prediction accuracy Brezocnik and Kovacic (2003). Kadirgama et al (2009) developed an RSM model reveal that feed rate is the most significant design variable to predict the surface roughness response as compared to other parameters. Experiments were conducted using RSM methodology to predict the surface roughness for various cutting conditions. Wang and Chang (2004) suggested that the input parameters considered were the cutting speed, feed, depth of cut, concavity and axial relief angles of the
end cutting edge of the end mill. Quintana and Ciurana (2009) demonstrated Surface roughness monitoring is based on artificial neural networks for end milling operation. The data was captured by the two unidirectional piezoelectric accelerometers measuring the vibrations occurring during the metal removal process. A Neuro-Fuzzy Hybrid Stochastic Search Technique (NFHSST), using an ANFIS network in tandem with Hybrid Stochastic Search Technique in determining the optimal machining parameters. The ranges of the cutting parameters of end milling operations along with measured surface roughness and machining time and the optimization results using NFHSST Hans raj et al (2009).

Alauddin et al (1996) derived a mathematical model by using Response surface design methodology can be used to predict the cutting forces in tangential, radial and axial directions. By using factors, cutting speed, feed rate and depth of cut, the mathematical models for surface roughness have been developed to optimize the surface roughness by response surface methodology. Brezocnik et al (2004) predicted Ra in CNC end milling of 6061 Al in terms of vibrations as machining parameters by using genetic programming. Wang et al (2004) optimized the cutting conditions in plain milling, the feed rate, speed and depth of cut are the set of constraints used to predict the surface roughness by using genetic simulated annealing (GSA). Saffar and Razfar (2010) demonstrated that incorrect adjustment of the machining parameters, feed rate and depth of cut, lead to tool deflection and consequently reduced surface quality. With increasing feed rate and depth of cut, the tool deflection is increased. Optimization of machining parameters using Genetic Algorithm leads to minimal machining errors.
2.4 MOTIVATION OF THE STUDY

From the literature sources it is found that, the machining of Al 6063 metal matrix composite is an important area of research, but only very few studies have been carried out on Vibration and surface roughness in end milling operation. In the present study, an attempt is made to investigate the effect of process parameters such as spindle speed, feed rate, radial depth of cut, axial depth of cut and radial rake angle on surface roughness in end milling using RSM approach. This methodology helps to obtain the best possible cutting conditions and tool geometry for dry milling of Al-6063 using HSS end mill cutters.

2.5 NEED FOR THE FURTHER RESEARCH

- Furthermore the optimization of cutting parameters such as tool geometry (cutter diameter, number of teeth, side cutting edge angle, shank diameter, helix angle, overall length of tool, nose radius, Axial rake angle etc.), torque, spindle motor current, cutting time, clearance angle, feed drive current and type of lubricants used.