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Full Length Research Paper

Monitoring and analysis of MRR-based feedrate optimization approach and effects of cutting conditions using acoustic sound pressure level in free-form surface milling

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Sculptured surface machining (SSM) is one of the continually used manufacturing processes for die/mold, aerospace(especially turbine blades), precision machine design, bio-medical devices and automotive industries. Developments of machining technologies for quality enhancement of machining results has become a very important fact in current real industry. Off-line feedrate adjusting is a new methodology to automatically decide optimum feedrates for G-code modification. Off-line re-adjusting feedrates based on changing surface geometry (concave, convex and flat surface) in sculptured surface machining could decrease milling time, reduce tool wear, deflection and improve surface texture quality. Monitoring of sculptured surface milling processes is a critical requirement in the implementation of any unmanned operation in a shop floor. During the last years, notable efforts have been made to develop reliable and robust monitoring systems based on different types of sensors such as cutting force and torque, motor current and effective power, vibrations, acoustic emission or audible sound energy. In automated machining processes, condition monitoring not only reduces the production costs by reducing downtime and unnecessary tool changes, but also improves the product quality by eliminating chatter and poor surface finish. This study examines the possibility of using sound pressure level to monitor the sculptured surface milling process at different machining conditions and to evaluate MRR based feedrate optimization applications. In this paper, audible sound is investigated as a dynamic approach is established to enhance our understanding of the relationship among cutting conditions, tool deflection, cutting forces and the sound signal generated from the cutting process.

Key words: Sound pressure level, tool condition monitoring, machining, sculptured surface machining, tool deflection, FFT, feedrate optimization, MRR, free-form surfaces.

INTRODUCTION

Monitoring of cutting processes is a critical necessity in the realization of any depeopled operation in a shop floor and, especially, in the establishment of Computer Integrated Manufacturing (CIM) where most of the processes and operations are applied in an automated way (Sokolowski and Kosmol, 2001; Shawaky et al., 1998; Brophy et al., 2002; Govekar et al., 2000; Cho et al., 1999). The aim of the monitoring of machining operations generally are relevant to the performance of the machine tool, progression of tool wear, dimensional tolerances, surface texture (roughness, waviness), tool deflection, and other features of the workpiece and the classification of chip shapes and formation. An active and effective process monitoring system should stimulate the operator and shut the NC machine down when critical and unsafely conditions are about to be reached. Effective and efficient tool condition monitoring systems (TCMSs) have for more than two decades been acquiring an importance in industry and machining research. For this reason, scientist have dedicated much time and effort in improving TCMSs (Salgado and Alonso, 2006; Franco-Gasca et al., 2006; Niranjan et al., 2004; Alonso and Salgado, 2005; Jemielniak, 1999, 2006; Scheffer et al., 2003; Haber et al., 2004; Lia et al., 2005; Silva et al., 2000; Jemielniak et al., 1998; Abu-Mahfouz, 2003). Nevertheless, only a few trustworthy TCMSs have as yet been established for industrial application (Jemielniak, 1999).

Condition monitoring not only decreases the manufacturing costs by reducing downtime and needless cutting tool changes, but also enhances the product quality by eliminating chatter, excessive tool deflection and poor part surface finish. Therefore, much study has been executed in the past 30 years (Dan and Mathew, 1990; Cook, 1980). Nevertheless, much more study is needed to develop a dependable and cost effective condition monitoring system for real industrial applications, particularly when dealing with variable machining conditions. Lately, considerable efforts have been made in the improvement of conditions monitoring approaches that permit for the observing and control of the above mentioned aspects (Burke and Rangwala, 1991; Chen et al., 1994; Chen et al., 1999; Chen, 2000). Over the past three decades, diverse types of sensors such as cutting force and torque, motor current and effective power, vibrations, accelerations, acoustic emission or audible sound energy, sound pressure power and displacement sensor (inductive and capacitive) have been generally applied to sense a special characteristic or a combination of characteristics such as tool wear, tool deflection, tool fracture, machine vibration, etc. (Jemielniak et al., 1998; Schaffer, 1983; Naerheim and Lan, 1988; Blum and Insaki, 1990; Tlusty and Andrew, 1983; Rangwala and Dornfeld, 1990; Okafor and Adetona, 1995; Desforges et al., 2004; Hutton and Yu, 1990; Lin et al., 2002; Sokolowski and Kosmol, 2001; Ouafi et al., 2000; Karlsson et al., 2000; Peng, 2004; Byrne et al., 1995; Chen and Chen, 1999; Dornfeld, 1992; Masory, 1991).

An operator commonly monitors the cutting condition by observing or listening to the conventional machining process. Acoustic emission (Cyra and Tanaka, 2000), cutting force (Ko et al., 1999), power consumption (Murata et al., 1993) and cutting sound (Banshoya et al., 1994) that are generated during machining have been studied to monitor and control the machining process automatically. Among these signal sources, the use of the machining sound signal is considered to be the effective approach in acquiring the beneficial information related to not only the cutting phenomenon, but also to the vibration of an NC machine. Audible sound observing is one of the most practical techniques ach that has not been greatly attempted and examined for applications in industrial process monitoring systems such as cutting tool failure and deflection monitoring, etc. although it is widely used by NC operators for decision making based on his experience and senses (mainly vision and hearing), to determine the process state and react adequately to any machine performance decay (Teti and Baciu, 2004; Lu and Kannatey-Asibu, 2000; Teti et al., 2004).

The major critical problem related to the application of this technique in real industry is the ability to preserve the sound sensor from the hazardous cutting environment and the environment noise (Teti and Baciu, 2004; Teti et al., 2004; Clark et al., 2003; Wilcos et al., 1997; Lu and Kannatey-Asibu, 2000). Cutting fluids or metal chips may damage the sound sensor. Noise from adjacent machines, motors, conveyors, etc. or processes may contaminate the signals. This effect can be mitigated by using noise cancellation methods in the signal processing algorithm. These are commonly easy to assemble on the machine, and particularly, near the point of cutting but without interfering with the NC machine and the machined part. Moreover, these sensors, actually microphones, are easy to use in combination with spectrum analyzers. These features of the audible sensors make the execution of the monitoring tests rather straightforward. The primary advantages of sound sensors for process monitoring are connected to the nature of the sensors employed in the acquisition of the sound signals. A number of scientists have used cutting sound measurement techniques to monitor machining conditions (Nagatomi et al., 1993) or cutting tool wear (Banshoya et al., 1994).

Many studies have been researched on acoustic emission (AE) to examine tool wear, chip formation, etc. as well as monitoring and controlling of cutting processes. Tanaka et al. (1988, 1990, 1993) suggested a new contactless approach of AE measurement using a microphone. Their results demonstrated that adaptive control systems, based on noncontact AE measurement, could produce the surface roughness demanded by automatic regulation of feedrate during milling. Anderson (1998) developed and patented an opinion in which the background noise was sensed by using a special sensor and its effect on signals associated with tool wear could be decreased.

Trabelsi and Kannatey-Asibu (1991) attained audible sound radiation from a microphone for tool breakage and wear detection in turning and deter-mined tool conditions using pattern-recognition methods. Delio, Tlusty, and Smith (1992) concluded that cutting sound measurement is a good method for detecting chatter during the machining process. In their study, sound is examined as a basis for tool wear monitoring and a dynamic model which is considered as a forced vibration system is established to improve our understanding of the relationship between tool wear and the cutting sound signal generated from the milling process.

The machining sound emerging from the mechanical vibrations produced in the interaction zone between the cutter and the workpiece has also been used to detect chatter and control its occurrence (Delio et al., 1992; Schmitz et al., 2001-a, 2002; Schmitz, 2003; Weingaertner et al., 2006). Schmitz et al. (2001-a, 2002) and Schmitz (2003) developed a new approach for chatter detection and recognition through statistical evaluations of the cutting sound variance with a synchronously sampled signal. This work examines the

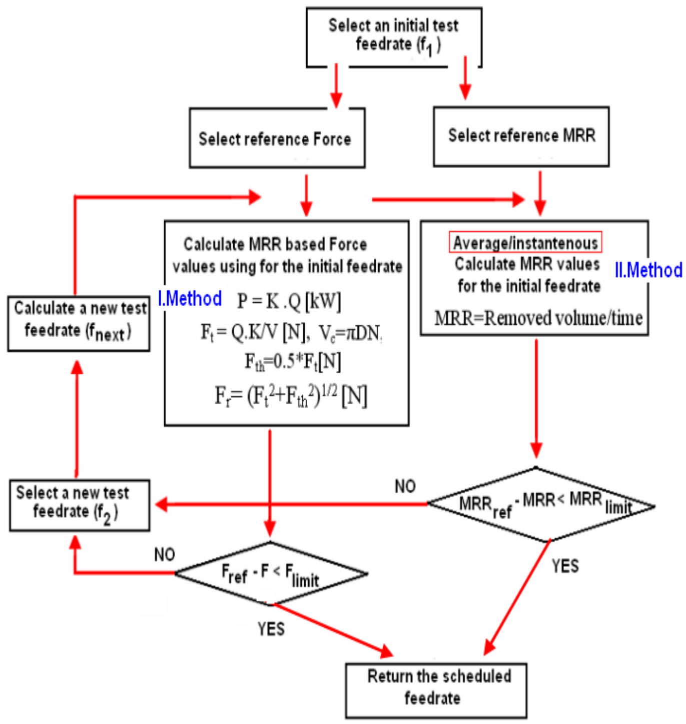

Figure 1. Traditional Block diagram of feedrate adjustment using MRR.

possibility of using sound pressure level to monitor the free form surface milling process at different machining conditions and to evaluate MRR based feedrate optimization applications. In this paper, audible sound is investigated as a systematic approach established to enhance the understanding of the relationship among cutting conditions, tool deflection, cutting forces and the sound signal generated from the cutting process.

Feedrate optimization/rescheduling

The feedrate scheduling/adjustment presented in the literature consist of two stages: the first stage is the calculation of an optimized feedrate based on a reference/target value (reference cutting force, MRR, chip thickness, chip volume, etc.) and the second stage is the modification of NC-code to accommodate these new feedrate values. Off-line rescheduling feedrates based on changing surface geometry in sculptured surface machining could decrease milling time, reduce tool wear, deflection and improve surface texture quality. Commonly speaking, feedrate rescheduling in free-form surface machining is to consider only one constraint at all machining segments such as keeping fixed chip thickness f, keeping constant MRR, keeping constant surface roughness Ra, keeping constant tool deflection value δ, or keeping constant resultant cutting force R. Chip thickness, MRR, surface roughness, tool deflection and resultant force can be defined as feedrate scheduling control/reference parameters.

Different feedrate scheduling strategies have various feedrate control parameters and should be integrated for better results based on machining time and cost optimization models (Li et al., 2008). Implementing feedrate scheduling in free-form surface milling has become popular and it is also used in some commercial CAM softwares (Cgtech, 2010; Mastercam, 2010; Powermill, 2010; VegaCNC, 2010; Ezcam, 2010) the traditional strategy used in feedrate scheduling is material removal rate (MRR) model (Figure 1). In this strategy, feedrate is expected to be proportional to either average or instantaneous material removal rate. Feedrate optimization approach based on volumetric analysis, which uses MRR, is commonly used by most researchers. In addition to MRR, feedrate optimization is performed also by using geometrical information such as chip cross-section and chip volume.

In the volumetric strategy we consider that the power (P) required to cut the material is proportion to the volumetric removal rate (Q) [cm^3/min](Wang, 1988; General Electric, 1980). Most investigators have improved and used a feedrate scheduling system based on volumetric analysis by using various MRR (chip volume per tooth, chip volume per NC block, chip-workpiece intersection area) calculation methods. Some of the first paper on feedrate re/adjusting algorithm was by Wang (1988), where he used a z-map description of the workpiece and a simple volumetric model to relate milling force to the MRR. The aim of Wang (1988) was a real time solid modelling based simulation of end milling for scheduling the MRR via adaptive feedrate control. The optimization system works as an off-line adaptive controller before CL files are downloaded to the CNC control unite. Average cutting force was analyzed using the removed material volume extracted via the solid model. This is based on the assumption that average cutting forces are proportional to the MRR and then, the feedrate is automatically scheduled to enhance the productivity under some boundary conditions.

The study of Fussell et al. (1992) has a resemblance with that of Wang. It is composed of development of a computer system for automatic re/generation feedrates for enhancing the performance of CNC cutting of free form surfaces using end milling process. Jang et al. (2000) showed a voxel-based simulation and verification system, for regulating feed rate using MRR. Besides, of the commercial feed rate scheduling modules, CGTech's Optipath (2009) and Mastercam's HiFeed (2009) typically use the volumetric method to adjust the feed rate. Li et al. (2003) offered an off-line feed rate scheduling based on MRR integrated with commercial CAD/CAM for 3 axis end machining. The improved new approach adopts MRR as the main model by relating the average power with MRR. After chip parameters necessary for predicting machining force was extracted, machining force was predicted using an empirical model. Then federate values

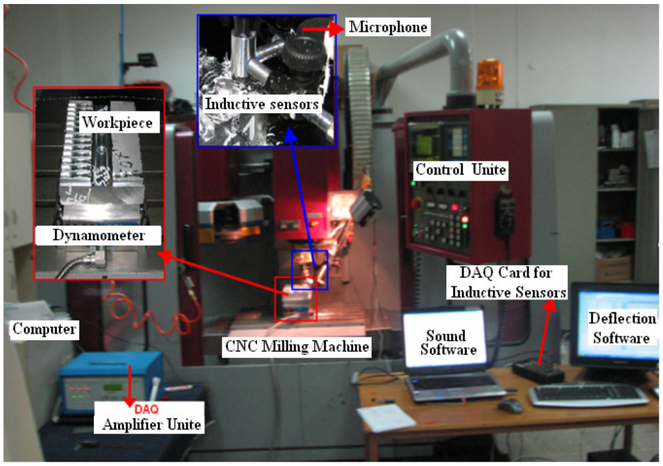

Figure 2. Experimental setup.

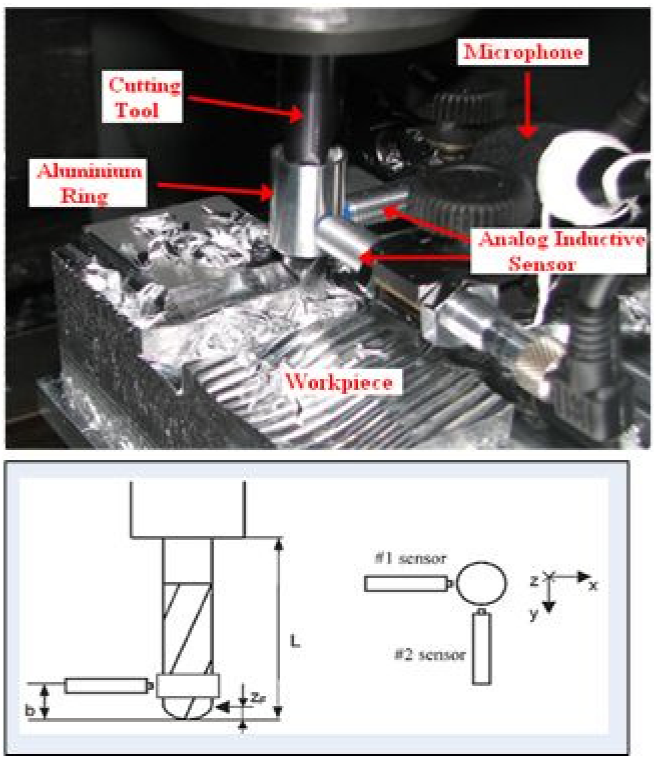

Figure 3. Close-up photo of experimental set-up for deflection measurement.

were adjusted to satisfy machining requirements such as productivity, accuracy and quality.

Ip (1998) proposed a MRR optimization strategy to regulate the variation of cutting speed and maintain a fixed cutting force by scheduling the cutting feedrate considering tool life, wear and surface gradient. Ip, Lau and Chan (2003) proposed a fuzzy-based MRR approach in order to augment the machining performance via using spindle power and specific energy. Lan (2007) suggested a mathematical model and the decision criteria in order to improve the optimal MRR control of a cutter. Bailey et al. (2002) used maximum cutting force constraint in rough machining operations for feedrate readjusting. Spence and Altintas (1994) as well as Bailey et al. (2002) improved a 2/1-2-axis milling process simulation and used a solid modeler. They can obtain volumetric intersection of the cutting tool and work piece. Feed speed values were adjusted based on maximum cutting force. Chen et al. (2005) optimized feedrate at the maximum MRR under the restriction of permissible surface roughness. Kloypayan and Lee (2002) decided feedrates by keeping the feedrate at the centroid of cutting cross area to be fixed. Karunakaran and Shringi (2008) proposed a solid model-based off-line adaptive controller for feed rate optimization for end milling process. In their paper, the basic input to the octree-based NC simulation system is the NC tool path either in CL format or G/M-code format. After the CL file is evaluated, the swept volume of the cutting tool is intersected with the blank at every small sampling interval along the tool path and the intersection is contemplated as the undeformed chip. The chip parameters necessary for forecasting the machining force are extracted and using the MRR model and milling force is predicted.

According to the computer simulation result the feed rate is scheduled based on force calculation to create optimized CL data. Kim et al. (2004) examined feedrate optimization using cutter location (CL) surface.

Experimental details

Measurement of cutting forces

Slot milling tests in absence of cutting fluids were performed on a Johnford VMC Model three axes CNC milling machine equipped with a maximum spindle speed of 12,000 rpm and a 10 kW drive motor as shown in Figure 2. CNC part programs are created by employing CATIA R17 CAD/CAM software on a personal computer, Intel Pentium IV at 2.80 GHz. A cutting experiment was developed to measure the tool forces using a Kistler 9257A three-axis load cell. The forces were generated during slot cutting with a ball end mill. The experiment involved collection of three orthogonal channels of force data while cutting the slot in a piece of Al 7075-T561 alloy at a different milling conditions using 12 mm diameter ball end mills.

Cutting deflection measurement

This measurement has been carried out using two precision inductive displacement sensors placed at 90° one from the other. For cutter deflection measurement, an aluminum ring was fitted to the flute part of the cutter and machined after being clamped in the spindle. Figure 3 shows the experimental apparatus for cutter deflection measurement.

Measurement of cutting sound pressure level (SPL)

The periodic impacts of the cutting tooth with the workpiece and the corresponding vibrations that arise due to this impact generate a

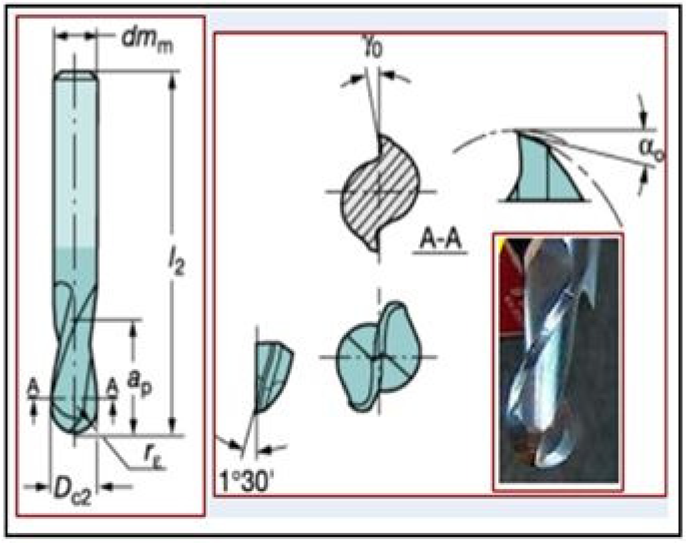

Figure 4. The ball end milling tool.

Table 1. The dimensional and mechanical properties of the cutting tool.

Tool diameter	12 mm
Flute	2 flute
Tool length	120 mm
Helix angle	30°
Shank type	Cylindrical

Table 2. Chemical composition of materials (wt %).

Zn	Si	Mn	Cr	Ti	Al	Cu
0.5	0.13	0.30	0.28	0.2	base	2.0

sound. This sound is a transmission of mechanical energy that propagates through the air and contains information about the process. Experienced users can usually extract information from it and correct or modify the milling conditions. Sound pressure level (SPL) or sound level is a logarithmic measure of the effective sound pressure of a sound relative to a reference value. It is measured in decibels (dB) above a standard reference level.

The commonly used "zero" reference sound pressure in air is 20 µPa RMS, which usually considered the threshold of human hearing (at 1 kHz). Sound pressure level (SPL) or sound level L_p is a logarithmic measure of the effective sound pressure of a sound relative to a reference value. It is measured in decibels (dB) above a standard reference level.

$$L_p = 10\log_{10}\left(\frac{{p_{\mathrm{rms}}}^2}{{p_{\mathrm{ref}}}^2}\right) = 20\log_{10}\left(\frac{p_{\mathrm{rms}}}{p_{\mathrm{ref}}}\right)\ \mathrm{dB},$$

where P_{ref} is the reference sound pressure and P_{rms} is the rms sound pressure being measured. Sometimes variants are used such as dB (SPL) or dBSPL. These variants are not recognized as units in the SI. The sound signal was acquired using a calibrated microphone amplified and logged, sampling at a rate of 50 kHz for 100 ms, using the data acquisition system. The microphone is connected to the amplifier, which conditions the signal to the appropriate voltage level in the range ±2V. The microphone was set a distance of approximately 50 mm from the cutting tool at an angle of 30° to the workpiece surface. Pressure levels of cutting sound were measured and also these cutting sounds were recorded using experimental setup in Figure 2.

In the present case, the monitoring tests are based on the use of a precision microphone. Then, the broadband sound pressure level of an audible signal is detected by means of a dedicated instrument to measure and display such type of signals. All audible sound signals detected are transferred and off-line analyzed on a PC. In order to verify the repeatability of the monitoring tests, the audible sound signal specimens should be recorded for each cutting condition several times (≥3).

Cutting tools and workpiece materials

Cutting tools used were chosen from Sandvik Coromant Tool Catalog to machine Aluminum 7075-T6. Cutting tools, 12 mm diameter with two teeth, were employed for milling of the experiment surfaces in the mold cavity (Figure 4). In this work, tool wear was not considered as the criterion affecting the result of cutting process since the material being utilized is soft. The dimensional and mechanical properties of the cutting tool are displayed in Table 1. In the experiments, samples with rectangular blocks (110 x 55 x 32 mm) that were made of Al 7075-T651 aerospace alloy materials were used as workpiece (Figure 5). Tables 2 and 3 provide detailed information on chemical compositions and mechanical properties of material.

Cutting conditions

The authors have made three groups of machining test for this workpiece: machining without any optimization with different federate and tool overhang values, machining after various MRR based feedrate optimizations with new inserted NC block and machining after MRR based feedrate optimization with not inserted new NC block. Feed rates of 48, 96,144 and 192 mm/min and tool clamping/overhang length of 60 and 75 mm were chosen as experimental conditions as shown Table 4. The feedrate optimization conditions for the free form surface are summarized in Table 5.

Results of MRR based feedrate optimizations

Implementing feedrate optimization in free-form surface machining has become widespread and it is also used in some commercial software packages. The common approach used in feedrate scheduling is material removal rate (MRR) model. In this approach, feedrate is expected to be proportional to either average or instantaneous volumetric removal rate. Feedrate scheduling is simulated using the NC verification model. The NC codes are using generated CAM software. First, feedrate scheduling based on the chip volume per NC block is performed, and a new feedrate is inserted in every existing NC block. When the feedrate exhibits a sharp change between two consecutive NC blocks, a new NC block is inserted between them. Figure 6 shows an example with a free form surface and the feed direction is also depicted. The initial constant feedrate value is taken as 96 mm/min in the original NC codes. The feedrate scheduling was executed to regulate the MRR values at a given reference levels. Results of the implementation of two different MRR-based feedrate optimization approaches can be

Table 3. Mechanical properties of material

Workpiece	UTS (MPa)	YS (MPa)	Density kg/m^3	Elongation (%)	Hardness (Bhn)
Al7075-T651	570	505	2800	11	160

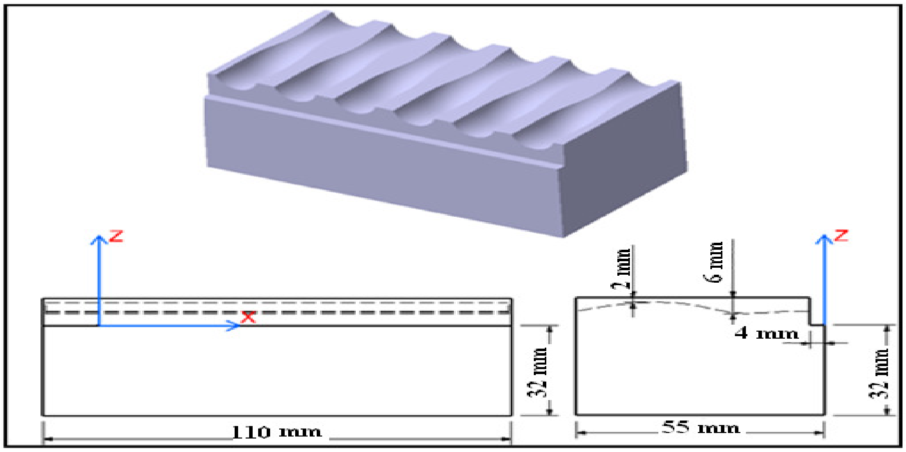

Figure 5. Samples used in the experiments.

Table 4. Cutting conditions.

Number of test	Feedrate (mm/min)	Tool clamping length (mm)
1	48	60
2	96	60
3	144	60
4	192	60
5	48	75
6	96	75
7	144	75
8	192	75

Table 5. The input parameters for MRR based federate optimization.

Test no.	Feedrate	MRR (mm^3/s)	Max feed (mm/min)	Min feed (mm/min)
Unoptimized constant feedrate	**96 mm/min**	**-**	**96 mm/min**	**96 mm/min**
OPT-1	-	20	50	130
OPT-2	-	30	50	130
OPT-3	-	15	50	130
OPT-4	-	20	50	130
OPT-5		20	50	130
D2- OPT-1		20	50	130

seen in Figures 7 and 8. This optimization approaches were applied to the slot milling process in free-form surface. In the first approach, MRR values were calculated for between the two consecutive G codes, and these values were used feed rate optimization without adding new NC blocks as shown in Figure 8. Feedrate scheduling based on the MRR per NC block is performed, and a new feedrate is inserted in every existing NC block.

In the second approach, in addition to the reference MRR values, some parameters such as segment length, minimum distance, maximum-minimum feed rate values, etc., were taken into

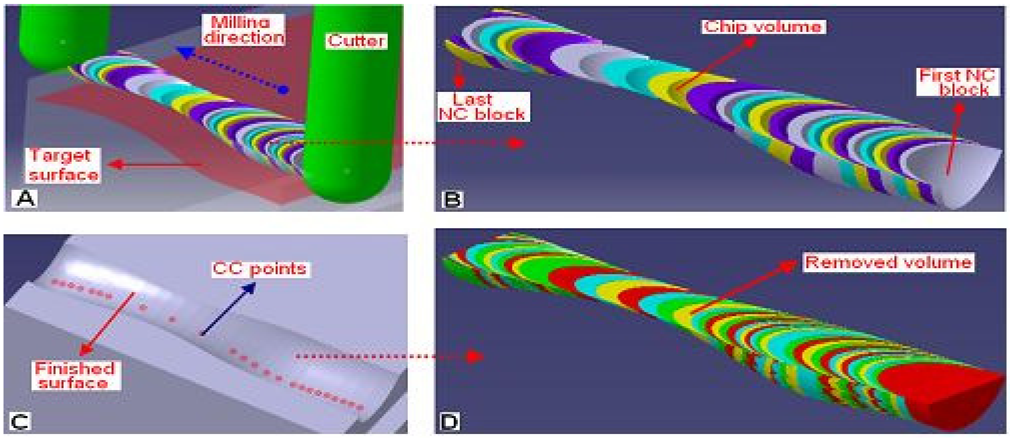

Figure 6. Concept of off-line feedrate optimization using MRR values.

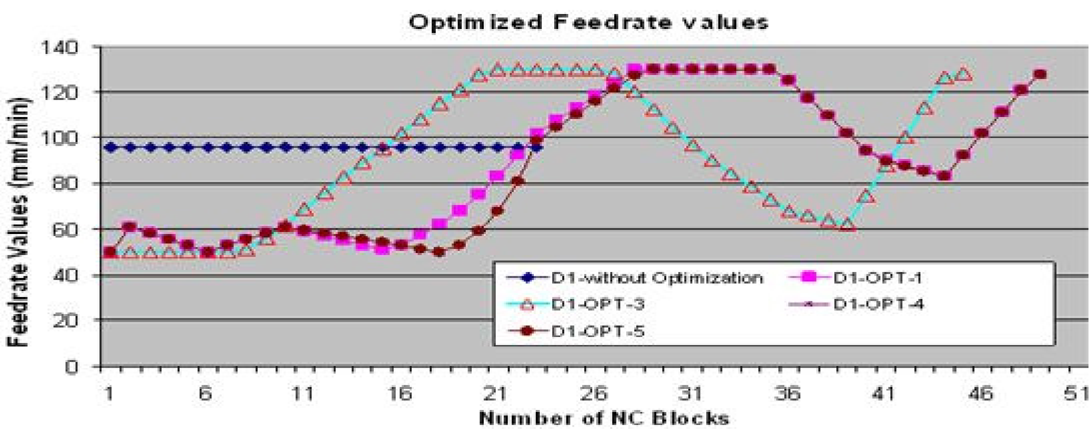

Figure 7. Feedrate changes for optimized feedrates with various reference MRR.

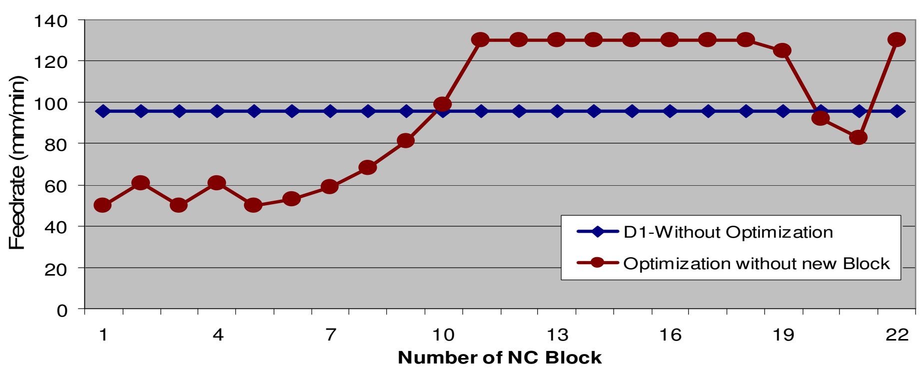

Figure 8. Original (constant NC block) and regulated feedrate values for the CL file

consideration for feedrate optimization with new inserted NC blocks as shown in Figure 7. In this approach, firstly, feedrate scheduling based on the MRR is performed, and a new feedrate is inserted in every existing NC block. When the feedrate and MRR values shows a sharp change between two consecutive NC blocks, a new NC block is inserted to regulate MRR between them. First, maintaining a fixed MRR at all milling locations is selected for federate scheduling. Figure 7 shows feedrate and number of NC block changes by keeping constant MRR for different reference MRR values. As it is seen from scheduled feedrate values, they are not constant. The feedrate values were again regulated according to a reference material removal rate value in the feed direction. The MRR values were readily regulated and controlled at the given level using the scheduled feedrates. Analyzed results of MRR-based

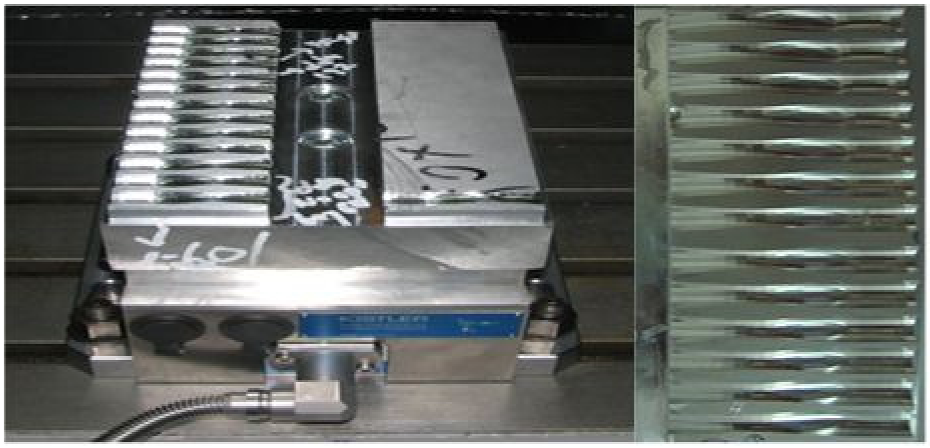

Figure 9. Real machined geometry.

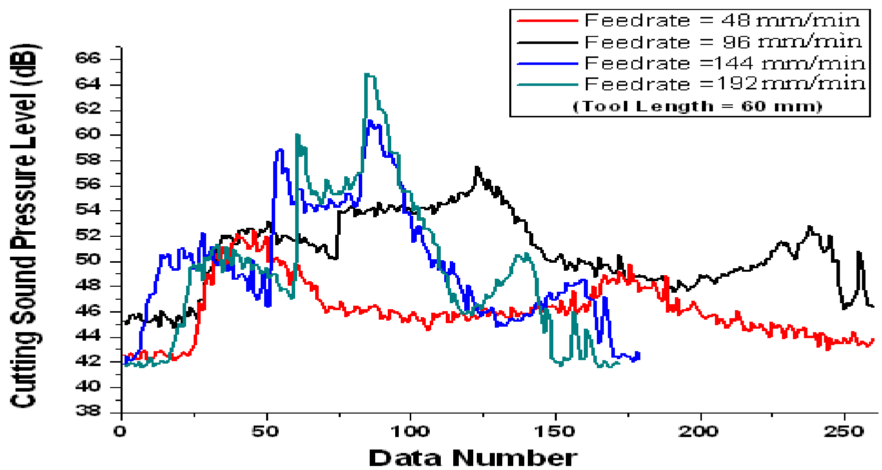

Figure 10. Effect of feedrate value on SPL for clamping length of 60 mm.

approach, the MRR increased in regions where the feed rate decreased and vice versa.

It is necessary to use MRR based feedrate without adding new NC block for rough machining due to the simpler and short calculation time. Second feedrate optimization approach (with new G codes) is more suitable for semi-finishing operations (Figure 8). The machined workpiece parts can be seen under the different cutting conditions and MRR based feedrate optimization parameters (Figure 9).

RESULTS

The effect of cutting feed rate on the sound pressure level

Sound generated by the machining process under different cutting conditions is digitized, recorded and processed in computer with our software was written using MATLAB. A 1024 point FFT is computed and the results are averaged to estimate the magnitude of the sound. Cutting sound pressure levels increased with the increase of feedrate values. In Figure 10, cutting sound pressure levels in different feedrate values are given and compared.

With the increase of feed rate, cutting force and cutting tool deflection also increased parallel to the increase of machining sound pressure levels. Cutting sound pressure levels occurred in 192 mm/min feed rate are a little higher than the sound pressure levels occurred in 144 mm/min feed rate. By decreasing the feed rate as 48 mm/min, the lowest cutting sound pressure levels and cutting tool deflection were obtained.

Figure 11 compares the frequency spectrums of the cutting sound for different feedrate values. In this paper, the sound pressure level at a frequency of 2.8 kHz was selected as the maximum value in order to investigate the relationship between the feedrate value and the sound pressure level. From Figure 11, it is clear that the amplitude of the frequency of the cutting sound increases dramatically when feedrate is raised. In Figure 12, cutter deflection for different feedrate values are compared.

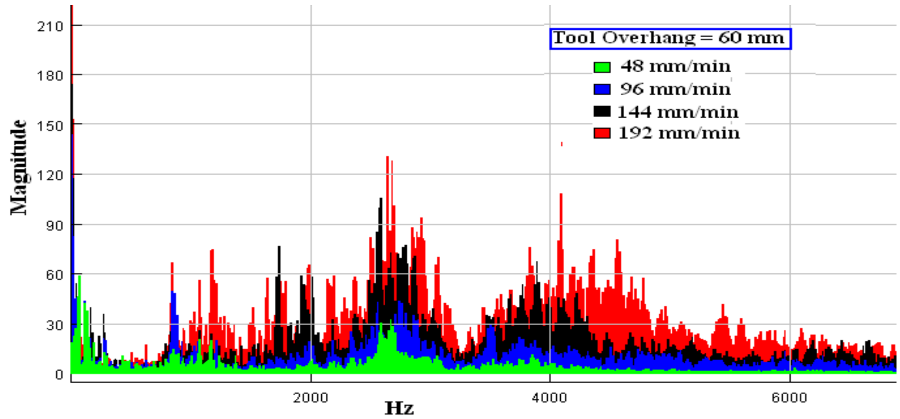

Figure 11. Frequency spectrum of cutting sound for different feedrate values.

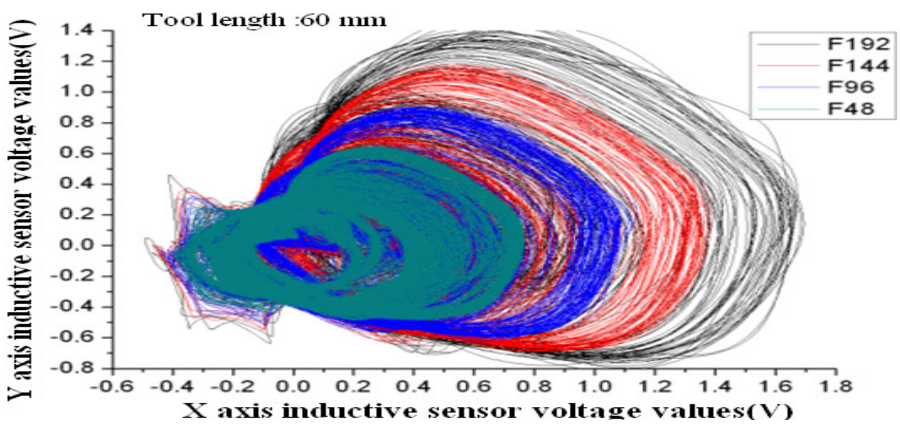

Figure 12. Effect of feedrate value on deflection value.

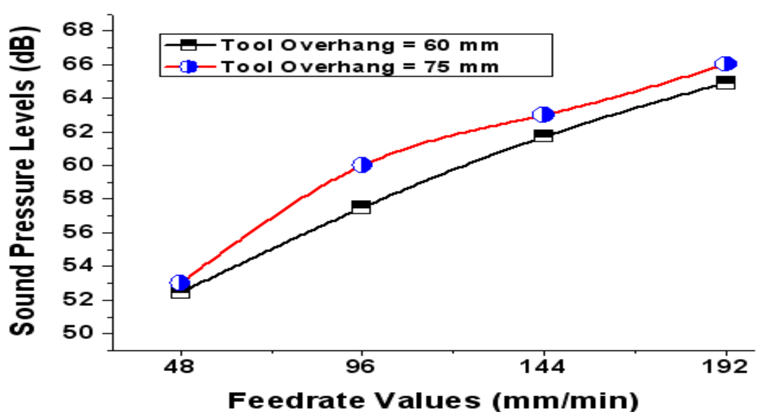

Figure 13. Influence of tool overhang length and feedrate values on SPL.

Influence of the tool clamping/overhang length on SPL

Cutting sound pressure levels occurred in 75 mm tool clamping length are a little higher than the sound pressure levels occurred in 60 mm tool clamping length as shown Figure 13. The graph represent the tendency to cutting sound when the same tool was used at different overhang lengths in a given applications. The tool slender parameter L^3/D^4; where L is the overhang length and D is

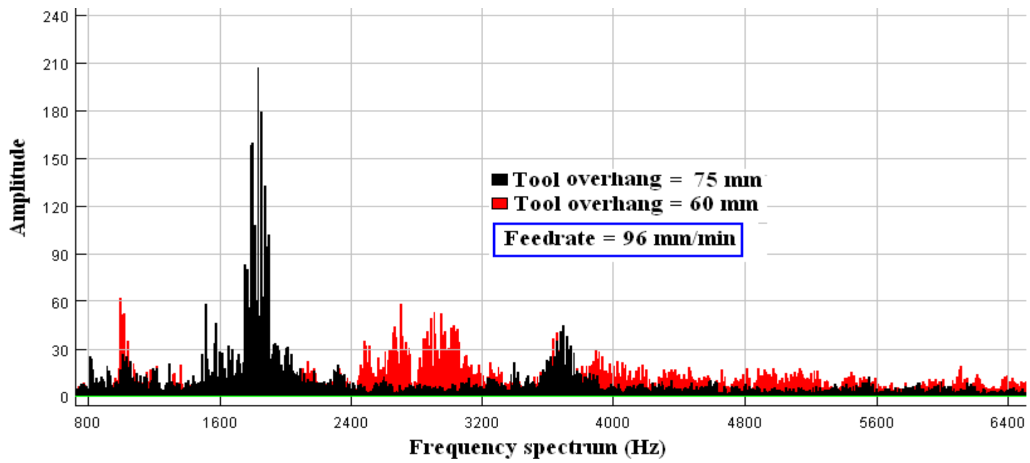

Figure 14. Frequency spectrums of cutting sound overhang values for different tool.

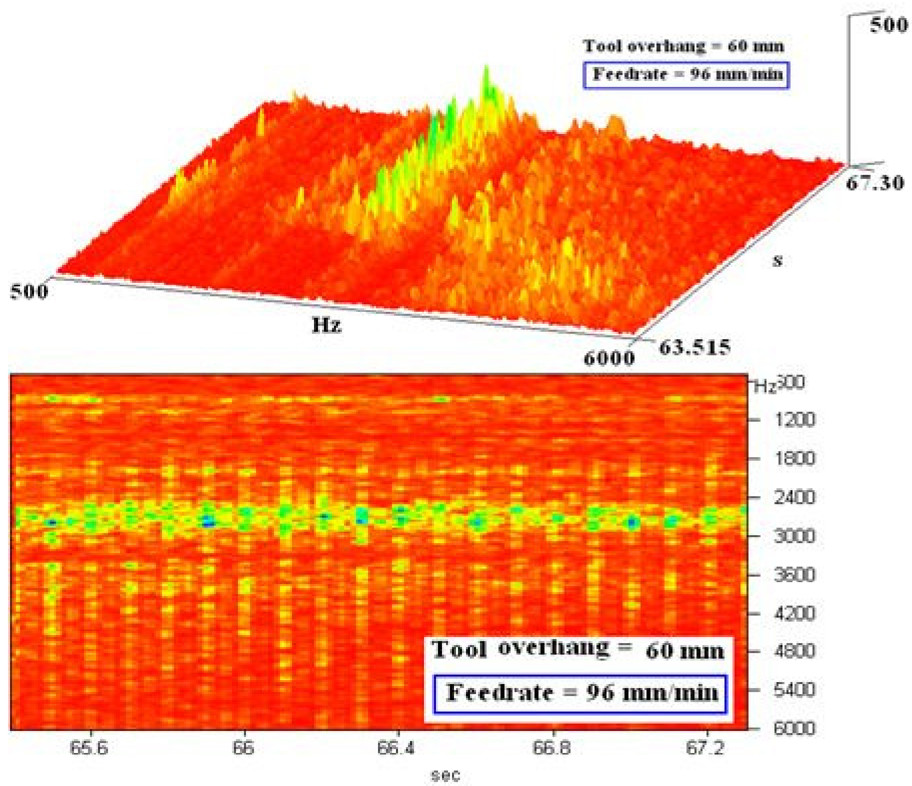

Figure 15. Frequency spectra for tool overhang length of 60 mm.

the tool diameter, the most important parameters in the static tool deflection. A larger cutting forces and deflection means the tendency to cutting sound is greater. In order to investigate the relationship between the tool overhang and the sound pressure level, the value of the sound pressure level at the frequency of 750 and 6500 Hz was used.

Figure 14 compares the frequency spectrums of the cutting sound for tool overhang of 60 and 75 mm at the feedrate of 96 mm/min. The amplitudes of the fundamental cutting sound frequencies when employing tool overhang of 75 mm were observed to be higher than that of overhang of 60 mm as shown Figures 14 to 16. More significantly for tool overhang length of 75 mm, the harmonics with significant intensities between 1600 and 2200 Hz were highly indicative that cutter deflections possibly due to cutter runout occurred with large magnitudes. Figures 15 to 16 shows 3D diagrams and

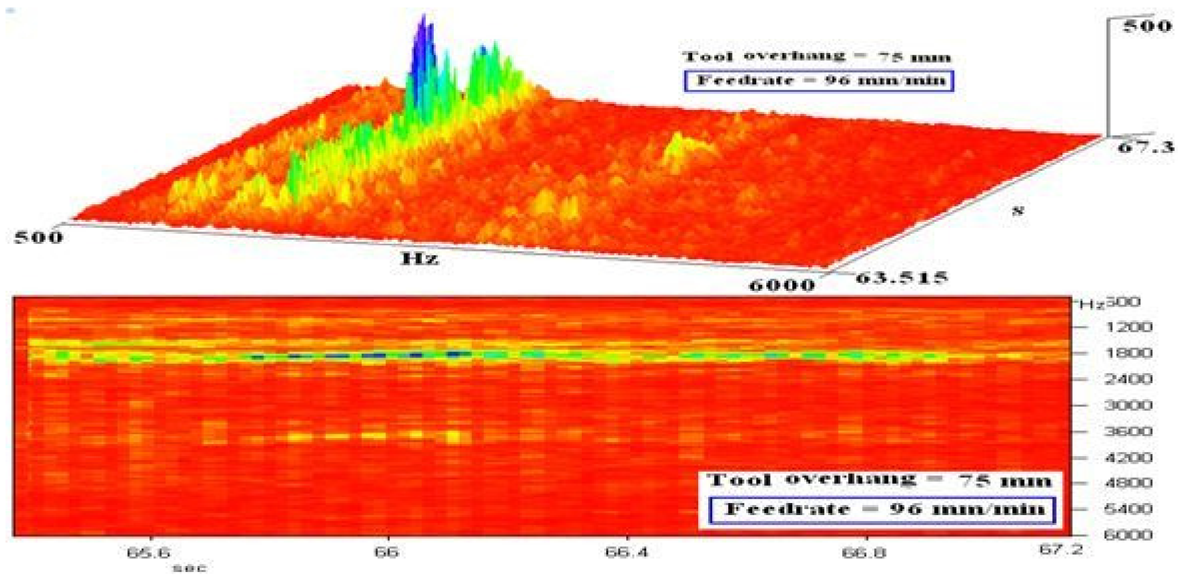

Figure 16. Frequency spectra for tool overhang length of 75 mm.

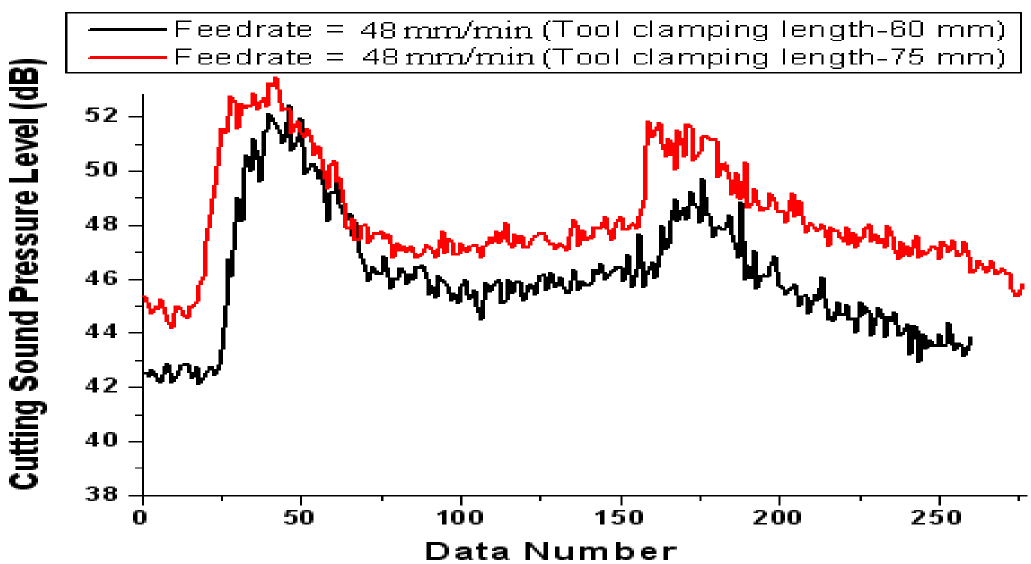

Figure 17. Effect of tool clamping length on cutting SPL; feed rate 48 mm/min.

spectrograms of the time tracking of the amplitude of cutting sound at the frequencies of 500 and 6000 Hz of the processing sound for different tool overhang values. When tool overhang value was increased from 60 mm to 75 mm, the amplitudes of the high frequency and very low frequency components increased.

In Figures 17, 18, 19 and 20, cutting sound pressure levels in different tool overhang and feedrate values are given.

The relationships between sound pressure level and tool clamping length at a feed-rate values of 48, 96, 144 and 192 mm/min (Figures 21 and 22) are again linear and positive, and both are statistically highly significant (0.994 and 0.957 for clamping length 60 and 75 mm, respectively). Cutter deflection occurred in tool overhang length of 75 mm are higher than the cutting deflection occurred in tool overhang length of 60 mm for 192 mm/min. In Figure 23, cutter deflection for different tool clamping lengths are given and compared.

The relationship between sound pressure level and cutter deflection

Cutting tool deflection values increased with the increase of feedrate values. In Figure 12, cutting tool deflection

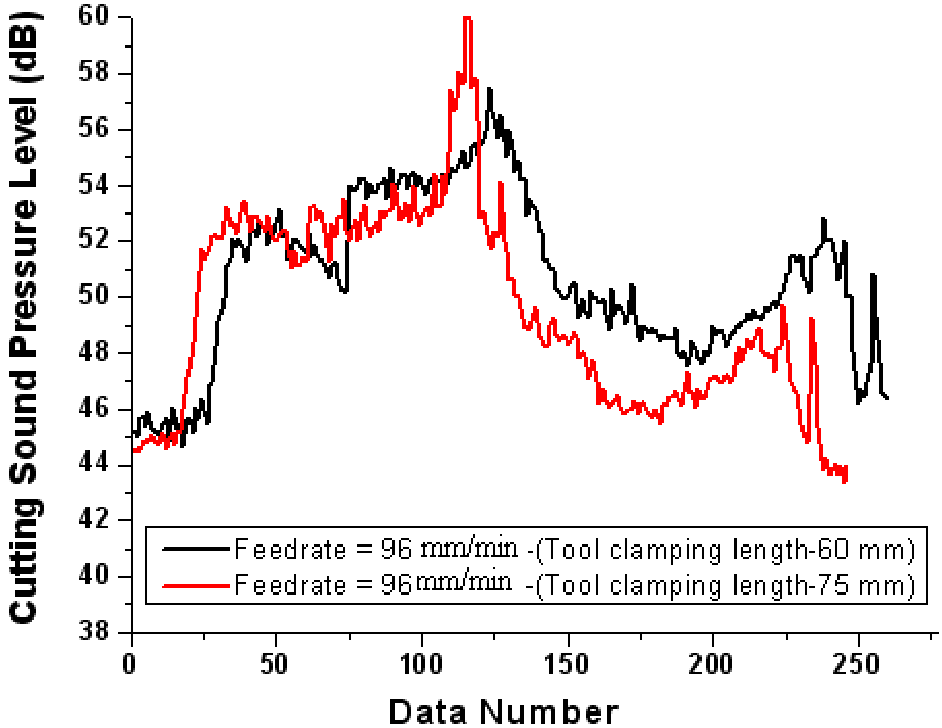

Figure 18. Effect of tool clamping length on cutting SPL; feed rate 96 mm/min.

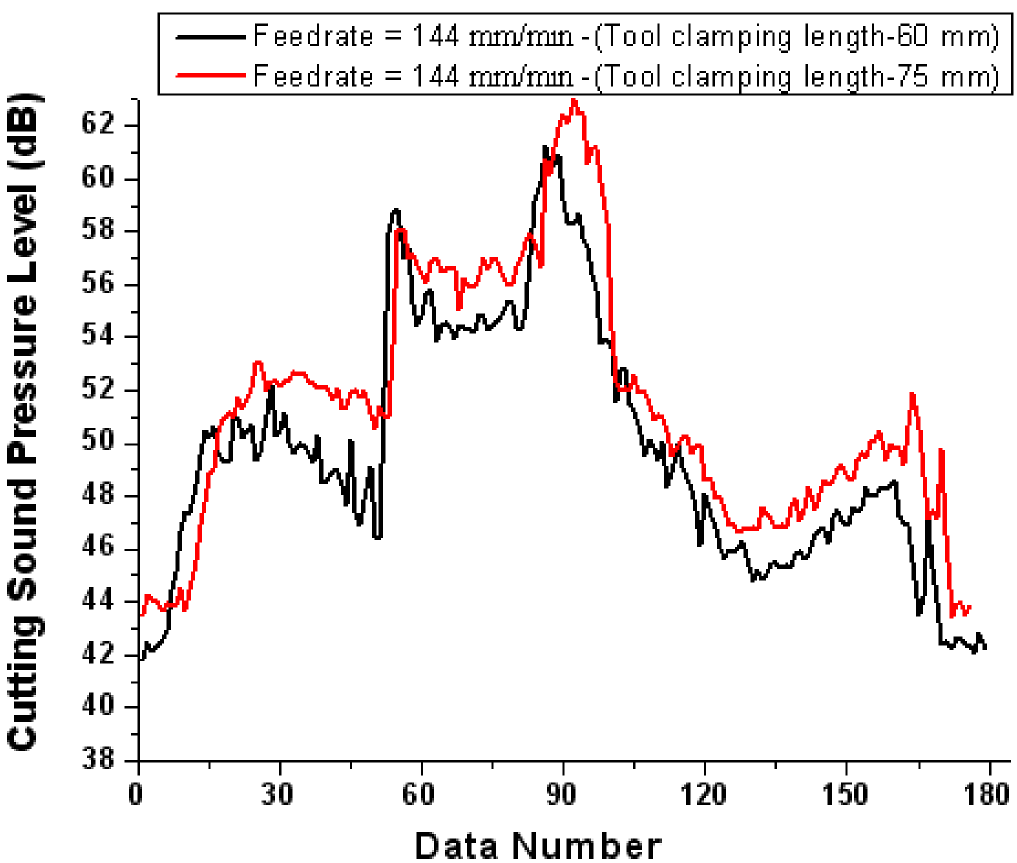

Figure 19. Effect of tool clamping length on cutting SPL ; feed rate 144 mm/min.

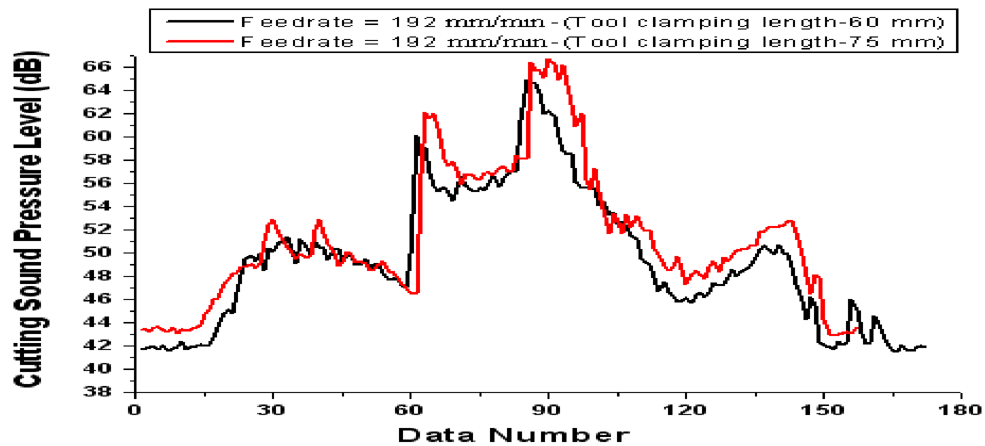

Figure 20. Effect of clamping length on cutting SPL; feed rate 192 mm/min.

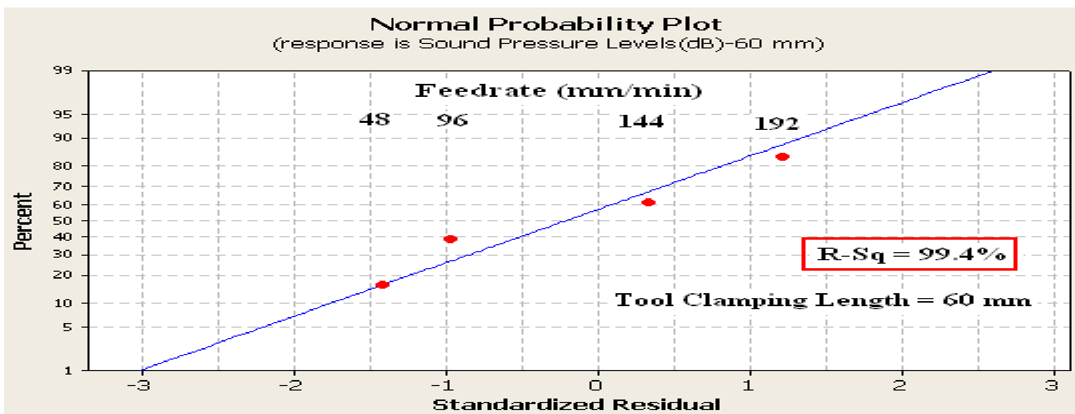

Figure 21. SPL as a function of feed rates at a tool length of 60 mm. Conditions: in Table 4.

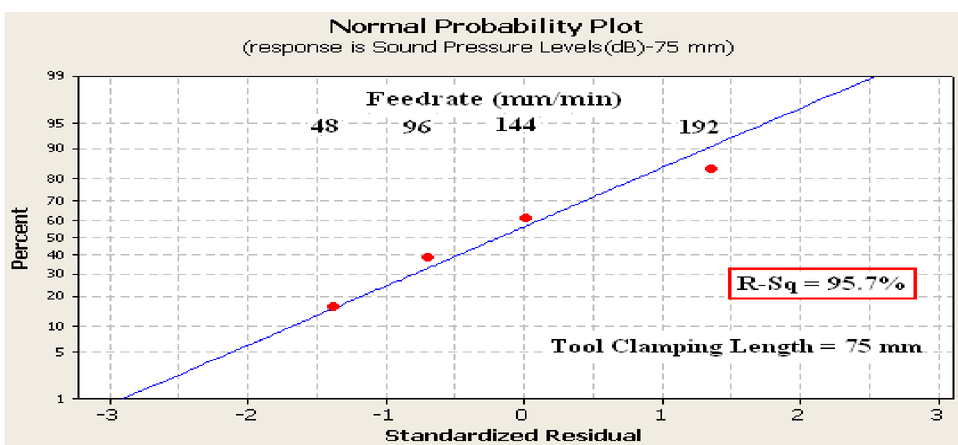

Figure 22. SPL as a function of feed rates at a tool clamping length of 75 mm.

values in four different feedrate values are compared. With the increase of feed rate, cutting tool deflection also increased parallel to the increase of machining sound pressure levels as shown in Figures 24 and 25 for clamping length of 60 and 75 mm. It may be possible to clarify the relationship between cutting tool deflection values and sound pressure level. Figures 24 and 25 showed the variations observed in SPL and cutting tool

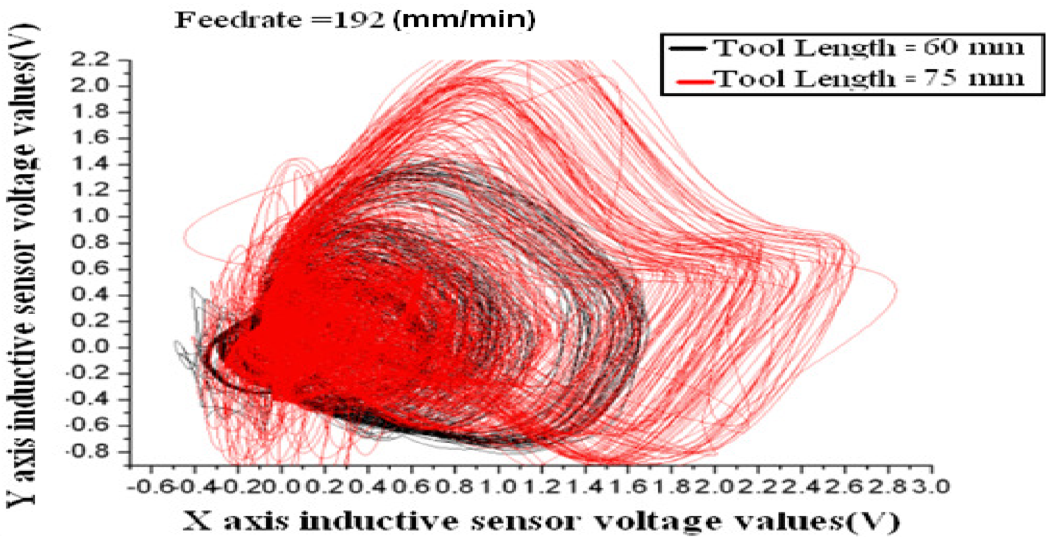

Figure 23. Effect of tool clamping length on cutter deflection value for 192 mm/min.

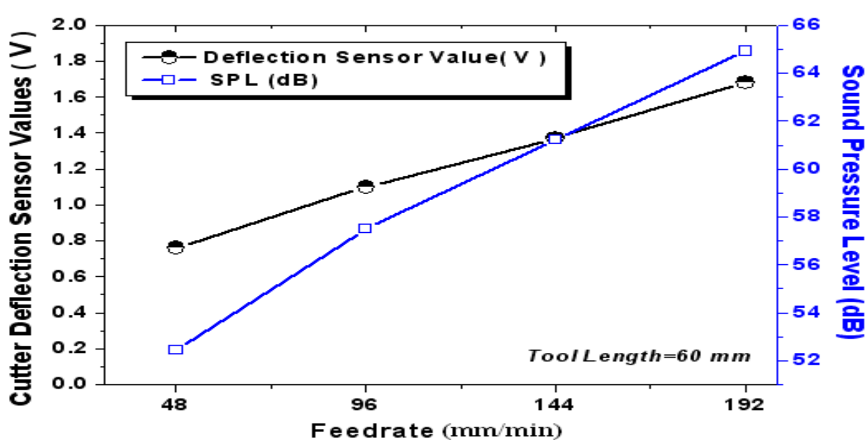

Figure 24. SPL and deflection as a function of feedrate values (Tool length-60 mm).

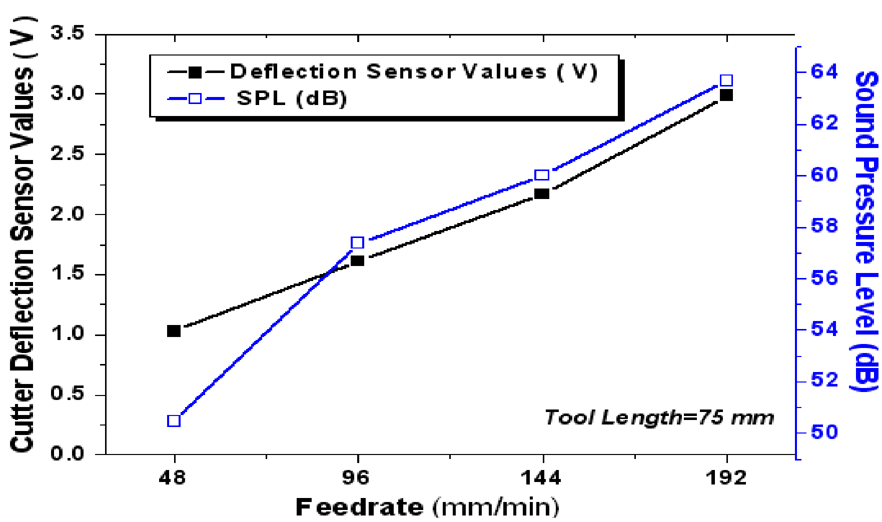

Figure 25. SPL and deflection as a function of feedrate values(Tool length-75 mm).

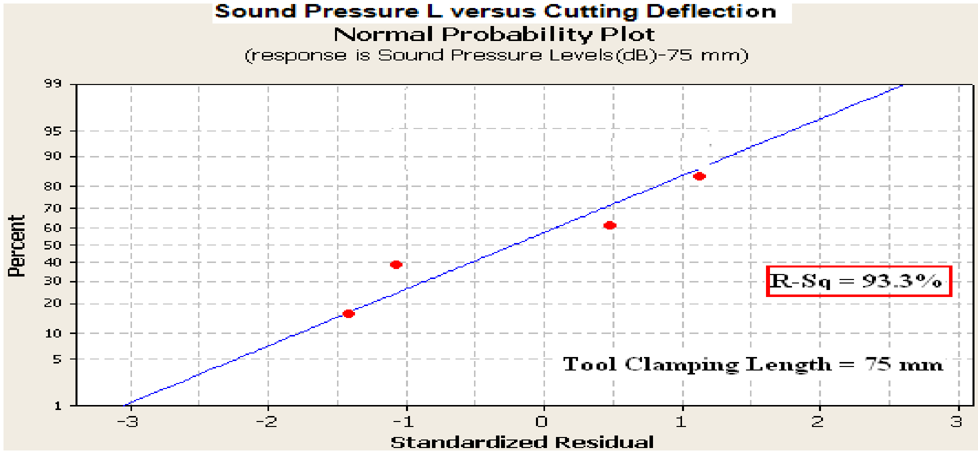

Figure 26. SPL as a function of tool deflection at a tool clamping length of 75 mm.

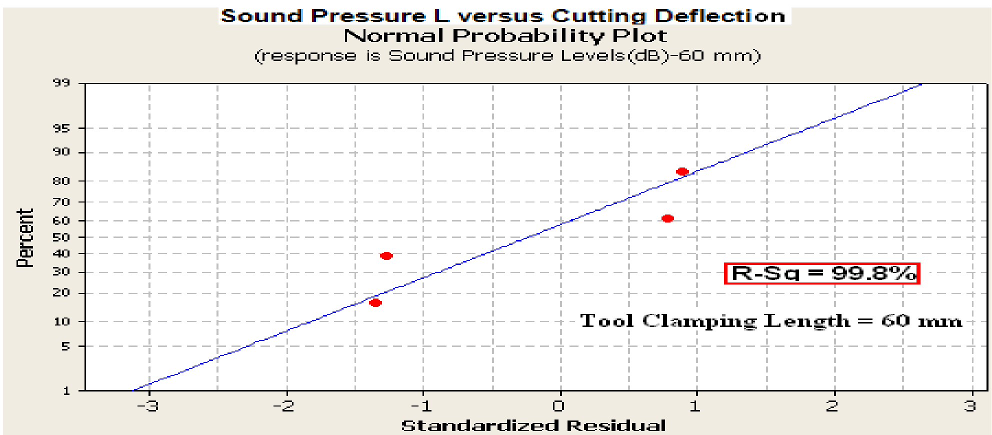

Figure 27. SPL as a function of tool deflection at a tool clamping length of 60 mm.

deflection as a function of the feedrate values for different clamping length.

The relationship between cutter deflection and sound pressure level during milling at all federate values (Figures 26 and 27) is positive, linear, and statistically significant (r = 0.998 for tool clamping length = 60 mm, r = 0.993 for tool clamping length = 75 mm). Correlation coefficients between tool deflection values and sound pressure level at all feed speeds were better than r = 0.7. This shows a distinct relationship that further suggests that monitoring of the sound pressure level signal is a viable method for monitoring and controlling free form surface milling.

The relationship between sound pressure level and cutting forces

Cutting forces values increased with the increase of feed-rate values. With the increase of feed rate, cutting forces also increased parallel to the increase of machining sound pressure levels as shown Figures 28 and 29 for clamping length of 60 and 75 mm. The potential relation between SPL and cutting forces was examined, as shown in Figures 28 and 29, which demonstrates the variations observed in SPL and cutting forces as a function of the feedrate values. The relation-ship between cutting forces and sound pressure level during milling at all federate values (Figures 30 and 31) is positive, linear, and statistically significant (r = 0.998 for tool overhang length = 60 mm, r = 0.964 for tool overhang length = 75 mm). Correlation coefficients between cutting forces and sound pressure level at all feed speeds were better than r = 0.7.

Evaluation of feedrate optimization approaches using SPL

The feedrate scheduling was executed to regulate the MRR values at a given reference levels. Figure 32 shows regulated MRR values, which are obtained feedrate

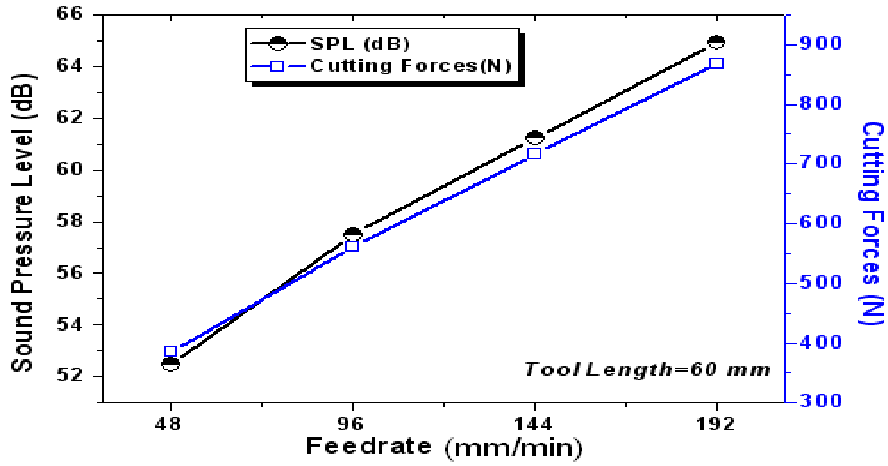

Figure 28. SPL and cutting forces as a function of feedrate (Tool length-60 mm).

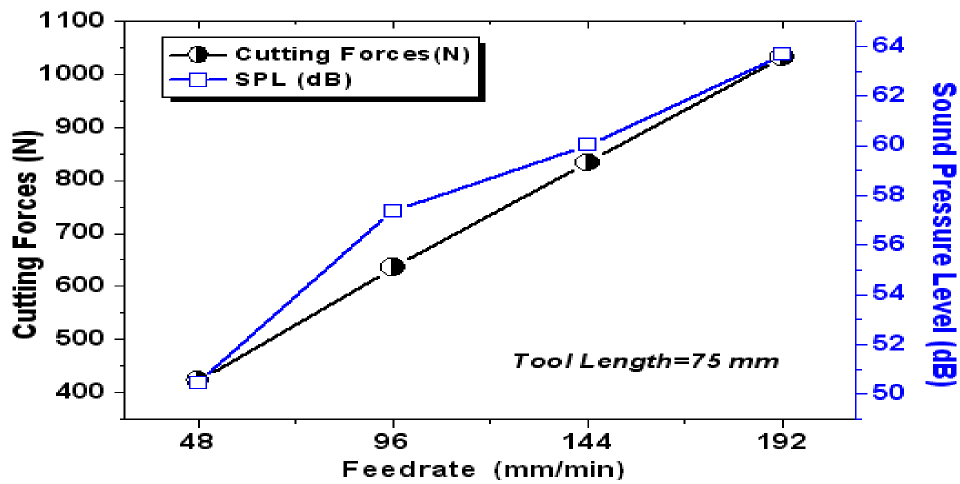

Figure 29. SPL and cutting forces as a function of feedrate (Tool length-75 mm).

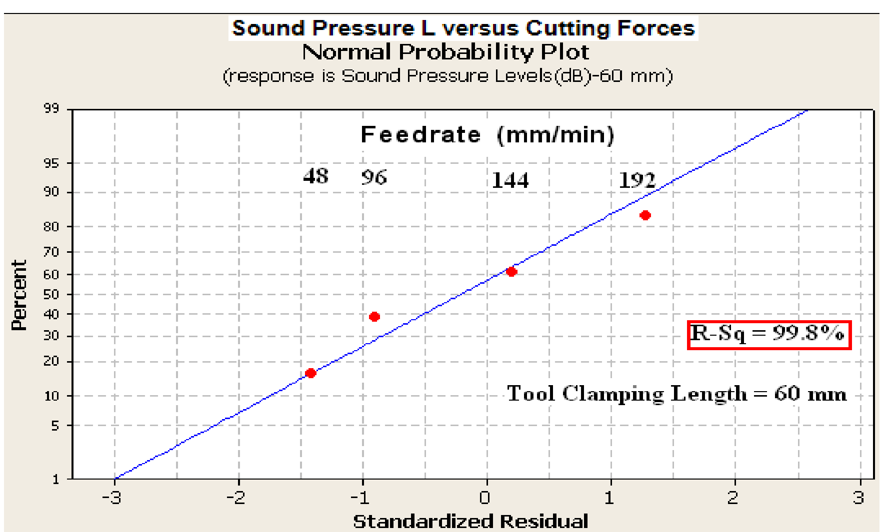

Figure 30. SPL as a function of cutting forces at a tool clamping length of 60 mm.

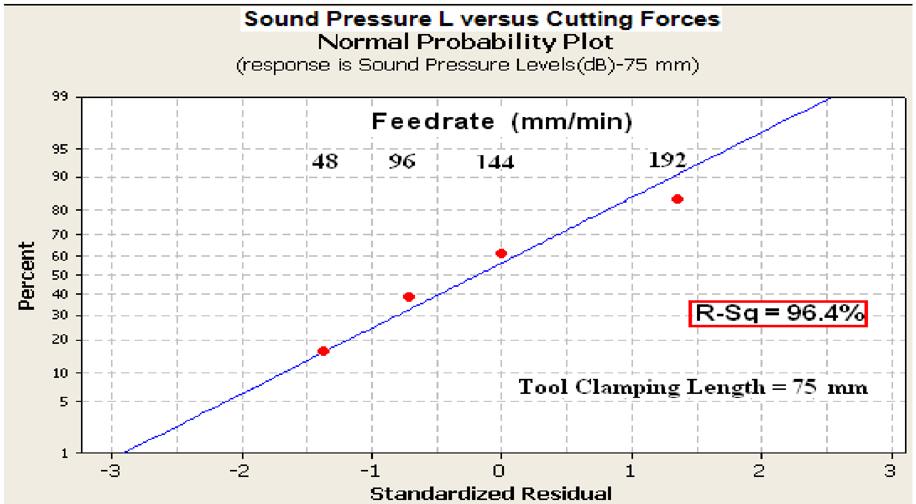

Figure 31. SPL as a function of cutting forces at a tool clamping length of 75 mm.

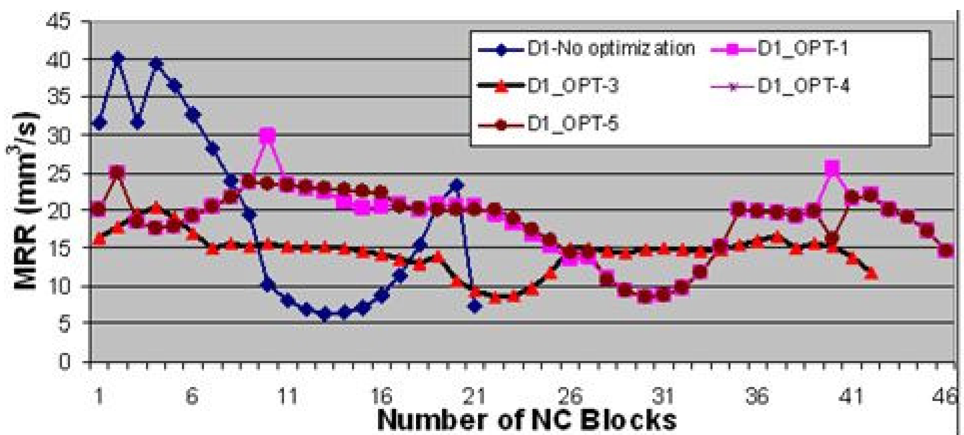

Figure 32. MRR changes for optimized feedrate with various reference MRR.

optimization process with different reference MRR. MRR-based feed rate optimization approaches were applied successful as can be seen clearly in Figures 7 and 8. After introducing MRR-based feedrate optimization for slot cutting of free-form surfaces, the results of sound pressure levels, cutting forces and cutting deflection values will be compared for these cases. It is obvious that MRR based feedrate scheduling cases gave lower sound pressure levels and cutting forces compared to fixed feedrate strategy. With the optimization of feed rate, cutting deflection values regulated parallel to the regulation of machining sound pressure levels as shown in Figures 33 and 34.

Reasonable behavior between cutting forces and sound pressure level thus shows promise for monitoring of cutting forces and cutter deflection using sound pressure level. Comparison made between the unoptimized and optimized milling indicate that the sound pressure level values when optimized condition were lower than the fixed feedrate conditions. The scheduled feedrate values output more stabile and lower SPL values are shown in Figure 35. When the feedrate optimized NC file was executed, the amplitudes of the cutting sound frequency components decreased as shown in Figures 36 to 38. Figures 37 and 38 presents 3D diagrams of the time tracking of the FFT frequency analysis of the cutting sound signatures obtained at the frequencies of 500 and 6000 Hz for constant and optimized feedrate values, respectively.

DISCUSSION

This paper discussed the possibility of using sound pressure level to observe the free form surface milling process at different machining conditions and to evaluate MRR based feedrate optimization approaches. Audible sound waves generated during machining are important

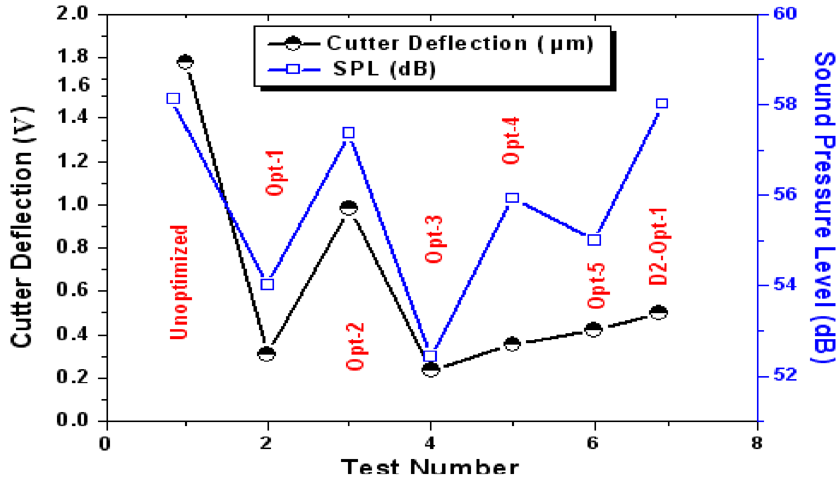

Figure 33. Comparison of effect of the fixed and optimized feedrate values on SPL and cutter deflection. Conditions: as in Table 5.

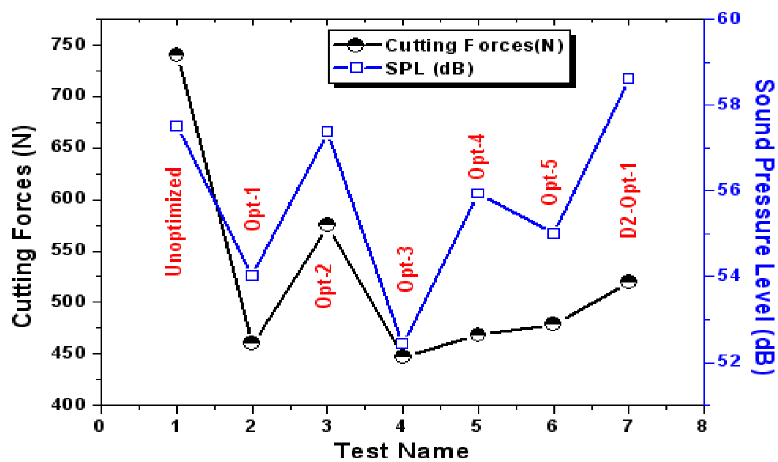

Figure 34. Comparison of effect of the fixed and optimized feedrate values on SPL and cutting forces. Conditions: as in Table 5.

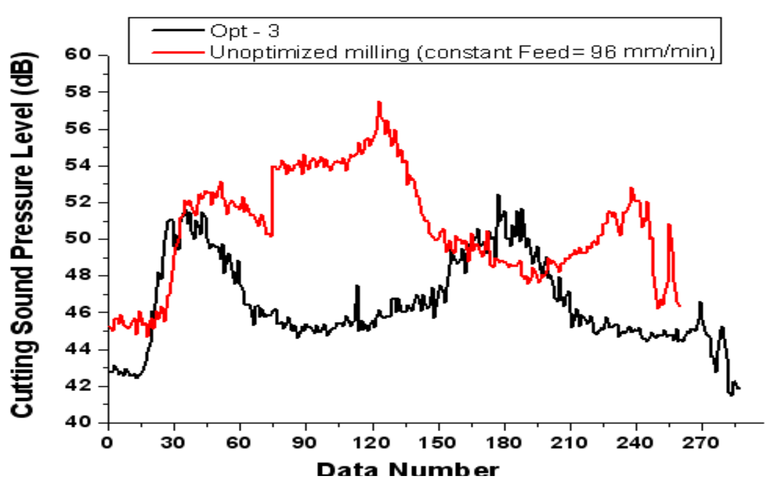

Figure 35. Comparison effect of fixed and scheduled (OPT-3) feedrate values on SPL.

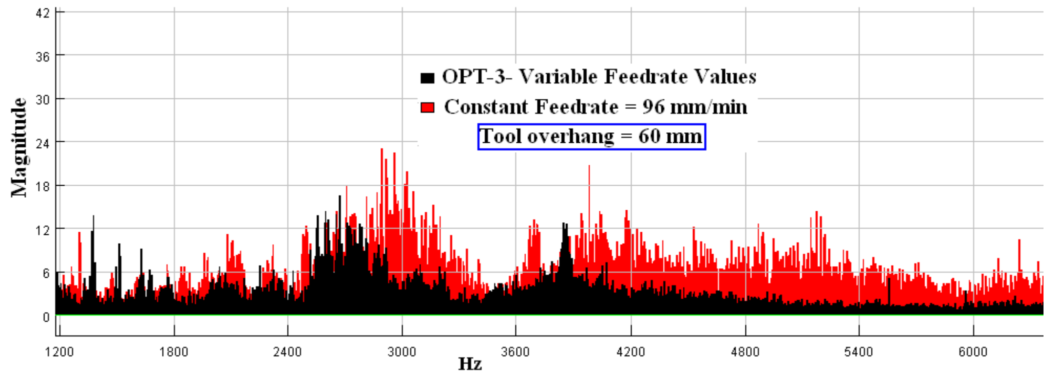

Figure 36. Comparison of frequency spectrums for fixed and optimized feedrate conditions.

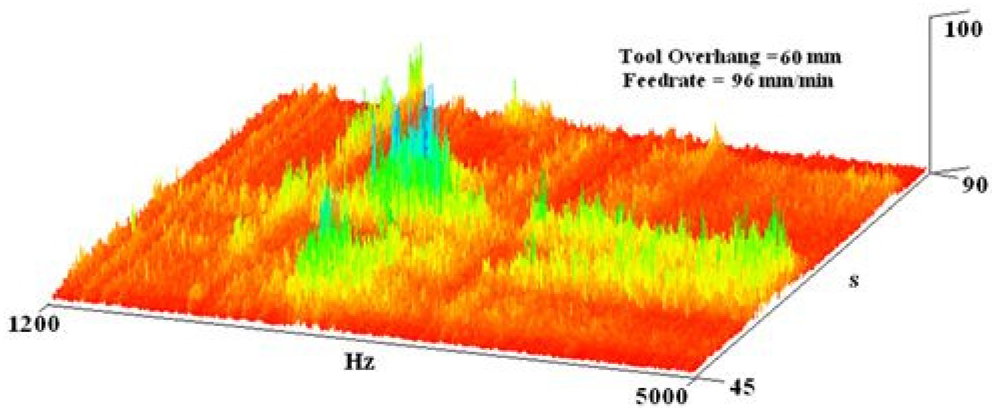

Figure 37. 3-D Frequency spectra for unoptimized feedrate cutting condition.

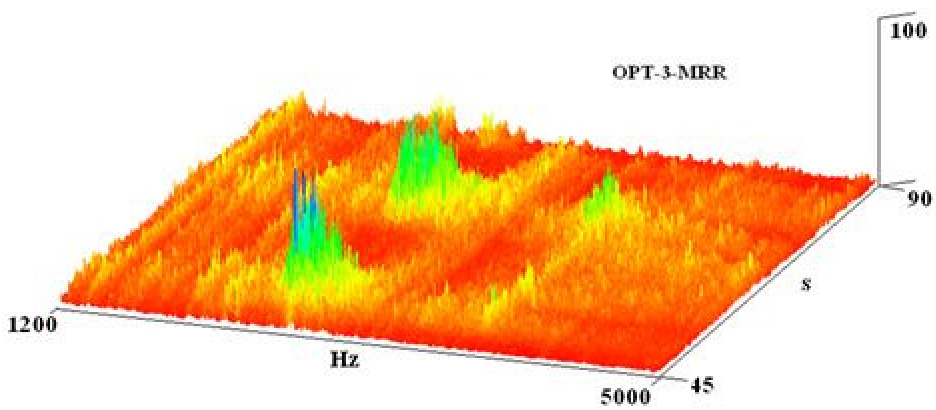

Figure 38. 3-D Frequency spectra for optimized feedrate cutting condition.

signals that can give an indication of cutter condition and machining process situation. An experienced operator can observe the change in the operational cutting sound generated from different machining conditions. A number of scientists have used cutting sound measurement techniques to monitor machining conditions (Nagatomi et al., 1993), cutting tool wear (Banshoya et al., 1994), tool breakage and wear detection in turning (Trabelsi and Kannatey-Asibu, 1991), effect of cutting parameters on chip shape and roughness (Tekiner and Yeşilyurt, 2004), effect of coating material and roughness (Kamguem, 2010) on slot milling, chatter detection and control (Delio et al., 1992; Schtmiz et al., 2001-a, 2002; Schmitz, 2003; Weingaertner et al., 2006).

In existing studies, cutting sound analysis approach applied to monitoring of the turning, laser cutting, slot milling of plane surface, sawing, grinding, drilling and wood machining operations. In our study, we analyzed and focused on milling of free form surfaces which the machining process is very complex than the others. When a tool moves into different regions of free form surface (concave, convex and flat surfaces) or changes its cutting direction in 3D sculptured surface machining, tool-workpiece engagement area, the engage angle, swept volume, cutter load, axial and radial depth of cuts are often changed. Therefore, selection of milling conditions is a very important step in order to avoid undesirable results such as tool wear, tool breakage or over-cut due to excessive cutting tool deflection. There is no study in the literature for monitoring of cutting process using sound pressure levels (SPL), focused on machining of sculptured surfaces and also related with tool deflection and cutting forces. Examination and monitoring of the sound pressure level generated during slot milling in free-form surface and the cutter deflection and cutting forces produced shows that:

i) Changes in the feed rate (48, 96, 144 and 192 mm/min) also affect both the sound pressure level signal and tool deflection in our work. With the increase of feed rate, cutting tool deflection also increased parallel to the increase of machining sound pressure levels. Our findings agree with those of Kamguem (2010), who observed that with the increase of feed rate values, parallel to the increase of milling sound pressure for slot milling cases with different flat end mills in plane surfaces. Similarly, this result is supported by the study of Tekiner and Yeşilyurt (2004). They investigated effect of cutting parameters on process sound during turning of AISI 304 steel. Shrikrishna et al. (2007) investigated effect of different wall thickness and depths of cavity on sound pressure levels using various spindle speed values in face milling process.

Our result is very similar to the findings of their study showed that the increase in SPL (in dB) with speed is almost linear for all the workpieces, suggesting a dominant effect of speed on sound pressure level. Additionally, Iskra and Tanaka (2005) found that strong, positive, linear relationships were observed between feed rate and sound intensity in wood machining process. From Figure 11, it is clear that the amplitude of the frequency of the cutting sound increases dramatically when feedrate is raised. Strong, positive, linear relationships were observed between feed rate and sound pressure level, as well as for the tool deflection. Correlation coefficients between tool deflection values and sound pressure level at all feed speeds were better than $r = 0.7$. This shows a distinct relationship that further suggests that monitoring of the sound pressure level signal is a viable method for monitoring and controlling free form surface milling.

ii) The relationship between cutting forces and sound pressure level during milling at all federate values is positive, linear, and statistically significant ($r = 0.998$ for tool overhang length = 60 mm, $r = 0.964$ for tool overhang length = 75 mm). This result is supported by the study of Jaromír Audy (2007), who monitored that sound pressure increased with the cutting forces due to increases in the cutting feedrates and depth of cuts for single point turning operations.

iii) Cutting sound pressure levels occurred in 75 mm tool overhang is a little higher than the sound pressure levels occurred in 60 mm tool overhang. When tool overhang value was increased from 60 to 75 mm, the amplitudes of the high frequency and very low frequency components increased.

iv) MRR based feedrate scheduling approaches gave more lower sound pressure levels, amplitudes of frequency, cutting deflection and cutting forces values compared to fixed feedrate strategy. These scheduled feedrate values output more stabile and lower SPL values. Moreover, the sound pressure signal which has a strong relation to the material removal rate is detected. Measurement of sound pressure level has considerable potential for use in monitoring and/or controlling of the free form surface milling process, including variation of the feedrate, tool clamping length and different MRR based feedrate optimization approaches.

Conclusions and future remarks

In this paper, audible sound is investigated as a dynamic approach is established to enhance our understanding of the relationship among cutting conditions, tool deflection, cutting forces and the sound signal generated from the cutting process. Finally, our experimental approach and its results show that the sound pressure level is very useful and practical methods for monitoring of the effect of machining conditions and variable feedrate values from optimization in sculptured surface milling process. In the next study, an adaptive on-line control system based on cutting sound pressure signal will develop and enable the integration of the CNC milling center for more efficient surface milling (desired surface quality or machining cost) by means of adjusting feedrate values.

REFERENCES

Abu-Mahfouz I (2003). Drilling wear detection and classification using vibration signals and artificial neural network. Int. J. Mach. Tools Man., 43 (7): 707-720.

Alonso FJ Salgado DR (2005). Application of singular spectrum analysis to tool wear detection using sound signals. Proceedings of the IMechE J. Eng. Man., 219 (9): 703-710.

Anderson D (1988). Method for Monitoring Cutting Tool Wear During a Machining Operation. The Boeing Company. USA, USP. 04744242.

Bailey T, Elbestawi MA, El-Wardany TI, Fitzpatrick P (2002). Generic simulation approach for multi-axis machining, Part 2: model calibration and feed rate scheduling. ASME Trans J. Man. Sci Eng., 124: 634-42.

Banshoya K, Ohsaki H, Nagatomi K, Murase Y (1994). Relationship

between cutting sound and tool wear in machine boring of wood and wood based materials. Mok. Gakkaishi., 40(4): 521-528.
Blum T, Insaki I (1990). Study on acoustic emission from the orthogonal cutting process. Trans. ASME J. Eng. Ind., 112 (3): 203-211.
Brophy C, Kelly K, Byrne G (2002). AI-based condition monitoring of the drilling process. J. Mater. Processing Technol., 124(3): 305-310.
Burke LI, Rangwala S (1991). Tool condition monitoring in metal cutting. A neural network approach. J. Intel. Man., 2(5): 269-280.
Byrne G, Dornfeld D, Inasaki I, Ketteles G, Knig W, Teti R (1995). Tool condition monitoring (TCM)-the status of research and industrial application. CIRP Annal., 44(2): 541-567.
Chen C, Lee S, Santamarina G (1994). An object-oriented manufacturing control system. J. Intel. Man., 5(5): 315-321.
Chen J, Huang Y, Chen M (2005). Feedrate optimization and tool profile modification for the high-efficiency ball-end milling process. Int J Mach Tools Manuf., 45: 1070-1076.
Chen JC (2000). An effective fuzzy-nets training scheme for monitoring tool breakage. J. Intel. Man., 11(1): 85-101.
Chen JC, Chen WL (1999). A tool breakage detection system using an accelerometer sensor. J. Intel. Man., 10(2): 187-197.
Cho DW, Lee SJ, Chu CN (1999). The state ofmachining processmonitoring research in Korea. Int. J. Mach. Tools Man., 39(11): 1697-1715.
Clark WI, Shih AJ, Hardin CW, Lemaster RL, McSpadden SB (2003). Fixed abrasive diamond wire machining-part I: process monitoring and wire tension force. Int. J. Mach. Tools Man., 43(5): 523-532.
Cook NH (1980). Tool Wear Sensors. Wear., 62: 49-57.
Cyra G, Tanaka C (2000). The effects of wood-fiber directions on acoustic emission in routing. Wood Sci. Technol., 34: 237-252.
Dan L, Mathew J (1990). Tool Wear and Failure Monitoring Techniques for Turning-A review. Int. J. Mach. Tools Man., 30: 579-598.
Delio T, Tlusty J, Smith S (1992). Use of audio signals for chatter detection and control. J. Eng. Ind., 114(2): 146-157.
Desforges X, Habbadi A, Geneste L, Soler F (2004). Distributed machining control and monitoring using smart sensors/actuators. J. Intel. Man.,15(1): 39-53.
Dornfeld DA (1992). Monitoring of machining process-literature review. CIRP Ann., 41(1): 93-96.
Franco-Gasca LA, Herrera-Ruiz G, Peniche-Vera R, Romero-Troncoso RJ, Leal-Tafolla W (2006). Sensorless tool failure monitoring system for drilling machines. Int. J. Mach. Tools and Man., 46(3-4): 381-386.
Fussell BK, Ersoy C, Jerard RB (1992). Computer Generated CNC Machining Feedrates. Proc. of the Japan-USA Symp. on Flexible Automation. CA., pp. 377-384.
Govekar E, Gradisek J, Grabec I (2000). Analysis of acoustic emission signals and monitoring of machining processes. Ultrasonics., 38(1-8): 598-603.
Haber RE, Jimenez JE, Peres CR, Alique JR (2004). An investigation of tool wear monitoring in a high-speed machining process. Sensors and Actuators A: Phys., 116(3): 539-545.
http://www.cgtech.com: Website of CGTech, USA.
http://www.ezcam.com
http://www.mastercam.com
http://www.powermill.com
http://www.vegacnc.com
Hutton DV, Yu Q (1990). On the effects of a built-up edge on acoustic emission in metal cutting. Trans. ASME J. Eng. Ind., 112 (3): 184-189.
Ip RWL, Lau HCW, Chan FTS (2003). An economical sculptured surface machining approach using fuzzy models and ball-nosed cutters. J. Mat. Proces. Technol., 138(1-3): 579-585.
Ip WLR (1998). A fuzzy basis material removal optimization strategy for sculptured surface machining using ball-nosed cutters. Int. J. Prod. Res., 36 (9): 2563-2571.
Iskra P, Tanaka C (2005). The influence of wood fiber direction, feed rate, and cutting width on sound intensity during routing. Holz als Roh- und Werkstoff., 63: 167-172.
Jang DJ, Kim KS, Jung JM (2000). Voxell-based virtual multi-axis machining. Int J Adv Manufact. Technol., 16(10): 709-713.
Jaromír A (2007). Machinability Assessment of an Eutectoid Steel by Measurement of Cutting Forces. J. Man. Eng., 3: 28-32.
Jemielniak K (1999). Commercial tool condition monitoring systems. Int. J. Adv. Man. Technol., 15: 711-721.
Jemielniak K (2006). Tool wear monitoring based on a non-monotonic signal feature. Proc. of the IMechE J. Eng. Man., 220 (2):163-170.
Jemielniak K, Kwiatkowski L, Wrzosek P (1998). Diagnosis of tool wear based on cutting forces and acoustic emission measures as inputs to a neural network. J. Intel. Man., 9: 447-455.
Kamguem R (2010). Qualite De Surface Et Emissions Acoustiques En Fraisage Haute Vitesse Des Alliages D'aluminium. Universite Du Quebec. MSc. Thesis. Canada.
Karlsson B, Karlsson N, Wide P (2000). A dynamic safety system based on sensor fusion. J. Intel. Man., 11(5): 475-483.
Karunakaran KP, Shringi R (2008). A solid model-based off-line adaptive controller for feed rate scheduling for milling process. J. Mater. Proces. Technol., 204(1-3): 384-396.
Kim SJ, Jung TS, Yang MY (2004). Feedrate optimization using CL surface. J. Korean Society Precision Eng., 21(4):39-47.
Kloypayan J, Lee YS (2002). Adaptive feedrate scheduling and material engagement analysis for high performance machining. Proc. of the IMECE-ASME.
Ko PL, Liu ZS, Cvitkovic R, Donovan M, Loewen R, Krishnapper G (1999). Tool wear monitoring for routing MDF. Proc. of the 14th Int. Wood Mach. Seminar., pp. 609-619.
Lan TS, Hsu KS (2007). The implementation of optimum MRR on digital PC-based lathe system. Int. J. Adv. Man. Technol., 35(3-4): 248-254.
Li Q, Budong Y, Shuting L (2008). Comparing and combining off-line feedrate rescheduling strategies in free-form surface machining with feedrate acceleration and deceleration. Rob. and Comput. Integr. Man., 24: 796-803.
Li ZZ, Zheng M, Zheng L, Wu ZJ, Liu DC (2003). A solid model-based milling process simulation and optimization system integrated with CAD/CAM. J. Mat. Proc. Technol.,138 (1-3): 513-517.
Lia W, Gonga W, Obikawab T, Shirakashic Y (2005). A method of recognizing tool-wear states based on a fast algorithm of wavelet transform. J. Mat. Proces. Technol.,170(1-2): 374-380.
Lin B, Zhu MZ, Yu SY, Zhu HT, Lin MX (2002). Study of synthesis identification in the cutting process with a fuzzy neural network. J. Mater. Proces. Technol., 129(1-3): 131-134.
Lu MC, Kannatey-Asibu EJr (2000). Analysis of sound signal generation due to flank wear in turning. Int. ME2000 Congress and Exposition.
Masory O (1991). Monitoring machining processes using multi-sensor readings fused by artificial neural network. J. Mater. Proces. Technol., 28(1-2): 231-240.
Metal Carboloy Systems Department (1980). Milling Handbook of High Efficiency Metal Cutting. General Electric Company. USA.
Murata K, Nishimura K, Ikami Y, Ebihara M (1993). Sawing performances of band saws treated with new filling methods II. Power consumption in sawing, sawing accuracy, and roughness of sawn surface. Mokuzai Gakkaishi., 39(11): 1239-1245.
Naerheim Y, Lan MS (1988). Acoustic emission reveals information about the metal cutting process and tool wear. Proc. of the 16th NAMR Conference. SME. pp. 240-244.
Nagatomi K, Yoshida K, Banshoya K, Murase Y (1993). Recognition of wood cutting conditions through cutting sounds I. Effects of tool system's stiffness and tool wear on the generation of sound in cutting parallel to the grain. Mokuzai Gakkaishi., 39(11): 521-528.
Niranjan Prasad K, Ramamoorthy B (2004). Monitoring of flank wear of coated tools in high speed machining with a neural network ART2. Int. J. Mach. Tools Man., 44(12-13): 1311-1318.
Okafor C, Adetona O (1995). Predicting quality characteristics of end-milled parts based on multi-sensor integration using neural networks, individual effects of learning parameters and rules. J. Intel. Man., 6(6): 389-400.
Ouafi AE, Guillot M, Bedrouni A (2000). Accuracy enhancement of multi-axis CNC machines through on-line neurocompensation. J. Intel. Man., 11(6): 535-545.
Peng Y (2004). Intelligent condition monitoring using fuzzy inductive learning. J. Intel. Man., 15(3): 373-380.
Rangwala S, Dornfeld D (1990). Sensor integration using neural networks for intelligent tool condition monitoring. Trans. ASME J. Eng. Ind., 112(3): 219-228.
Salgado DR, Alonso FJ (2006). Tool wear detection in turning operations using singular spectrum analysis. J. Mater. Proces.

Technol., 171 (3): 451-458.
Schaffer G (1983). The ears and eyes of CIM. Report No. 765. Am. Machinist, 127(7): 109-124.
Scheffer C, Kratz H, Heyns PS, Klocke F (2003). Development of a tool wear monitoring system for hard turning. Int. J. Mach. Tools Man., 43(10): 973-985.
Schmitz TL (2003). Chatter recognition by a statistical evaluation of the synchronously sampled audio signal. J. Sound Vibration., 262(3): 721-730.
Schmitz T, Davies M, Kennedy M (2001a). Tool point frequency response prediction for high-speed machining by RCSA. J. Man. Sci. Eng., 123: 700-707.
Schmitz TL, Medicus K, Dutterer B (2002). Exploring once-per-revolution audio signal variance as a chatter indicator. Mach. Sci. Technol., 6(2): 215-233.
Shawaky A, Rosenberger T, Elbestawi M (1998). In process monitoring and control of thickness error in machining hollows shafts. Mechatron, 8: 301-322.
Silva RG, Baker KJ, Wilcox SJ (2000). The adaptability of a tool wear monitoring system under changing cutting conditions. Mech. Syst. Signal Proces., 14 (2): 287-298.
Sokolowski A, Kosmol J (2001). Selected examples of cutting process monitoring and diagnostics. J. Mater. Proces. Technol., 113(1-3): 322-330.
Spence AD, Altintas Y (1994). A Solid Modeler Based Milling Process Simulation and Planning System. Trans. ASME., 116: 61-69.
Tanaka C, Nakao T, Takahashi A (1988). A new technique for adaptive control optimization in circular sawing. Mokuzai Gakkaishi., 34(9): 769-771.
Tanaka C, Nakao T, Takahashi A, Schniewind AP (1990). On-line control of feed-speed in circular sawing. Holz Roh-Werkstoff, 48: 139-145.
Tanaka C, Zhao C, Nakao T, Nishino Y, Takahashi A (1993). An adaptive control optimization for circular sawing. Forest Prod. J., 43(9): 61-65.
Tekiner Z, Yesilyurt S (2004). Investigation of the cutting parameters depending on process sound during turning of AISI 304 austenitic stainless steel. Mat. Design., 25: 507-513.
Teti R, Baciu IL (2004). Neural network processing of audible sound parameters for sensor monitoring of tool conditions. Intel. Comp. Man. Eng., 4: 385-390.
Teti R, Baciu IL, Rubio EM (2004). Neural network classification of audible sound signals for process monitoring during machining. Proc. of the 15th Int. DAAAM Symp.
Tlusty J, Andrew GC (1983). A critical review of sensors of unmanned machining. CIRP Ann., 32(1): 563-577.
Trabelsi H, Kannatey-Asibu, EJr (1991). Pattern-Recognition Analysis of Sound Radiation in Metal Cutting. Int. J. Adv. Man., Technol., 6: 220-231.
Wang WP (1988). Solid modeling for optimizing metal removal of three-dimensional NC end-milling. J. Man. Sys., 7(1): 57-65
Weingaertner WL, Schroeter RB, Polli ML, Gomes J.de Oliveira (2006). Evaluation of high-speed end-milling dynamic stability through audio signal measurements. J. Mater. Proces. Technol., 179(1-3): 133-138.
Wilcos SJ, Reuben RL, Souquet P (1997). The use of cutting force and acoustic emission signals for the monitoring the tool insert geometry during rough face milling. Int. J. Mach. Tools Man., 32(4): 481-494.