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Process Monitoring Systems for Machining Using Audible Sound Energy Sensors

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1. Introduction

In the last fifty years, many manufacturers have chosen the implementation of Flexible Manufacturing Systems (FMS) or Computer Integrated Manufacturing (CIM) in their shop floor or, at least, the automation of some of the operations carried out therein with the intention of increasing their productivity and becoming more competitive (Shawaky, 1998; Sokolowski, 2001; Cho, 1999; Govekar, 2000; Brophy, 2002).

With reference to machining operations, the implementation of these systems requires the supervision of different aspects related to the machine (diagnostic and performance monitoring), the tool or tooling (state of wear, lubrication, alignment), the workpiece (geometry and dimensions, surface features and roughness, tolerances, metallurgical damage), the cutting parameters (cutting speed, feed rate, depth of cut), or the process itself (chip formation, temperature, energy consumption) (Byrne, 1995; D'Errico, 1997; Tönshoff, 1988; Grabec, 1998; Inasaki, 1998; Kopac, 2001; Fu, 1996; Masory, 1991; Huang, 1998; Teti, 1995; Teti, 1999).

For the monitoring and control of the above mentioned aspects, it has been necessary to make notable efforts in the development of appropriate process monitoring systems (Burke & Rangwala, 1991; Chen *et al.*, 1994; Chen *et al.*, 1999; Chen, 2000). Such systems are typically based on different types of sensors such as cutting force and torque, motor current and effective power, vibrations, acoustic emission or audible sound (Desforges, 2004; Peng, 2004; Lin, 2002; Sokolowski, 2001; Ouafi *et al.*, 2000; Karlsson *et al.*, 2000; Chen & Chen, 1999; Jemielniak *et al.*, 1998; Byrne, 1995; Dornfeld, 1992; Masory, 1991). However, despite all the efforts, standard solutions for their industrial application have not been found yet. The large number and high complexity of the phenomena that take place during machining processes and the possibility to choose among numerous alternatives in each implementation step of the process monitoring system (e.g. cutting test definition, type and location of sensors, monitoring test definition, signal processing method or process modeler selection) are the main responsible for the existence of more than one solution.

The review and analysis of the relevant literature on this topic revealed that it is necessary to develop and implement an experimental system allowing for the systematical

characterizarion of the different parameters that influence the process before realizing a process monitoring system applicable to industry (Hou, 2003; Jin & Shi, 2001; Hong, 1993; Malakooti *et al.*, 1995; Venkastesh *et al.*, 1997; Xiaoli *et al.*, 1997; Xu & Ge, 2004). This will allow to establish an adequate knowledge and control of the critical factors involved in the process monitoring system by means of single factor variations. Moreover, it will be also possible to identify the variations produced by potential spurious sources when the process monitoring system is applied to real situations in the shop floor.

This work reports on the approach for the development of a machining process monitoring system based on audible sound sensors. Audible sound energy appears as one of the most practical techniques since it can serve to replace the traditional ability of the operator, based on his experience and senses (mainly vision and hearing), to determine the process state and react adequately to any machine performance decay (Lu, 2000). This technique has been attempted for decision making on machining process conditions but it has not been extensively studied yet for applications in industrial process monitoring (Teti, 2004; Teti & Baciu, 2004). The main critical issues related to the employment of this technology in industry are the need to protect the sensor from the hazardous machining environment (cutting fluids and metal chips) and the environment noise (from adjacent machines, motors, conveyors or other processes) that may contaminate the relevant signals during machining (Lu, 2000; Teti & Baciu, 2004; Teti *et al.*, 2004; Wilcos, 1997; Clark, 2003).

The principal benefits of audible sound sensors for machining process monitoring are associated with the nature of the sensors employed in the acquisition of the signals. These are, in general, easy to mount on the machine tool, in particular near the machining point, with little or no interference with the machine, the tool, the workpiece or the chip formation. Besides, these sensors, basically microphones, are easy to use in combination with standard phonometers or spectrum analysers. These characteristics of audible sound sensors make the realization of the monitoring procedure quite straightforward. In addition, their maintenance is simple since they only require a careful handling to avoid being hit or damaged. Accordingly, they usually provide for a favourable cost/benefit ratio.

The key novelties of the approach proposed in this work are, on the one hand, the application of a systematic methodology to set up the cutting trials allowing for a better comparison with other similar experimental works and, as a result, the advance in the standardization for the development of such systems. On the other hand, the independent signal analysis of the noise generated by the machine used for the cutting trials and by the working environment allows to filter this noise out of the signals obtained during the actual material processing. Lastly, the possibility has been verified to apply the results of this approach for the development of process monitoring procedures based on sensors of a different type, in particular acoustic emission sensors, where the stress waves produced within the work material do not travel through air but only in the work material itself. The combined application of audible sound energy sensors and acoustic emission sensors could allow for the acquisition of more exhaustive information from both low frequency (audible sound) and high frequency (acoustic emission) acoustic signal analysis. This would decidedly contribute to the realization of the concept of sensor fusion technology for process monitoring (Emel, 1991; Niu *et al.*, 1998).

The described methodology was applied to characterize the audible sound signals emitted by different cutting conditions during milling processes. The classification of audible sound signal features for process monitoring in milling was carried out by graphical analysis and

parallel distributed data processing based on artificial neural networks. In the following sections, the methodology, the experimentation, the sensor signal detection and analysis methods, and the obtained results are reported and critically assessed.

2. Methodology

The methodology proposed for the design and implementation of a process monitoring system based on audible sound energy sensors includes the steps described below.

Cutting tests definition. All the elements involved in the cutting tests, along with their basic characteristics and properties, should be defined in this step, as reported in the systematic methodology proposed in (Rubio & Teti, 2005) for the establishment of tool condition monitoring systems. In particular, the cutting operation, the machine tool, the workpiece (material and size), the tools (type, material, coating, dimensions and fresh/worn state), the cutting parameters (cutting speed, feed rate, depth of cut) and the possible use of cutting fluid, should be defined. Although this seems obvious and there are in the literature works that report thorough descriptions of the cutting tests (Teti & Buonadonna, 1999), most of the authors do not provide, or not with the desired detail, all the necessary information to allow for a correct analysis of the results and an adequate comparison with the results obtained by other authors.

Process monitoring tests definition. The monitoring tests dealt with in this work are based on the use of audible sound energy sensors. The broadband sound pressure level of the audible signals is detected by means of sensing devices dedicated to the measure and display this type of signals. All detected audible sound signals are transferred on PC and off-line analysed. In order to verify the repeatability of the monitoring tests, the audible sound signal specimens should be recorded several times (≥ 3) for each cutting condition. The noise of the machine tool running unloaded should be recorded as well in order to be able, later, to characterise the audible sound signals from the cutting process deprived of the disturbing noise generated by both machine and working environment.

Selection of signal processing and decision making methods. To select the most adequate signal processing and decision making methods, a review of the main advanced signal processing (Rubio *et al.*, 2006a) and decision making procedures (Rubio *et al.*, 2006b) used in machining process monitoring based on acoustic sensors was carried out. As a result, the Fast Fourier Transform (FFT) was selected for signal processing and feature extraction whereas supervised Neural Network (NN) paradigms were adopted for signal feature pattern recognition and process conditions decision making.

Experimental layout. The most essential aspects of the experimental layout concern the audible sound sensor location and protection: firstly, the selection of the distance between sensor and cutting point in order to detect the signals correctly, and, secondly, the way to protect the sensor from the chips, the cutting fluid and other pollutants during machining. Besides these actions, particular attention must be paid to isolate the experiments from environmental noise that could seriously contaminate the signal detection.

Performance of the cutting and process monitoring tests. Once all the previous steps have been completed, the machining tests with process monitoring must be carried out. As stated earlier, the tests should be rehearsed several times in order to verify their repeatability. Furthermore, the noise of the machine tool running unloaded should be recorded for its later subtraction from audible sound signals detected during the material removal process.

Signal processing and decision making. After the sensor monitoring tests, the processing and analysis of the recorded signals by means of the methods selected earlier must be carried out together with the decision making procedure applied to significant signal features: in this work, the FFT for signal processing and supervised NN paradigms for decision making.
Design and implementation of the process monitoring system. On the basis of the issues of the previous steps, the implementation procedure for an on-line machining process monitoring system based on audible sound energy sensors can be proposed.

3. Application

According to the methodology described in the previous section, experimental applications were carried out as outlined below.
Cutting tests definition. Following the methodology for the definition of the cutting tests (Rubio & Teti, 2005), the machining operation was defined as a milling process carried out on a conventional DORMAC FU-100 milling machine. The workpiece was a plate of size of 100 x 200 x 40 mm made of T4-6056 Al alloy. The tool was a fresh 5-teeth milling cutter of 12.16 x 8.18 x 5.16 mm, made of WC-Co inserts coated with TiN. The cutting conditions were: spindle speed, S = 800 and 1000 rpm; feed rate, f = 40, 80 and 160 mm/min and depth of cut, d = 0.5 and 1 mm. The tests were conducted under dry cutting conditions. Table 1 summarizes the cutting test description.

Element	Type/ Characteristics/Properties
Cutting operation	Milling
Machine Tool	Conventional: DORMAC FU-100 milling machine
Workpiece	Material: 6056 aluminium alloy with T4 thermal treatment Dimensions: 100 x 200 x 40 mm
Tool	Type: 5-teeth milling cutter Material: tungsten particles and cobalt matrix carbide (WC-Co) Coat material: titanium nitride (TiN) Dimensions: 12,16 x 8,18 x 5,16 mm State: Fresh
Cutting conditions	Cutting speed, S = 800 - 1000 rpm Feed rate, f = 40 – 80 - 160 mm/min Depth of cut, d = 0.5 - 1 mm
Coolant	No

Table 1. Summary of the cutting test description.

Process monitoring tests definition. The audible sound energy monitoring system was composed of a Larson Davis 2800 Spectrum Analyser, a standard Larson Davis preamplifier model PRM 900B, a ½" free field high sensitivity sensor and a ½" pre-polarized microphone (Fu, 1996). All audible sound signals detected by the Larson Davis 2800 Spectrum Analyser were transferred on PC for off-line analysis.

Selection of signal processing and decision making methods. The selected signal processing and feature extraction method was the FFT and the signal features pattern recognition for decision making was based on supervised NN data processing since this approach had been used in previous works with satisfactory results (Teti, 2004; Teti & Baciu, 2004).
Experimental layout. Figure 1 shows the experimental layout. The distance between the microphone and the cutting point was set in such a way that, during each machining operation, was approximately equal to 85 mm. Particular attention was paid to protect the microphone from the chips by means of a plastic mesh and to isolate the experimental area from environment noise that could contaminate the detected signals.

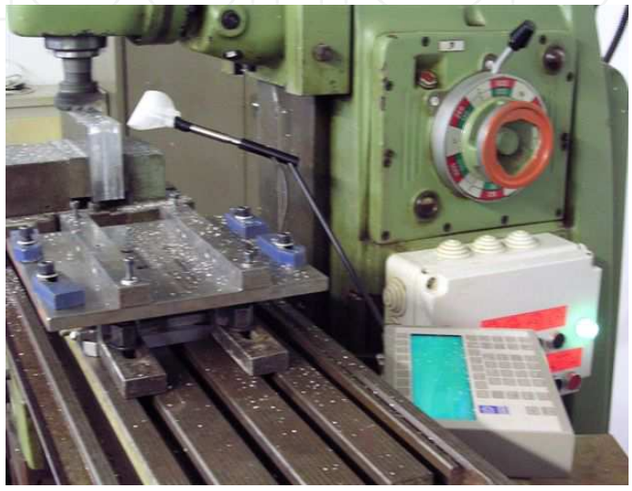


Fig. 1. Experimental layout.

Performance of the cutting and process monitoring tests. The experimental tests carried out with the different cutting conditions are reported in Table 2. Each test was rehearsed 3 times in order to check for repeatability. Simultaneously, the sensor monitoring procedure was applied during each test.
Signal processing and decision making. The spectrum analyser was set to 800 lines acquisition mode and a FFT zoom was set equal to 2. In this way, as the capture interval was from 0 to 10000 Hz, by dividing this frequency interval into 800 lines, a step of 12.5 Hz was achieved. Besides the audible sound signal detected in sound Level Meter mode, a series of signal parameters (SUM (LIN) SUM (A), SLOW, SLOW MIN, SLOW MAX, FAST, FAST MIN, FAST MAX, IMPULSE, LEQ, SEL, PEAK, Tmax3 and Tmax5) were obtained and recorded as well. The option "by time" allowed to save the measurements automatically, with end time equal to 10 seconds and step equal to 1 second. The transfer velocity was set at 9600 Baud, which was the same as the velocity imposed to the PC for file transfer. For graphical data processing and display, Spectrum Pressure Level-Noise (Spectrum Pressure Lave, 1998) and Vibrations Works (OS Windows) (Noise and Vibrations Works, 1998) and CA Cricket Graph III (OS Mac) (CA-Cricket Graph III,1992) software packages were used. For NN data processing, the Neural Network Explorer software package was used (Masters, 1993).

Test Id.	*S (rpm)*	*f (mm/min)*	*d (mm)*
1	800	---	---
2	800	---	---
3	800	---	---
4	1000	---	---
5	1000	---	---
6	100	---	---
7	800	40	0.5
8	800	40	0.5
9	800	40	0.5
10	800	80	0.5
11	800	80	0.5
12	800	80	0.5
13	800	160	0.5
14	800	160	0.5
15	800	160	0.5
16	800	40	1
17	800	40	1
18	800	40	1
19	800	80	1
20	800	80	1
21	800	80	1
22	800	160	1
23	800	160	1
24	800	160	1
25	1000	40	0.5
26	1000	40	0.5
27	1000	40	0.5
28	1000	80	0.5
29	1000	80	0.5
30	1000	80	0.5
31	1000	160	0.5
32	1000	160	0.5
33	1000	160	0.5
34	1000	40	1
35	1000	40	1
36	1000	40	1
37	1000	80	1
38	1000	80	1
39	1000	80	1
40	1000	160	1
41	1000	160	1
42	1000	160	1

Table 2. Cutting test parameters.

Design and establishment of the process monitoring system. Once the audible sound signals have been fully characterized for each of the diverse cutting conditions, it becomes possible to compare these reference signals with the new ones detected during the normal process operation in such a way that the differences between reference signals and current signals

allow for the reliable sensor monitoring and control of the machining process. The target is to achieve an on-line monitoring system using as reference the signals conditioned through machine tool and working environment noise filtering and suppression.

4. Results

After audible sound signals detection, the repeatability of the tests was verified by calculating the differences between recorded signals and dividing the result by 800 (number of acquisition lines of the spectrum analyser). All the computed values were less than 5%. Then, a reference signal for the machine and environment noise was established as the average of the 3 signals obtained from each of the unloaded machine tool running tests. Figure 2 shows the reference signal in terms of amplitude, *Sa* (dB), versus frequency, *f* (Hz), for the 5th second of the cutting test with *S* = 800 rpm and *f* = 80 mm/min. Along with the reference signal for the machine and environment noise, the average signals for *d* = 0.5 mm and *d* = 1 mm under the same *S* and *f* conditions were plotted as well.
The reference signal was subtracted from the audible sound signals detected during the actual machining tests to obtain a "difference signal" for classification analysis. All further analyses were carried out using these difference signals (Figure 3).

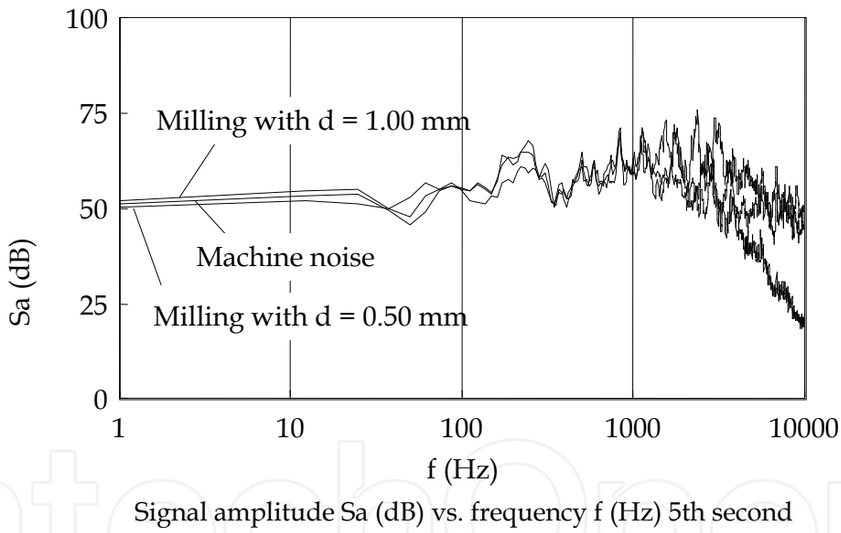


Fig. 2. Signal amplitude *Sa* (dB) vs. frequency *f* (Hz) of the audible sound signals for the 5th second of each test. Namely, milling with *S* = 800 rpm, *f* = 80 mm/min, *d* = 0.5 mm; milling with *S* = 800 rpm, *f* = 80 mm/min, *d* = 1 mm, and machine tool running unloaded at *S* = 800 rpm.

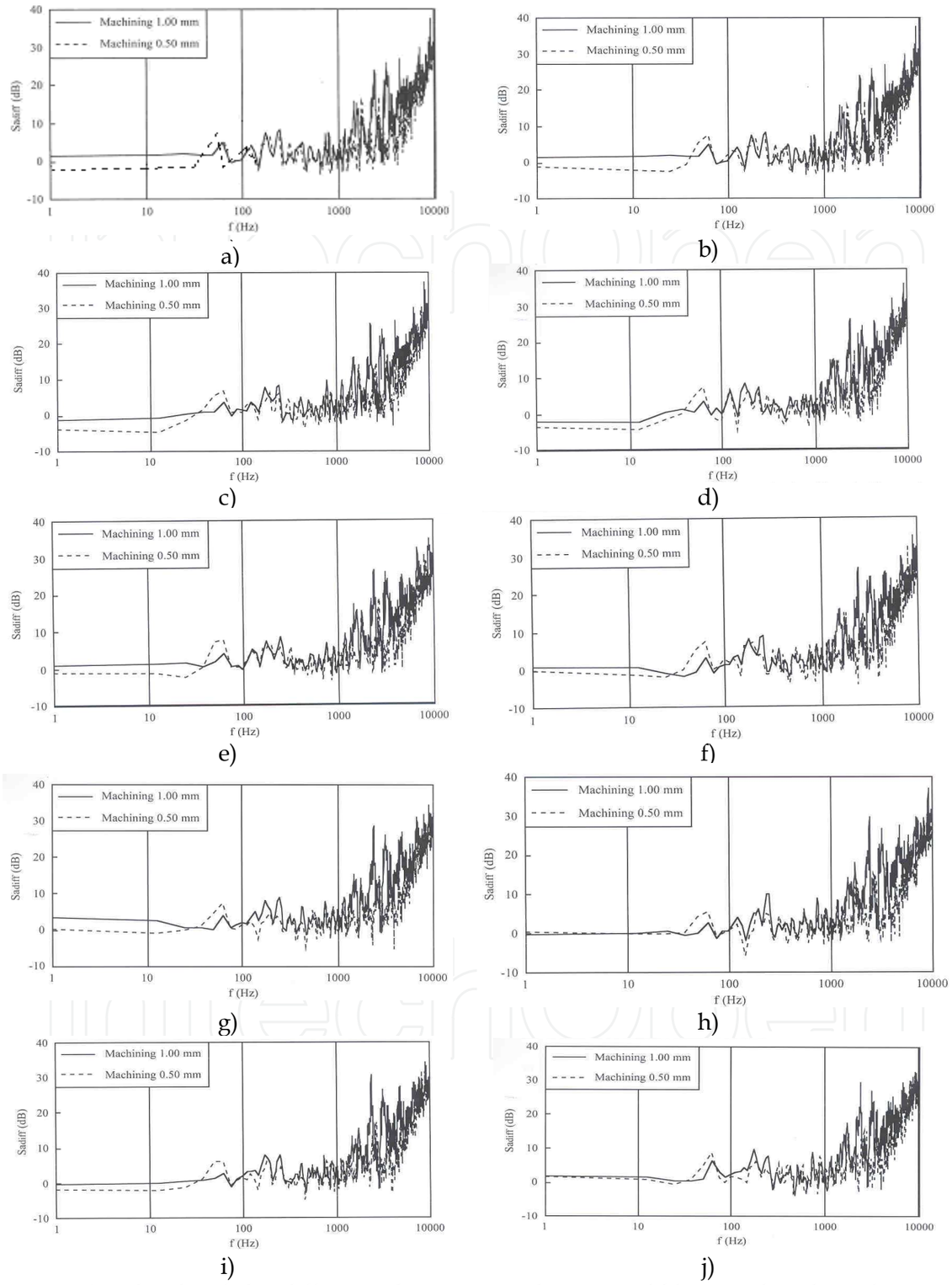


Fig. 3. Amplitude of the difference between machining audible sound and machine tool noise (”difference signal”) for each of the ten seconds of cutting test: a) first; b) second; c) thrird; d) fourth; e) fifth; f) sixth; g) seventh; h) eighth; i) ninth; j) tenth second.

The maximum amplitude of the "difference signal" was evaluated for each frequency interval and for each second of cutting test. The six frequency intervals selected for audible sound signal processing were: 0-0.25, 0.25-0.5, 0.5-1, 1-2.5, 2.5-5, 5-10 kHz. Figure 4 reports examples of the "difference signal" maximum amplitude $Sa\ diff_{MAX}$ (dB) versus frequency intervals Δf (Hz) for cutting tests with S = 800 rpm, f = 80 mm/min and d = 0.5 mm or 1 mm cases, for each of the ten seconds of each cutting test. The figure shows that for frequency values higher than 1 kHz it is possible to discriminate audible sound signals obtained from machining with different depth of cut values.

Graphical representation of data in high dimensions (> 3) feature spaces is not feasible. Thus, the results are presented in a 2 dimensions feature space by pair-wise plotting of frequency intervals maximum signal amplitude as shown in Figure 5 for two low frequency intervals, in Figure 6 for two medium frequency intervals, and in Figure 7 for two high frequency intervals. The figures show that for the two high frequency intervals the separation between cluster points characteristic of the two depth of cut values is very good.

The same can be seen if the "difference signal" maximum amplitude is plotted versus depth of cut as shown in Figure 8 for low, medium and high frequency intervals.

At low frequencies (0-0.25 kHz; 0.25-0.5 kHz), the $Sa\ diff_{MAX}$ value is around 10 dB for both depth of cut values (0.5 and 1 mm). In this case, depth of cut discrimination is unfeasible. However, at high frequencies (1-2.5 kHz; 2.5-5 kHz) the $Sa\ diff_{MAX}$ value is around 10 dB for depth of cut 0.5 mm and around 30 dB for a depth of cut 1 mm and recognition becomes feasible.

A supervised NN data processing was utilized for pattern recognition using the 6-component feature vectors made of the "difference signal" maximum amplitudes for the 6 frequency intervals. A three-layers feed-forward back-propagation NN was built with the following configuration: input layer with 6 nodes; hidden layer with 3 nodes determined by the cascade learning procedure (Teti & Buonadonna, 1999); output layer with 1 node.

The 6-3-1 NN was trained and tested according to the leave-k-out procedure with k = 2 (Teti & Buonadonna, 1999), using a number of learning steps comprised between 1000 and 14000. In Figure 9, the NN output is reported versus the number of input patterns for 12000 and 14000 learning steps. From this figure, it can be seen that the NN Success Rate (SR) in the identification of depth of cut becomes 100% after 14000 learning steps.

Figure 10 reports the NN SR versus learning steps for different treshold values. From the figure, it can be noted that the NN SR is 85% as early as 2000 learning steps.

Figure 11 reports the NN SR versus threshold value for variable numbers of learning steps. From the figure, it can be observed that the NN SR starts decreasing gradually only for threshold values < 0.3, except in the case of the lowest number of learning steps (i.e. 1000) for which a rapid SR reduction is expectedly verified.

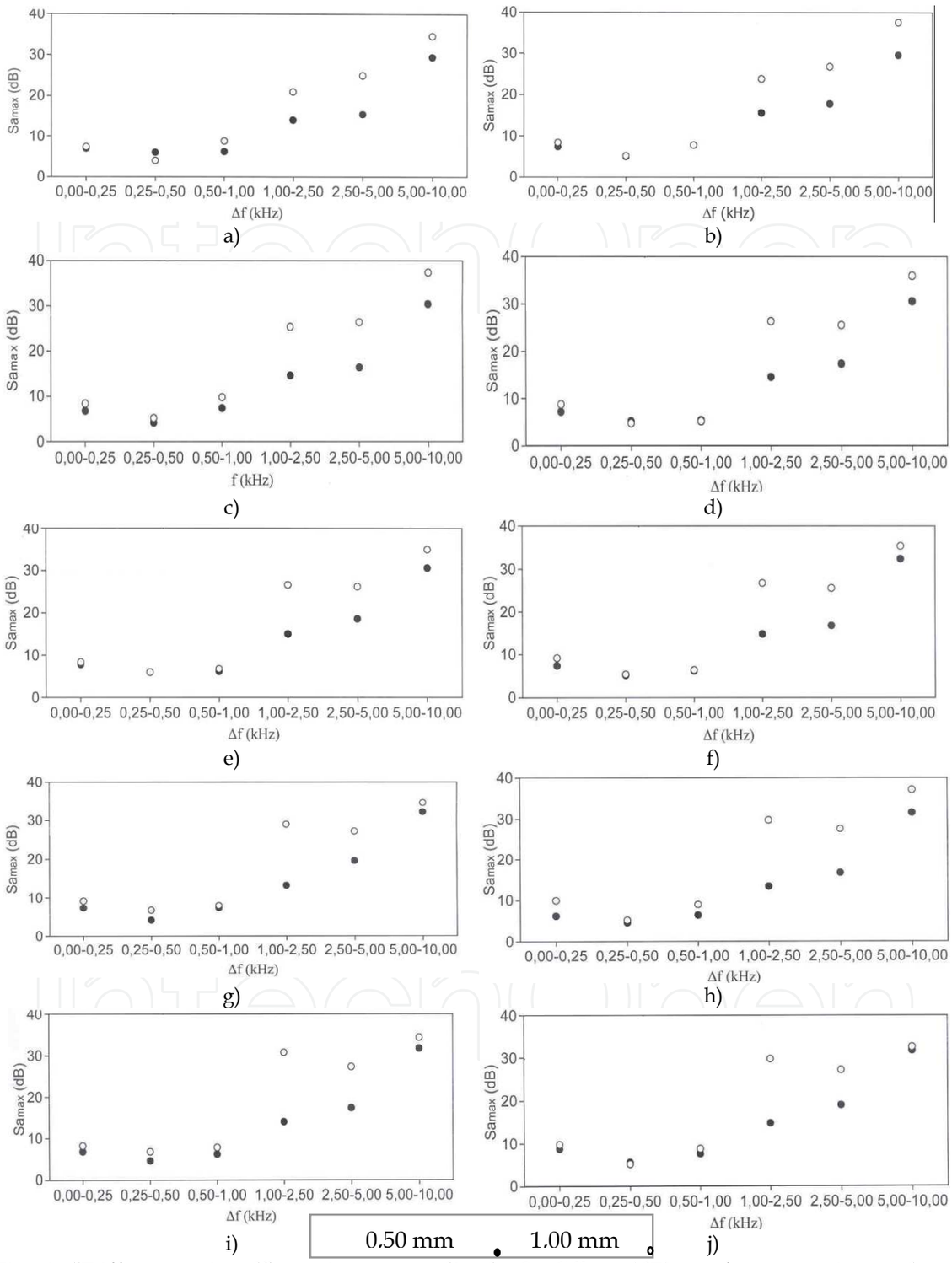


Fig. 4. "Difference signal" maximum amplitude *Sa diff*$_{MAX}$ (dB) vs. frequency intervals *Δf* (Hz) for the *S* = 800 rpm, *f* = 80 mm/min, and *d* = 0.5 or 1 mm cases, for each of the ten seconds of cutting test: a) first; b) second; c) third; d) fourth; e) fifth; f) sixth; g) seventh; h) eighth; i) ninth; j) tenth second.

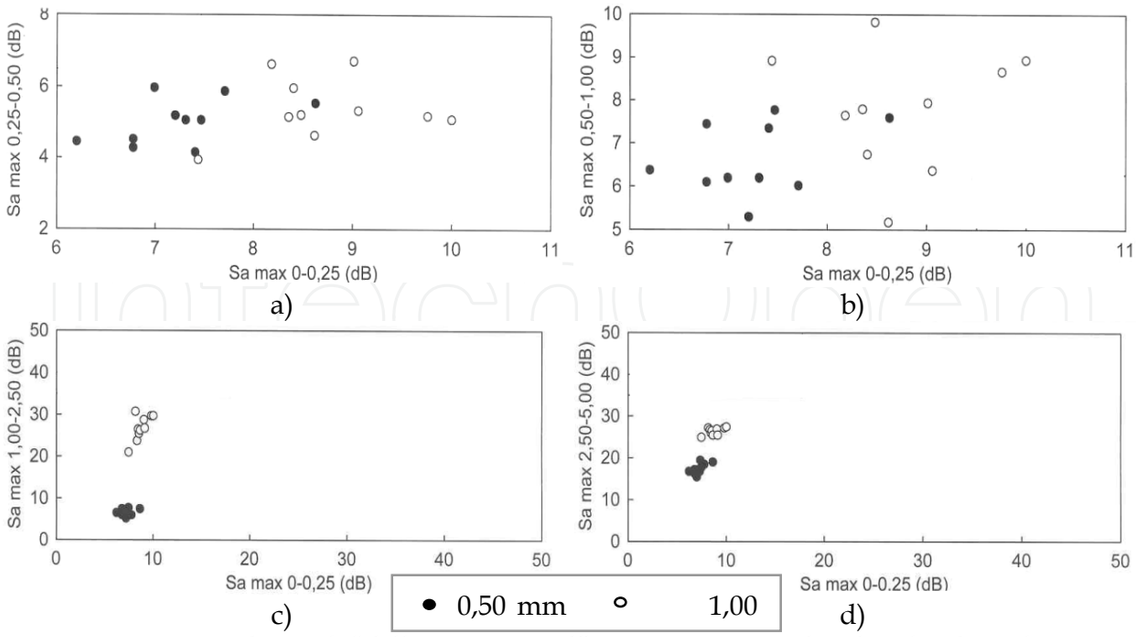


Fig. 5. Pair-wise plots of "difference signal" maximum amplitudes for low frequency intervals.

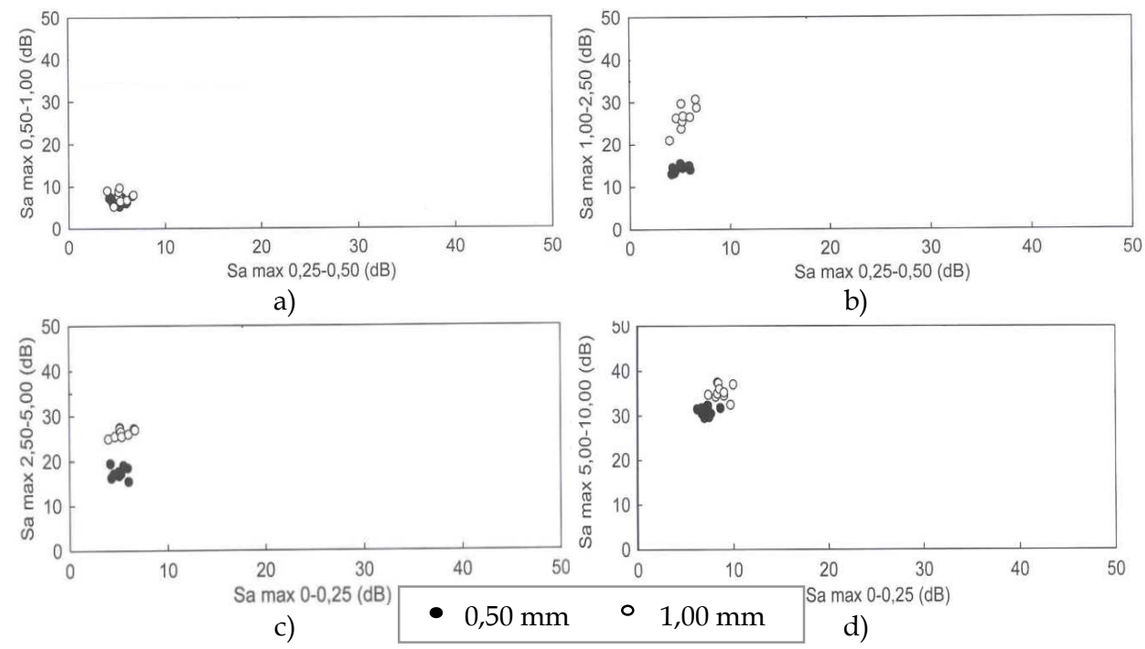


Fig. 6. Pair-wise plots of "difference signal" maximum amplitudes for medium frequency intervals.

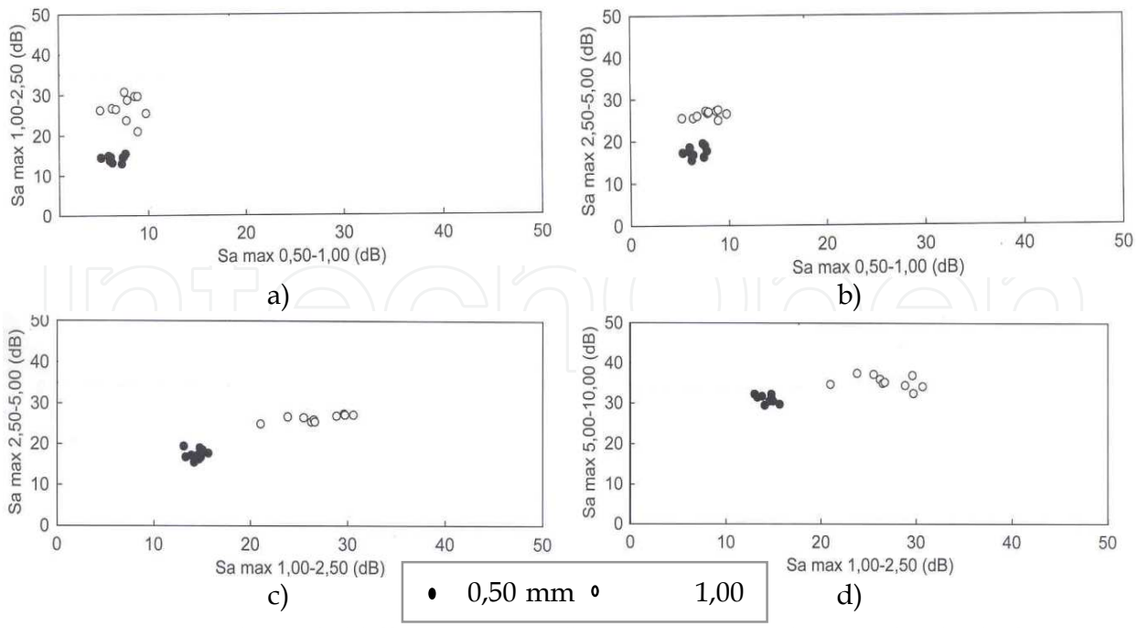


Fig. 7. Pair-wise plots of "difference signal" maximum amplitudes for high frequency intervals.

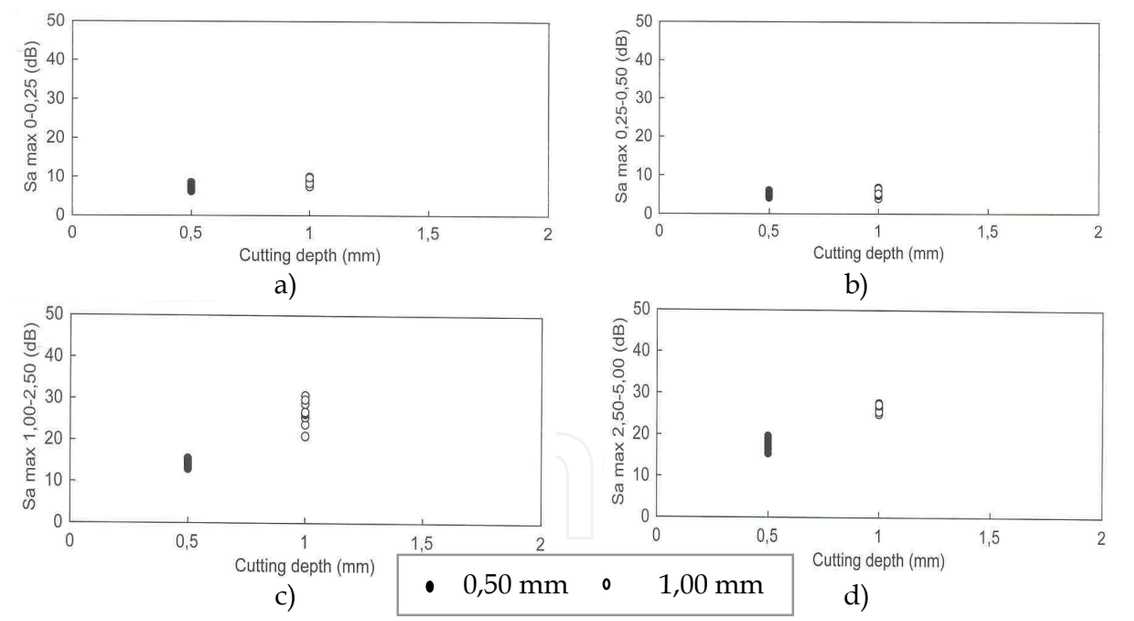


Fig. 8. "Difference signal" maximum amplitudes vs. depth of cut.

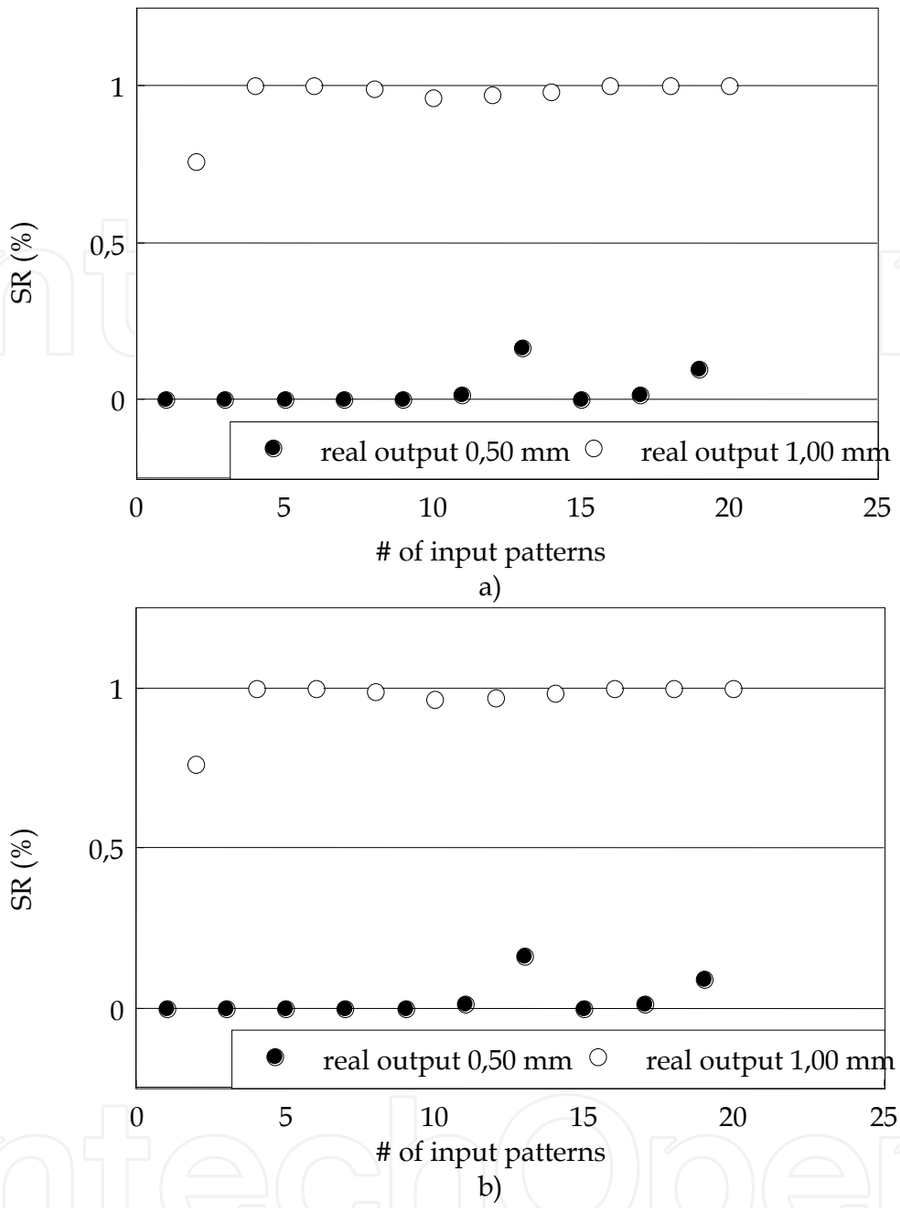
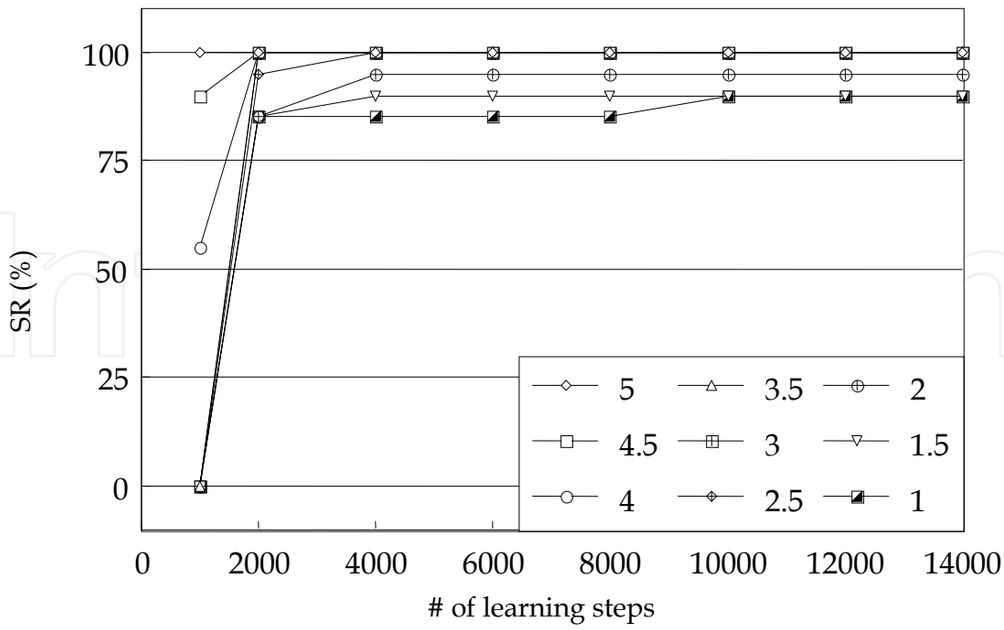


Fig. 9. Neural Network output vs. number of input patterns for: a) 12000 and b) 14000 learning steps.



a)

Fig. 10. Neural Network Success Rate vs. number of learning steps for different threshold values.

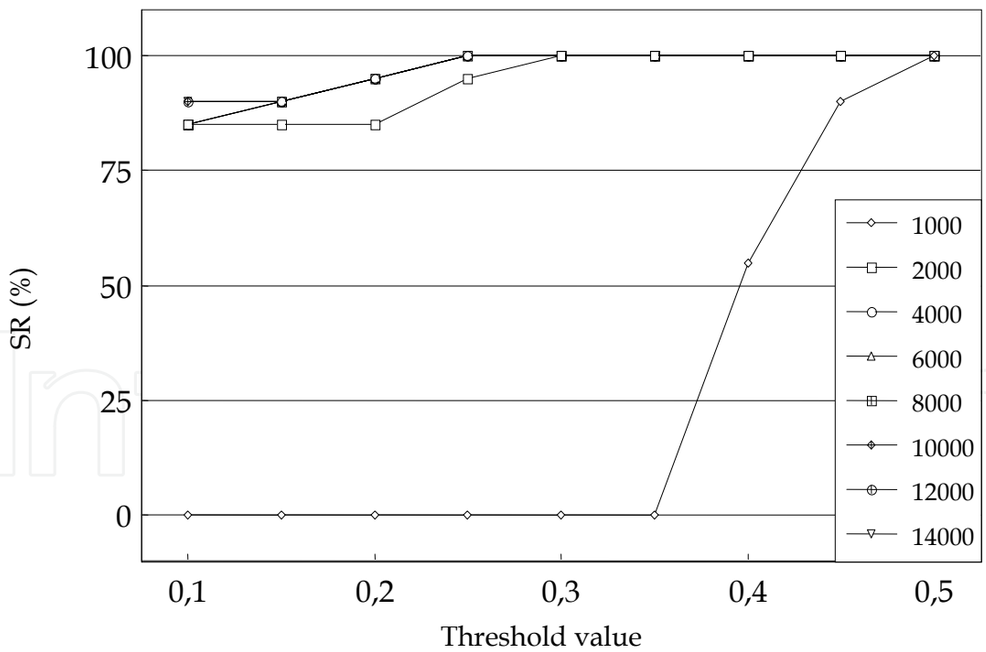


Fig. 11. Neural Networks Success Rate vs. threshold value for different numbers of learning steps.

5. Conclusion

During the last years, notable efforts have been made to develop reliable and industrially applicable machining monitoring systems based on different types of sensors, especially in production environments that require fully unmanned operation such as Flexible Manufacturing Systems (FMS) or Computer Integrated Manufacturing (CIM).

The main focus of this work is the establishment of a methodology to implement a process monitoring system based on audible sound energy sensors for application to milling operations.

In order to characterise the audible sound energy signals emitted by different cutting conditions during milling of T4-6056 Al alloy plates, machining parameters were varied and the corresponding acoustic signals were detected and processed in the frequency domain by a real-time spectrum analyser.

The classification of audible sound signal features was performed in two-dimensional space by graphical analysis and in multi-dimensional spaces by parallel distributed data processing using a supervised Neural Network paradigm.

The experimental results showed that the identification of depth of cut variation can realised only with reference to high frequency ranges. Besides, the supervised Neural Network data processing proved that the recognition of depth of cut value can be reliably achieved independently of the frequency range.

The proposed approach allows to state that: (1) the application of a systematic methodology to set up the cutting tests permits a more thorough comparison with other similar experimental works; (2) sensor signal analysis independent of the noise generated by the machine tool and the working environment is obtainable by subtracting the noise characteristic signal from the signals detected during the cutting tests; (3) the results obtained in this approach can be utilized for the development of process monitoring procedures based on sensors of different types, such as acoustic emission sensors where the high frequency (> 20 kHz) stress waves produced within the work material do not travel through air but only in the material itself. The combined application of audible sound energy sensors and acoustic emission sensors could make available more comprehensive information on process conditions through both low frequency (audible sound) and high frequency (acoustic emission) signal analysis, realizing the concept of sensor fusion technology.

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