Handbook of Machine Tool Analysis

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Preface

The past two decades have been characterized by the dynamic development of many technical and scientific domains, and the development of machine tools has been on this same trajectory. The complexity of machine tools has increased, as well as their intersection with other fields, primarily electronics. The new generation of machine tools is very different from the previous generation, from which a large amount of experience has been gained. The modern systems of machine tools have new rules of design, research, and fabrication.

This book presents the new research in this large domain of machine tools and tools. The book’s main contribution is the establishment of technical diagnosis by the aid of the evolution of machine parameters, which can be correlated with the functionality of the machine tool as well as that with the tool.

Two factors have contributed to these developments: one is the increase in the complexity of machine tools and their integration in flexible manufacturing systems, and the second is the success of the monitoring and diagnosis of other fields. By correlation of these aspects with the development of computer hardware, the book details the replacement of conventional systems with virtual instrumentation. This represents the step from an “art” in the field of machine tools to the science of the diagnosis of these systems. The specialized software systems create
the possibility of scientific diagnosis and monitoring of the technological systems.

Together with the traditional instruments used in the monitoring and diagnosis of machine tools (investigating such aspects as forces, vibrations, and acoustic emission), the expert system is presented together with neural processing of the information.

The first chapter reviews general notions about technical diagnostics of machine tools. The second chapter is dedicated to the state of the art of research concerning vibroacoustic diagnosis of machine tools. Chapter 3 presents an original systematization and application of a package of vibroacoustic methods to establish the technical diagnostics of machine tools. Chapter 4 describes the experimental research in diagnostic analysis of the mechanical system of the feed kinematics chain. Virtual instrument packages for diagnosis by vibroacoustic methods are described in Chapter 5. Specific elements from the feed kinematics chain are diagnosed by virtual instrument packages in Chapter 6. Chapter 7 deals with a neural approach to the problem of establishing technical diagnosis for machine tools. In Chapter 8, we conclude by presenting the original research on which this book is based. In order to prove that the method works, a few case studies are presented in the three appendixes.

This book is a joint effort with my former professor, Constantin Ispas, a well-known specialist in machine tools in Romania, and one of his graduate students, now Dr. Dan Boboc. The topic of the book was the main theme of Dr. Boboc’s dissertation a few years ago.

The authors would like to express their gratitude to two of their graduate students, Dr. Radu Pavel and Liviu Luca of the Precision Micro-Machining Center at The University of Toledo, Ohio, for assisting with the manuscript. I give special thanks to my wife, Jocelyn, for her patience in polishing the English of this book, which was written by native Romanian authors. I also thank Rita Lazazzaro and Barbara Mathieu of Marcel Dekker, Inc., for their help and for keeping us on track.

Ioan D. Marinescu
Contents

Preface

1. General Notions About the Introduction of Technical Diagnosis for Machine Tools
   1.1 Introduction: The Place and the Role of Diagnosis in Modern Technical Systems
   1.2 Monitoring, the First Step in Establishing the Technical Diagnostic
   1.3 Application of Vibroacoustic Diagnosis to Machine Tools
      1.3.1 Sources of Machine Tool Vibration and Noise
      1.3.2 Requirements for Machine Tool Diagnostic Systems
      1.3.3 Stages of Technical Diagnosis Implementation on Machine Tools
      1.3.4 Efficiency of the Diagnostic Systems
   1.4 Virtual Instrumentation for Establishing Technical Diagnosis
2. The State of the Art of Research Concerning Vibroacoustic Diagnosis of Machine Tools

2.1 Diagnosis of Rolling Bearings
2.2 Diagnosis of Slipping Bearings
2.3 Diagnosis of Gear Wheel Transmissions
2.4 Diagnosis of Belt Transmissions
2.5 Diagnosis of Driving Electrical Motors
   2.5.1 Vibroacoustic Phenomena of Mechanical Nature
   2.5.2 Vibroacoustic Phenomena of Magnetic Nature
   2.5.3 Vibroacoustic Phenomena of Aerodynamic Nature
2.6 Diagnosis of Some Deviations of the Rotational Parts
   2.6.1 Imbalance (Lack of Poise)
   2.6.2 Axial Imbalances
   2.6.3 Dimensional and Shape Deviations
   2.6.4 Mechanical Plays
2.7 Diagnosis of the Tool and Cutting Process
   2.7.1 Diagnosis of the Cutting Tool
   2.7.2 Diagnosis of the Cutting Process
2.8 Technical Diagnosis in Flexible Processing Systems
2.9 Conclusions: Theoretical and Experimental Research Perspectives

3. Systemization and Application of a Vibroacoustic Methods Package to Establish Machine Tool Technical Diagnostics

3.1 Theoretical Methods to Establish Technical Diagnostics
   3.1.1 Statistical Methods
   3.1.2 Probabilistic Methods
3.2 Experimental Methods to Establish Technical Diagnostics
   3.2.1 Specific Parameters Common to Vibroacoustic Methods of Diagnosis
   3.2.2 Diagnostic Surface Methods
   3.2.3 Profoundness Diagnosis Methods
3.3 Recommendations Concerning the Use of Diagnosis Methods for Machine Tools
4. Theoretical and Experimental Research: Diagnostic Analysis of the Feed Kinematic Chain Mechanical System
   4.1 Introduction to Mechanical Systems Analysis
   4.2 The Experimental Stand
   4.3 Theoretical Analysis of the Kinematic Feed Chain Mechanical System
       4.3.1 The Method and Images 3D Algorithm
       4.3.2 Discretization of the Physical Model
       4.3.3 Statistical Analysis of Physical Model
       4.3.4 Modal Analysis of Physical Model
   4.4 Experimental Analysis of Kinematic Feed Chain Mechanical System
   4.5 Conclusions and Implications of Diagnostic Analysis in Future Research

5. Designing and Manufacturing a Virtual Instrument Vibroacoustic Method Diagnostic Package
   5.1 Virtual Instrumentation: LabVIEW Graphical Programming Environment
   5.2 Structure of LabVIEW Virtual Instrument
   5.3 Virtual Instrumentation for Surface Diagnosis
   5.4 Virtual Instrumentation for Profoundness Diagnosis

6. Theoretical and Experimental Research: Diagnosis of Some Feed Kinematic Chain Structure Elements
   6.1 Vibration and Noise Sources During Feed Kinematic Chain Operation
   6.2 Calculus of the Characteristic Frequencies of Bearings
   6.3 Calculus of Frequencies that Characterize the Ball Screw-Nut Mechanism
   6.4 Calculus of Characteristic Frequencies for the Tankette with Rolls
   6.5 Preliminary Experimental Research
       6.5.1 Experimental Research with General Use Instrumentation
       6.5.2 Experimental Research Using Frequency Analysis

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6.6 Experimental Research in Virtual Instrumentation
   6.6.1 Structure of Data Acquisition and Process System in Virtual Instrumentation
   6.6.2 Experimental Research in Surface Diagnostics
   6.6.3 Experimental Research in Profoundness Diagnostics
   6.6.4 Advantages of the Use of Virtual Instrumentation in Technical Diagnosis

7. A Neural Approach to Establishing Technical Diagnosis for Machine Tools
   7.1 Introduction to Neural Network Theory
      7.1.1 Information Neural Processing
      7.1.2 The Learning Process in Neural Networks
   7.2 Utilization of Neural Networks in Machine Tool Diagnostics
      7.2.1 Multicriteria Application for “Good/Defective” Classification
      7.2.2 Application for Neural Diagnosis of the Working State
   7.3 Final Remarks and Prospects for Utilizing Neural Networks for Machine Tool Diagnosis

8. Final Conclusions and Original Contributions
   8.1 General Aspects and Conclusions—Recommendations
   8.2 Original Contributions
      8.2.1 Perspectives for Continuing Research

Appendix 1. Surface Diagnosis Through Virtual Instrumentation
Appendix 2. Profoundness Diagnosis Through Virtual Instrumentation
Appendix 3. General Notions Regarding the Diagnosis of the Functioning State of Machine Tools

References
1

General Notions About the Introduction of Technical Diagnosis for Machine Tools

1.1 INTRODUCTION: THE PLACE AND THE ROLE OF DIAGNOSIS IN MODERN TECHNICAL SYSTEMS

The diagnosis of technical systems can be defined as a process of functional faults and their causes, on the basis of data obtained by control, supervising, or monitoring. The rudiments of establishing technical diagnosis have been present for a long time regarding the estimation of the functioning state of a machine or equipment. Thus, it was natural that the functioning anomalies be noticed by the operator of the machine, such as: modifications of level or type of emitted noise, too much energy consumed, low output, the vibration level increasing, or local or global excessive heating. On the basis of these observations the operator could intervene to correct the deficiencies or to decide to stop the machine.

Even by this subjective elementary diagnosis method, some important advantages could be identified:

- Increased sensorial accuracy of the operators
- Enhanced “database” of the operator’s memory, built upon accumulated experiences

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The possibility to control, analyze, diagnose, and intervene during the machine’s functioning, before reaching the faults.

Objective diagnosis, on the basis of some precise techniques and methods, has been propelled during the last decade by two important factors: the large scale introduction of automated production processes, and the development of data acquisition, measuring, and signal processing equipment. In these conditions, it becomes necessary to use some supervisory/control systems to ensure machine reliability.

What is the role of such systems? In short it can be described as:

- To supervise the functioning state of the production system to prescribed performances
- To reduce and even avoid accidental breaks in functioning by supervising some significant factors during the technological process
- To avoid the limit situations, which can generate faults and damages
- To reduce, even eliminate, fabrication waste by supervising every step in the evolution of the product, parallel with the reduction of materials consumption
- To analyze functioning state tendencies, locally or globally, in order to plan interventions

The supervising/diagnosing system for the technological process may be identified as an auxiliary system that has the possibility of being integrated in a reaction buckle.

The signal, from a mechanical, pneumatic, acoustic, thermic, or such nature, is captured by adequate sensors and then converted to electrical signals, and sent to a postprocessing block (Figure 1.1). The white noise and the parasite signals are eliminated here; and the characteristic parameters of the supervised signal are extracted. Interpreting these signals on the basis of adequate software, the supervising/diagnosis block, which is the ensemble of electronic devices, offers data for fault recognition and their causes, and identification of where and when the fault arises. Depending upon the integrating degree of the supervising/diagnosing system, the reaction buckle can be:

- **Half-closed** (warning/alarming reaction; stopping of the technological process) or
- **Closed** (continuing the data acquisition, concentrating on the element predisposed to fault, with the beginning of some testing procedures; the modification of some parameters of the tech-
nological process to improve the functioning state; warning the experts and stopping the process to the limit)

1.2 MONITORING, THE FIRST STEP IN ESTABLISHING THE TECHNICAL DIAGNOSTIC

Monitoring is defined as the activity of gathering information about the functioning state in a given system, by means of adequate observation
of instruments and measuring apparatus in order to supervise and intervene for correction purposes. The axiom of maintenance by monitoring is that the intervention maintenance/repairing is done only when the measurements show its necessity (Figure 1.2).

The monitoring technical system can have two functions:

The protection or preventive function, which imposes a warning or automatically stops the equipment if it senses the possibility of a fault.

The analysis and prediction function, which selects the main state modifications and surveys their evolution; the system expert will provide efficient solutions for remedy before any final damage.

Preventive monitoring is recommended for machines that are not integrally doubled or where unplanned interruption would lead to large production loss. In this case, the monitoring is directed to those components whose failure (in a shorter time than estimated) would have serious consequences for the entire assemblage.

Predictive monitoring is mainly oriented to those machines and equipment with a continuous technological flux, and which might have accidental stops or revision/repairing periods implying considerable production loss; it is also oriented to complex production systems where the damage of a subsystem would block the entire flux. In this case, the

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**Figure 1.2** Levels of necessary intervention.
functioning state is intermittently or continuously supervised until the modification of the supervised parameters is able to signal imminent or predictable spoiling, and then take the imposed measures.

The stages that have to be crossed to build the monitoring schema are as follows.

1. Make schematic descriptions of the machine, equipment, or installation, divided on technological subassemblies and groups, from the functional and constructive point of view.

2. Make schematic descriptions of each component, marking the controlled elements and the monitored control points. An adequate monitoring for the fixed control points and for arranging and retaining the recordings should be used. The number of control points depends on the system complexity and on the spoilage consequences. This number will determine the complexity of the monitoring schema and also the number of qualified personnel required for analyzing and supervising.

3. The conceived monitoring schema will be implemented into the system and will provide information concerning the system functioning state. Based upon this information, graphics can be drawn manually or automatically which will show the evolution of the studied parameters, and indicate the values considered normal. Preliminary diagnostics can be established, and preventive repairing can be planned. Previous special events, faults, and other evaluation criteria, in short, “the machine history,” can be added to these data by adequate description.

1.3 APPLICATION OF VIBROACOUSTIC DIAGNOSIS TO MACHINE TOOLS

Modern machine tools are dynamic complex assemblies composed of mechanical subsystems (gears, bearings, cam mechanisms, couplings, belt transmissions), hydraulic equipment (pumps and hydraulic engines, distribution equipment, etc.), and electric equipment (motors, contactors, etc.). Because of this structural complexity, it is very difficult to establish technical diagnostics for machine tools. From the same point of view, the diagnosis of the cutting tools is much simpler and much of the present research is oriented in this domain.
1.3.1 Sources of Machine Tool Vibration and Noise

Not only the functioning of subsystems and subsystems of the machine tool but also the cutting process generates vibration and noise. A rapid way to identify the sources of this phenomenon, which might generate damage, is represented by the connection (gradual, separate, or in diverse combinations) of the functional elements of the machine (electrical motors, transmissions, main kinematic chain, feed kinematic chains, lubricating system, etc.), by analyzing each time the vibrograms result in the measurement points. Figure 1.3 presents the internal and external vibration and noise sources that determine the vibroacoustic behavior of the machine tools [76].

1.3.1.1 Free Vibrations

The free vibrations appear in the absence of some perturbing forces, as components of some transitory processes of the machine tool. These processes and vibrations have a relatively short duration, as the vibrations imply.

Free vibrations develop with the self-frequency of the elastic systems where they were born, and this phenomenon is interesting from the point of view that the generating transitory systems can determine or influence the dynamic behavior of the machine tool. Considering this, some important transitory processes can be mentioned.

The on/off chip contact of the tool leads to deformation variations of the elastic fixing system in a transitory process whose duration surpasses the time of a complete rotation of the main shaft; this sometimes happens during the entire passage. Analysis of this process has established an exponential law of variation of the $y$ deformation of the elastic system:

$$y = a_o \exp \left( \frac{t}{\tau} \left(1 + 2R_{SE}K_a\right) \right)$$

(1.1)

where $a_o$ is the nominal thickness of the cutting layer, $t$ is the time, $\tau$ is the duration of a rotation or technological cycle, and $R_{SE}$, $K_a$ are the static characteristics of the elastic system and cutting process. It must be noted that the numerator of the exponent represents the time constant $T$ of the technological process. Generally its duration is appreciated to be $t = (3 \ldots 5)T$. 

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FIGURE 1.3 Internal and external vibration and noise sources that determine the vibroacoustic behavior of the machine tools.
Accelerating/breaking of the mobile elements appears when the still state or the uniform movement of some mobile subassemblies is changed, such as tables, sledges, supports, and traverses. The developing law of these processes is also exponential, similar to that previously presented. The experimental results have established the value of the time constant of this process at 0.3 to 1 sec, so the transitory process could take maximum 5 sec.

Inverting the direction of movement is a more complicated process, consisting of three phases: breaking the movement, stopping, and restarting in a new direction. This process is accompanied by a series of complex dynamic phenomena: shocks, changing the direction of the friction forces, the modification of the pressure repartition on the guiding, abrupt temperature variations in the kinematic couple, and so on. Also taking into consideration the presence of the plays from the kinematic couplings, it can be shown that changing the direction of movement is a random process with unfavorable consequences for the dynamic of the machine tools. The greater the number of masses in movement, the greater are the consequences.

The study of machine tool free vibrations is important because the dynamic parameters of the elastic systems that compose them are determined with the help of linear differentially homogeneous equations which describe the free vibrations of these systems.

1.3.1.2 Autovibrations

The autovibrations are kept-up vibrations, caused by excitation factors generated from the vibration movement. These can be as follows.

1. The interdependence between the magnitude of the cutting force and the relative displacement between the tool and semiprodct: due to an external cause, the cutting force varies, making a resultant mechanical work positive per variation cycle, and the energy resulting from this keeps up the vibration process. The rise of autovibrations depends upon the values and the ratio of the rigidities from the elastic system, and also upon the position of the main rigidity directions, while the frequency of the autovibrator process is very close to the self-frequency of the elastic system, without being equal to it. Figures 1.4a, b, c illustrate the influence of the cutting process parameters (respectively $v$, $s$, $t$) over the
It can be observed that the cutting depth has a very powerful influence on the autovibrational process and is able to raise the vibration amplitude to 140 µm. The depth of cut (when the stability of the elastic system to vibrations is surpassed), is called critical depth, and it is adopted as a parameter for evaluation of the vibration stability of the elastic system of the machine tools.
2. The dependence between the friction force and the sliding speed from the kinematic couples: the autovibrations of this process manifest as jerky motions that appear with the movement of the mobile assemblies with speeds under a specific critical value. This phenomena is known as stick-slip. These autovibrations, also called “of relaxation,” can be attenuated by an adequate selection of the couple of materials, rational lubrication, and discharging of the contact surfaces.

3. The phase difference between the variation of the cutting force and move away: this autovibration type highlights the copying kinematic chains. Their occurrence is favored by the presence in the elastic system of the nonlinearity of playing type, hysteresis, and instabilities. The frequency of these vibrations is approximately equal to the self-frequency of the excited elastic system.

4. The regenerative vibrations appear due to the existence of surface waves that were manufactured at the previous pass and which, at a new pass, generate dynamic forces conditioned by the intensity of the dependence between the variation of the chip depth and the cutting force. The effect of regenerating vibrations then has the proportional variation of the autovibration frequency function of the main shaft or tool rotation.

A characteristic aspect of autovibrations consists of the possibility of raising the amplitudes in time that lead to the trepidation occurrence, which is a very dangerous phenomenon.

Concerning noise and acoustical emission, the machine tools cover a very large domain:

- **Infrasounds** (vibrations with a frequency lower then 16 Hz) due to structural dislocations, phase transforming, and the like
- **Sounds** (the audible domain: 16–20,000 Hz) due to the functioning of diverse types of mechanisms that compose the kinematic chains and are grouped in low sounds (16–360 Hz), medium sounds (360–1400 Hz), and high sounds (1400–20,000 Hz)
- **Ultrasounds** (vibrations having their frequency higher then 20 kHz) due to the increasing occurrence of crackings, microfrictions on the level of cracked surfaces, microcollisions with and between the microscopic particles, and so on

Noise measurement allows us to estimate the “silence” of the machine tools when running out of job, from the point of view of the technical criteria of execution and operator protection. It permits us to establish if the level of maximum noise produced by a machine tool is
within the admitted limits imposed by the standards. This also allows us to locate the machine elements that produce high-level noise and to make a comparison between the noise levels produced by the same type of machines.

The machine tool whose noise level is measured has to be completely equipped (with all the covers and guards), adjusted for proper functioning, and run in and installed on a basis plate under the same conditions that it is installed for exploitation. The noise level is measured when the machine is idle-running with the usual rotations and advances.

The measurement points are disposed on a measurement line whose trace in the horizontal plane is situated at a height of 1.5 m from the basis plane, and at a distance of 1 m from the contour line of the machine tool. The nonnoisy prominences are not taken into consideration. For each type of machine tool, the location of the measuring points is established in a concrete way. Their minimum number is four, and other supplementary points can be chosen as a function of the machine tool sizes. The placement of the measuring points for different types of machine tools is shown in Figures 1.5a to k, and the admissible values of the noise levels for these machines are presented in Table 1.1 [64, 149, 150].

Acoustical emission is a succession of high frequency elastic waves (>100 kHz), generated by freeing the internal energy stored in a structure. It allows detection of fissures and/or ruptures. When the cutting process is running on the machine tools, the sources of acoustical emission are numerous: continuous or discontinuous chip forming, processed material deformation, fissuring of the semiproduct or the tool, friction among the tool, semiproduct, chip breaker, fracture, and collision of the chip. In addition to all of the above, other sources of acoustical emission come from the functioning of some mechanical subassemblies (gear wheels, bearings) and high-frequency electrical sources.

1.3.2 Requirements for Machine Tool Diagnostic Systems

Utilization of the diagnostic systems should correspond with the importance of the supervised system of the production system, with its complexity, and with its performance. Usually the monitoring is oriented to numerical command machine tools, processing centers, cells, flexible processing lines, and also to cutting tools.
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FIGURE 1.5 Placement of the measuring points on different types of machine tools: (a) universal grinding machine; (b) surface grinding machine; (c) centerless grinding machine; (d) shaping machine; (e) portal milling machine; (f) reaming and milling machine; (g) vertical milling machine; (h) radial boring machine; (i) boring machine with column; (k) normal and revolver lathes.
**Table 1.1** Admissible Values of the Noise Level for Different Types of Machine Tools

<table>
<thead>
<tr>
<th>Machine type</th>
<th>Turn rpm</th>
<th>0–500 dB (A)</th>
<th>500–1000 dB (A)</th>
<th>1000–2000 dB (A)</th>
<th>2000–4000 dB (A)</th>
<th>4000–8000 dB (A)</th>
<th>8000–16000 dB (A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grinding</td>
<td>1.0–1.6</td>
<td>75</td>
<td>70</td>
<td>78</td>
<td>75</td>
<td>81</td>
<td>75</td>
</tr>
<tr>
<td>machines</td>
<td>2.5–4.0</td>
<td>—</td>
<td>—</td>
<td>80</td>
<td>75</td>
<td>83</td>
<td>80</td>
</tr>
<tr>
<td></td>
<td>4.0–6.3</td>
<td>—</td>
<td>77</td>
<td>70</td>
<td>80</td>
<td>75</td>
<td>83</td>
</tr>
<tr>
<td></td>
<td>6.3–10.0</td>
<td>—</td>
<td>77</td>
<td>70</td>
<td>80</td>
<td>75</td>
<td>83</td>
</tr>
<tr>
<td>Shaping</td>
<td>1.6–2.5</td>
<td>75</td>
<td>70</td>
<td>78</td>
<td>75</td>
<td>81</td>
<td>75</td>
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<td>2.5–4.0</td>
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<td>80</td>
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<tr>
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<td>4.0–6.3</td>
<td>82</td>
<td>80</td>
<td>80</td>
<td>75</td>
<td>83</td>
<td>80</td>
</tr>
<tr>
<td></td>
<td>6.3–10.0</td>
<td>85</td>
<td>80</td>
<td>80</td>
<td>75</td>
<td>83</td>
<td>80</td>
</tr>
<tr>
<td>Portal</td>
<td>10.0–16.0</td>
<td>79</td>
<td>75</td>
<td>82</td>
<td>80</td>
<td>85</td>
<td>80</td>
</tr>
<tr>
<td>milling</td>
<td>16.0–25.0</td>
<td>81</td>
<td>80</td>
<td>84</td>
<td>80</td>
<td>87</td>
<td>80</td>
</tr>
<tr>
<td>machines</td>
<td>25.0–40.0</td>
<td>83</td>
<td>80</td>
<td>86</td>
<td>80</td>
<td>89</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>6.3–10.0</td>
<td>10.0–16.0</td>
<td>16.0–25.0</td>
<td>1.6–2.5</td>
<td>2.5–4.1</td>
<td>4.0–6.3</td>
<td>6.3–10.0</td>
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<td>Reaming and</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>milling</td>
<td>64</td>
<td>75</td>
<td>82</td>
<td>79</td>
<td>77</td>
<td>81</td>
<td>82</td>
</tr>
<tr>
<td>milling</td>
<td>80</td>
<td>85</td>
<td>80</td>
<td>85</td>
<td>80</td>
<td>85</td>
<td>80</td>
</tr>
<tr>
<td>Vertical and</td>
<td>84</td>
<td>80</td>
<td>87</td>
<td>84</td>
<td>83</td>
<td>85</td>
<td>87</td>
</tr>
<tr>
<td>universal</td>
<td>82</td>
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<td>milling</td>
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<td>75</td>
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<tr>
<td>Vertical and</td>
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<td>55</td>
<td>56</td>
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<tr>
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<td>67</td>
<td>67</td>
<td>63</td>
<td>63</td>
<td>67</td>
<td>67</td>
</tr>
<tr>
<td>machines</td>
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<td>55</td>
<td>55</td>
<td>56</td>
<td>56</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>Boring</td>
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<td>67</td>
<td>67</td>
<td>63</td>
<td>63</td>
<td>67</td>
<td>67</td>
</tr>
<tr>
<td>machines</td>
<td>56</td>
<td>55</td>
<td>55</td>
<td>56</td>
<td>56</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>Normal and</td>
<td>63</td>
<td>67</td>
<td>67</td>
<td>63</td>
<td>63</td>
<td>67</td>
<td>67</td>
</tr>
<tr>
<td>revolver</td>
<td>56</td>
<td>55</td>
<td>55</td>
<td>56</td>
<td>56</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>lathes</td>
<td>63</td>
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<tr>
<td>6.3–10.0</td>
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<td>88</td>
<td>85</td>
<td>80</td>
<td>88</td>
<td>85</td>
</tr>
</tbody>
</table>
In order to efficiently detect and supervise the spoilage that can appear, the supervising and diagnosis systems must follow a minimum set of requirements:

Adequate match to the supervised machine tool or tool, having the necessary precision and ability to detect the faults.
Fault warning must be made on time, and false alarms must be avoided.
Location of the faults must be determined in order to minimize the intervention time for repairs.
Correlation of many parameters that accompany the machine functioning (vibration, noise, temperature, pressure) must be ensured in order to have as much complete and correct information as possible.
The reliability of the supervising/diagnosis system must be superior to the reliability of the measured system.
The system has to be easy to use and maintain, and be resistant to dust, dump, and industrial liquids, low and high temperatures, and sometimes to radiation.
The system must not be connected to the same energy sources as the supervised system but to special stabilized and protected sources.
The cost of the supervising system, including its installation, should have reduced weight, usually under 10% of the cost of the supervised system.

1.3.3 Stages of Technical Diagnosis Implementation on Machine Tools

It is possible to establish technical diagnostics for complex systems such as machine tools only after knowing their dynamics and kinematics. By comprehending these elements, the parameters that have to be supervised, the types of transducers able to be used, and also the points where they will be installed can be established. When processing the signals, it is necessary to keep in mind the normal and maximum admitted levels of the supervised parameters. Figure 1.6 presents a pyramid of the stages that must be crossed in order to conceive a diagnostic system for a given machine tool or manufacturing process.

The sensible points of the supervised systems are: the signal processor, which has to extract from the raw signal the necessary data, and the diagnosis processor, which has to use the data in order to identify the
state of the supervised system and to locate and isolate the fault. This should be done according to the specific algorithms of the diagnostic proceeding used.

1.3.4 Efficiency of the Diagnostic Systems

The term “efficiency” designates the ratio between the ensemble of the effects obtained as the result of an activity and the totality of effort (expenses) that this activity implies. In the case of technical systems, we can speak of the introduction efficiency of technical diagnosis.

Concerning the expenses implied by the introduction of the diagnosis system, the following must be taken into consideration.

- The supervising/diagnosing equipment has to be adjusted to the supervised parameters.
- The sizes and the complexity of the supervising system.
- The cost of the supervising system, installation, and maintenance.
- The cost of training personnel.

Concerning the useful effects, these are manifested by the following.

- Significant increase of effective production time. It was noticed that for machine tools without monitoring only 10% of the theoretical production time could be reached, and for machine tools having supervising systems and diagnosis, the production time increased up to 60% from the theoretical production time.
- Reduction of accidental interruption times, and also decreasing of the time necessary for repairing.
Decrease in the consumption of cutting tools and elimination of waste because of the supervising during the time of the cutting process, including wear and breakage of the tool.
Sustaining the adaptive command for using the intensive cutting regimes in order to increase productivity.

Recent studies have shown the economic efficiency of introducing diagnostic systems, estimated on the basis of the above criteria, increased on average from 2 to 3% of the value of the net production. Of this percentage, 65% is the effect of avoiding production stoppage, and 34% is the effect of reduction of maintenance and repairing costs [54, 108].

1.4 VIRTUAL INSTRUMENTATION FOR ESTABLISHING TECHNICAL DIAGNOSIS

The analysis and measurement branch of industry is undergoing spectacular changes because of rapid developments in hardware and software technology. In research, designing, testing, measuring, and control activities, PC computers are being used more and more, so companies producing instrumentation have reoriented methodologies and measurement equipment in order to better exploit the PC’s hardware and software resources. On the other hand, the limits imposed by the rigid architecture of traditional instruments has generated, during this time, nonconcordances between the offer and the functionality request, namely, between what the instrument producers offer and what the user wants.

In the last decade, the idea of combining a new measuring instrument programmable by standard PC computer has led to the creation of a new concept, that of “virtual instrumentation,” whose functions are defined by the user and not by the producer. This innovation became possible only after the appearance of digital instruments and the communicating interface type GPIB (general purpose interface bus). Through this interface, these digital instruments can now be controlled by a program. The current generation of technical measurement offers more flexibility and performance since the instrument itself is built as a component of the PC.

In 1986 National Instruments (Texas) Company launched the first release of virtual instrumentation software for engineering purposes, named LabVIEW (Laboratory Virtual Instrument Engineering Workbench) 1.0. This software uses a graphical programming language G in order to create programs shaped as block diagrams, without sacrific-
ing any of the power of a traditional programming language. LabVIEW uses terminology, symbols, and ideas familiar to researchers and engineers, based on graphical symbols rather than on textual language for describing programming activities. LabVIEW combines the most recent operating system technology with specialized programming techniques (OOP, object-oriented programming techniques) in order to obtain a simple and flexible operating environment.

Under the slogan, “The software is the instrument,” the National Instruments Company identifies and structures the steps for use of the virtual instrument (Fig. 1.7):

At the first level, the virtual instrument uses hardware controllers and interface type GPIB for connection with the programmable instruments.

At the medium level, the virtual instrument uses standard hardware architectures and corresponding drivers (specific driver packet containing libraries for the functions that operate the hardware).

The superior level is represented by the software applications LabVIEW or LabWINDOWS.

The Danish firm Brüel & Kjaer, specializing in measurement equipment for the vibroacoustic domain, in 1992 culminated their efforts of

![Virtual instrument usage steps](image)

**Figure 1.7** Virtual instrument usage steps.
integrating the computer in the measuring chains by launching the software *Modular Test System Type 3538*. The company, which has had exceptional experience in the field of signal processing with dedicated traditional equipment, created a virtual instrumentation that couples widely used classic instruments with a powerful software capable of providing the instrumental functions that the user needs. Moreover, using the X-Window System and Motif application, the user can create and use his own instrument, front panels, and graphical interfaces. The performance of the virtual instrumentation launched by B & K is based on two special qualities: the precision of the digital/analogue and analogue/digital conversion and the processing power of the digital signal.

Figure 1.8 presents the front panel of one of the most powerful virtual instruments offered by the B & K company, a double-channel spectral analyzer, Spectrum and System Analyzer Type 7627. It includes not only the measuring instrument but also the signal generator and realizes a large range of procedures such as spectral analysis, measurement of frequency response, measurement of harmonic distortions, simultaneous measurements in time and frequency (wave shape, magnitude spectrum,
and the phase, coherence, and correlation functions), and finally, testing and finding the measurement schema faults.

The flow of information in this measurement and analysis system is indicated in Figure 1.9. The physical signals enter the instrument by the hardware module, which is controlled by a dedicated driver. The server for measurements controls this driver, conceiving an interface between the hardware and the virtual instrument. The virtual instrument takes over and processes the data on the basis of its functions, and the results are communicated to the operator by the front panel.

The well-known German firm, Hottinger Baldwin Messtechnik, has merged with the Group Spectris concern, which produces control and measurement equipment and has introduced in its turn virtual instrumentation as a working environment. The new generation of Hottinger equipment is adapted to acquisition, computerized processing, and analysis of signals. Moreover, one of the fields of interest of the company is monitoring industrial processes.

A virtual instrument is defined as being a software/hardware interface that is added to the computer in such a way that the user can interact with it as she interacted with the traditional instrument. This instrument can accomplish a compulsory family of functions.

1. The function of data gathering is executed through a data acquisition board, connected straight to the processor bus; the memory registers from this board are accessible to addresses from the I/O space of the computer memory. The computer controls the data acquisition
board, and the data transfer between the board and processor is made using hardware interruptions on DMA dedicated channels. The problem that arises when performing this function is that of the speed of data acquisition: the computer can not compete with the dedicated processor of traditional instruments, even though the computer is completely occupied with solving the operation executed by the virtual instrument.

The computer interruptions have priorities, and they are stored in a waiting file that results in an increase of the working time. Traditional instruments can usually gather data with a speed of 10 GHz, but an acquisition board does not surpass the speed of 1 MHz. The solution for this problem is to endow the acquisition board with counter/timer chips that use internal frequencies up to 10 MHz. In this way, the data acquisition will be made correctly by the virtual instrument, which means to the speed specified by the user. The concurrence of tasks that have to be solved by the computer’s processor eventually may delay data storage and/or the presentation of the results.

2. The data analysis and control functions are completely carried out by the hardware already existent in the computer and by the software that, to a large measure, is already familiar to users. The virtual instrument uses, as do traditional ones, software modules from a large package, but the difference is that as traditional instruments close this software on its RAM memory, the virtual instrument holds the functions on the computer’s hard drive or on a floppy disk that can be installed on every computer. Moreover, many virtual instruments can coexist on the same computer, using the same display, independently or in direct relation with one another.

3. The function of results display is another compulsory function. The existence of a driver with a graphical interface enormously diminishes the handling and control of the application. The instrument is presented on the virtual panel display on the computer’s monitor, and may look like the front panel of traditional instruments. The virtual panel has in its background the software program, which means the instrument commands that are blended into that application, together with the acquisition routines, data analysis, graphical presentation, and finally the capacity to eventually store data/results in files. This construction of the virtual instrument makes possible, for the first time, for its functionality to be defined entirely by the user. The virtual instrument uses standard hardware architectures and corresponding drivers, which is a specific package with libraries that operate the hardware.
In principle two programming methodologies exist for the use of virtual instrumentation:

- Graphic programming, such as LabVIEW software
- Programming in a traditional language, which is the case of LabWindows/CVI (C for virtual instruments) software [160]

Launched on the market during the second half of the 1990s, virtual instrumentation has seen great development and, nowadays, is a standard factor in testing and control.
The State of the Art of Research Concerning Vibroacoustic Diagnosis of Machine Tools

Monitoring and diagnosis of machine tools and technological equipment on the basis of vibration and noise analysis has greatly expanded in the last twenty years. Although a relatively young field of research, this domain is marked by important theoretical and experimental findings that are selectively presented in this chapter.

2.1 DIAGNOSIS OF ROLLING BEARINGS

Bearings are a major source of vibration and noise in machine tool manufacturing. Their vibration and noise level correlate with their functioning state, indicating the presence and eventually the evolution of some damage. Thus, interventions must be made in order to avoid serious damage.

For bearings in a nonmounted state a sum of characteristic frequencies is highlighted: the rotation frequency of the bearing cage $f_c$, the frequency of the ball running on the internal inner $f_{I}$, and the ball rotation frequency $f_{b}$. These frequencies depend on the rotation frequency of the spindle $f_{n}$. Table 2.1 presents the values of these frequencies for several types and sizes of bearings. It can be observed that the $f_{c} < f_{n} < f_{e} < f_{e} < f_{I}$ relation always exists. Maintaining the relation...
TABLE 2.1

<table>
<thead>
<tr>
<th>Characteristic Frequencies for Bearings in Nonmounted State</th>
<th>Bearing 6206</th>
<th>Bearing 6209</th>
<th>Bearing 7309</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency (Hz)</td>
<td>$f_c$</td>
<td>0.391</td>
<td>0.402</td>
</tr>
<tr>
<td>$f_n$</td>
<td>3.132</td>
<td>3.621</td>
<td>4.506</td>
</tr>
<tr>
<td>$f_e$</td>
<td>4.868</td>
<td>5.379</td>
<td>6.497</td>
</tr>
<tr>
<td>$f_b$</td>
<td>2.191</td>
<td>2.460</td>
<td>4.022</td>
</tr>
</tbody>
</table>

Between the characteristic frequencies shows that the shape and sizes of the rolling bodies influence these frequencies only in small measure [46].

The vibrations and noise produced by the bearings in a mounted state manifest themselves not only by direct effects (acoustic radiation, vibration), but also indirectly (on the level of other elements, on the route source-receiver). The main causes that lead to an increase of the noise and vibrations on the mounted bearings are:

1. Changing the position of the rolling bodies in the charged (respectively, uncharged) zone of the bearing, taking into consideration the elastic contact deformations and the working play.
2. The nonuniform movement of the rolling bodies, which leads to friction and collisions of the rolling bodies with the rings and the cage.
3. The contact that appears on the rolling movement on the surfaces with dimensional, shape, and position deviations (deviations of diameter, axial or radial runout of the rolling paths, eccentricity, ovalization, polygonality, waviness).
4. Passing of the rolling bodies over the impurities from the contact surfaces or over damages or local deterioration (pitting or peeling, abrasive wear, prints).

Table 2.2 synthetically presents relations concerning the position of the peak in the frequency spectrum for these damages; the data have been considered for the bearing with turning internal ring ($f_i = f_n = n/60$) and fixed external ring. The notations represent: $f_{ci}$, turning frequency of the cage function of the internal ring; $f_{ce}$, turning frequency of the cage function of the fixed external ring; and $f_{be}$, the turning frequency of the rolling bodies function of the fixed external ring.
### TABLE 2.2

<table>
<thead>
<tr>
<th>Element Deviation</th>
<th>Position of peak in spectrum, Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal Radial runout</td>
<td>$f_i$</td>
</tr>
<tr>
<td>Ring Waviness</td>
<td>$m_zf_i$</td>
</tr>
<tr>
<td>Linear effects</td>
<td>$ci$</td>
</tr>
<tr>
<td>Nonlinear effects</td>
<td>$pmf_i$</td>
</tr>
<tr>
<td>Spherical damage</td>
<td>$fc_i$</td>
</tr>
<tr>
<td>Waviness/singular</td>
<td>$m_zce$</td>
</tr>
<tr>
<td>External Radial runout</td>
<td>$mf_c$</td>
</tr>
<tr>
<td>Diameter variation</td>
<td>$mf_b$</td>
</tr>
<tr>
<td>Waviness/2</td>
<td>$pmf_c$</td>
</tr>
<tr>
<td>Internal Radial runout</td>
<td>$f_i$</td>
</tr>
<tr>
<td>Ring Waviness</td>
<td>$m_zf_i$</td>
</tr>
</tbody>
</table>

The frequency that corresponds to the succession in-out of the rolling bodies from the singular damages can be estimated with the equation:

$$f_t = \frac{\pi D_m n}{1 - (D_b D_m \cos \alpha B)^2 / 2}$$

where $b$ is the damage length on the circumference of the rolling path.

Monitoring of the vibration level can indicate nearly all types of mechanical faults of the dynamical equipment. An increased vibration level signals imbalance, nonalignment, general wear, or play between subassemblies; a high shock impulse level signals a nonalignment, an incorrect lubrication, or the existence of an overload on the bearing.

A rapid and efficient method of monitoring the functional state of the bearings, named the shock impulses method, has been patented by the Swedish company SPM (Shock Pulse Meter). The principle and mathematical apparatus of the method are presented in great detail in this paper. The level of shock impulses of a bearing depends on the size of the bearing, the rotation speed, and the working conditions. The SPM equipment can indicate the limit values for good, reduced, and unsatisfactory functioning conditions for any kind of bearing. Figure 2.1 presents a monitoring system for simultaneous supervision of 16 measuring points. The scavenged frequency domain is between 10 and...
FIGURE 2.1 Monitoring system. 10,000 Hz, corresponding to the ISO 2372 recommendations (equivalent to BS4675 and VDI2056). The measurement is made on (a) channel ALERT, which is mainly used to monitor significant increase of the vibration level due to wear, a channel with a discrete adjustable level from 25 to 75 dB; and (b) channel ALARM, which is used to warn and to stop voltage feeding of the monitored machine. Figure 2.2 illustrates the estimation graphics of the functioning state of the bearings.

Frequency analysis of the vibration signal is the most efficient diagnostic method for bearings. During the first investigation, the vibration level in the large band (third octave) or narrow band (10%, 3%, 1%) can be analyzed. This way the power of the signal can be appreciated, and the frequency peaks can be located in order to diagnose them (see Table 2.2). This process is complicated by the fact that the frequency peaks do not manifest themselves in a uniform way on the whole spectrum: at low frequencies they can be masked by white noise, and at high frequencies the danger of resonance appears. It must be noted that the position in the frequency spectrum presented previously depends on the bearing turn, because the position in the frequency spectrum previously presented is independent of turn (Figure 2.3).

Because of the presence in the spectrum of numerous harmonics that disturb the signal interpretation (some of them hide significant frequencies), Cepstrum analysis is recommended in bearings diagnosis [19]. This way it is possible to detect the periodicity in the spectrum (families of harmonics and lateral bands), the analysis also being insensitive to perturbations that appear on signal transmission. Detection by Cepstrum analysis of damage in a large-sized bearing (Figure 2.4) highlights the presence in the spectrum of the frequency of the pass of the
FIGURE 2.2

Estimation of the functioning state of the bearings.

rolling bodies over a pit from the external ring (FTBO), and also its first harmonics.

Frequency analysis has given birth to a spectacular method of investigation of the vibration signal, a method of comparing the spectra. The Danish company, Brüel & Kjær, launched the method and made it operational. The differences between the measured current spectrum and the spectrum templates come from the boarding of the reference signal. If the current spectrum surpasses the tolerance template, a warning signal is emitted and, if the limit template is surpassed, the emitted signal is one of damage and in parallel the machine is stopped. The method
can be completed by an analysis of the tendency of the frequencies that bypass the tolerance templates, the analysis that approximates the time until the final damage. Figure 2.5 illustrates the use of this method as a diagnostic of large-sized bearings: (a) comparing the current spectrum with the tolerance template; (b) graphic highlighting of the spectrum.
FIGURE 2.5
The method of spectrum comparison: (a) comparing the current spectrum with the tolerance template; (b) graphic highlighting of the spectrum displacements on narrow frequency bands; (c) selection of the alarming bypasses of over 6 dB; (d) drawing the tendency graphic for one of the selected frequencies.
displacements on narrow frequency bands; (c) selection of the alarming bypasses of over 6 dB; and (d) drawing the tendency graphic for one of the selected frequencies.

Another powerful method of frequency analysis, useful in diagnosis of bearings and also of gears and hydraulic elements is frequency analysis of the evolute of an intermediate signal from the time domain. The sure advantages of this method consist of highlighting the periodicity of the peaks corresponding to the damages from the bearing, their separation from the signals with close frequencies, or from the frequencies excited by resonance. Dr. D. Pupaza used this method with good results in the diagnosis of roller bearings, in the frame of a specialization at the University of Leicester (United Kingdom). He applied the method to diagnose the bearings of the main shaft of a NC milling machine (Figure 2.6).

The tests were made at idle running (2400 rpm) to minimize slippage and contact angle variation. The results obtained at the introduction of damage on the internal ring confirmed the increase in amplitude at the frequency estimated by calculus [126].

Acoustic signals are used for the diagnosis of bearings in the non-mounted state. Because of the reduced noise general level, the diagnosis of the bearings mounted in an assembly that contains other sources presents serious difficulties. The bearing under research is placed on a stand having very quiet characteristics, located in an anechoic chamber having inferior minimum frequency under 250 Hz. The placement of the free field microphone is indicated in Figure 2.7.

In his doctoral thesis, D. Radauceanu [128] analyzed the problem of noise dependence of the radial bearings upon the manufacturing and functioning conditions, and highlighted some interesting general aspects: A correlation exists between the noise and vibration levels of the same bearing under the same measuring conditions, and is evident in the frequency analysis of large band and less perceptible to frequency analysis of narrow band.

The shape deviations of the rings and rolling bodies (microgeometry, waviness, roughness) negatively influence the noise and vibration levels.

Ball bearings are quieter than roller bearings (5 to 10 dB). A watertight bearing, lubricated with low viscosity grease has a noise level smaller than an open one (3 to 4 dB). Mounting a roller in a soft gearing box (i.e., silicone rubber) or in a fixed position, reduces the noise with 6–10 dB.
FIGURE 2.6
Diagnosis of main spindle bearings of a milling machine using frequency analysis of the evolute of an intermediate signal.
FIGURE 2.7
Diagnosis of main spindle bearings using spectrum comparison.

Load influences the noise level of the bearings very little, but the rpm considerably influences it (the acoustic pressure is approximately proportional to the square of the turn).

No relevant differences of the noise level were observed between lubrication with low viscosity level and oil lubrication [128].

2.2 DIAGNOSIS OF SLIPPING BEARINGS
Slipping bearings are less frequently used in machine tool manufacturing. However, they may determine supplementary perturbations in the...
functioning of kinematic chains, usually with minor effects. The axle bearing in this case constitutes the main cause of the noise and vibrations. If radial plays in this kinematic couple also exist, they generate in spectrum peaks of the frequency of the axle $f_0$ and of the subharmonics of this frequency ($f_0/2$, $f_0/3$).

If the following phenomena are present: insufficient feeding with lubricant of the bearing, overloading of the axle (forces and moments), changing the rotation direction of the axle, and instability of the lubricant film at high rpm, then these lead to a thinner lubricant film and the occurrence of the "fiddlestick" phenomenon, which produces a noise with spectrum peaks at the rotation frequency of the axle $f_0$ and at the harmonics of this frequency ($2f_0$, $3f_0$, ...).

The diagnosis of these bearing types is chiefly carried out by supervising the noise and the acoustic emission. The acoustic signal is detected, amplified, and filtrated by filter pass-up and then analyzed in the time domain. The averaging of the signal in amplitude (RMS) and the recording of the impulses that pass over a limit value, adjustable, of the amplitude are executed [39].

The change from the hydrodynamic friction to the mixed frequency is indicated by the occurrence of some peaks in the domain of the high frequencies, emitted as a result of going beyond the carrying capacity of the bearing. The frequency analysis puts in evidence the phenomenon through a dominant in front of the rotation frequency of the shaft.

The spectral density of the impulse function can correlate very well with the functioning state of the bearing, as highlighted in Figure 2.8.
Chapter 2

The upper part of the figure presents the spectrum of the impulse density for the hydrodynamic bearing in perfect condition, and the lower part of the figure presents the spectrum of the same bearing, this time damaged. In order to reduce the noise and vibrations generated by the slipping bearings, some measures can be taken:

- Choosing an eccentricity relatively bigger than an admissible value $\varepsilon = 0.2–0.3$, ensuring the stability of the axle
- Ensuring a correct lubrication
- Modifying the shaft rpm in order to avoid functioning at the critical rpm or double of this critical rpm
- Equilibrating the shaft in bearings, by the mean of the marks that are mounted on the axle

2.3 DIAGNOSIS OF GEAR WHEEL TRANSMISSIONS

The gears constitute one of the most important sources of noise and vibration in the machine tool structure. The gears' vibroacoustic behavior becomes more defective as the transmitted power and the rpm increase, and with the decrease in the size of gears. The parameters that determine the vibroacoustic behavior of the gears can be grouped depending upon their nature:

- Constructive parameters (module, inclination angle, covering extent, number of teeth, material, etc.)
- Technological parameters (the class of precision, execution errors, roughness, etc.)
- Functional parameters (rotation speed, load, moment, existence of lubricant)

Table 2.3 synthetically presents the influence of the constructive parameters on the vibroacoustic level of the gear wheel transmissions. It should be noted that the main factor influencing the vibroacoustic level of the gear wheel transmissions is the teeth inclination followed by the stiffness of the gear wheel material. The gear's behavior on the dynamic regime is especially influenced by the parameters belonging to the two groups. The execution and mounting errors determine supplemental relative movements of the wheels, which superimpose those determined by the variable stiffness of the gear. The most important increase of the noise level (up to 20 dB) is determined by the shape errors.
TABLE 2.3

<table>
<thead>
<tr>
<th>Analyzed parameter</th>
<th>Values increase on noise level</th>
<th>Analyzed parameter domain (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tooth inclination</td>
<td>0–40 ↓</td>
<td>20</td>
</tr>
<tr>
<td>Material stiffness</td>
<td>— ↑</td>
<td>12</td>
</tr>
<tr>
<td>Tooth flank</td>
<td>0–0.02 mm ↓</td>
<td>6</td>
</tr>
<tr>
<td>Covering extent</td>
<td>1–2.2 ↓</td>
<td>3</td>
</tr>
<tr>
<td>Module</td>
<td>1–12 mm ↑</td>
<td>2</td>
</tr>
<tr>
<td>Number of teeth</td>
<td>z –2 z ↑</td>
<td>3</td>
</tr>
<tr>
<td>Specific deviation of profile</td>
<td>0.092–0.883 ↓</td>
<td>1</td>
</tr>
<tr>
<td>Width of tooth</td>
<td>— Low effect</td>
<td></td>
</tr>
</tbody>
</table>
| Tooth bulging, stiffness, mass of frame box errors of tooth of the profile. They imply increased frequencies that can coincide with the natural frequency of the transmission. The decrease of the working surfaces' roughness (by shaving, grinding) leads to a decrease of 3 to 4 dB of the noise level. If the relative error of the base step is positive, the gearing begins and ends beyond the theoretical gearing line; thus, the entrance and exit of the tooth from the gearing is made in shock conditions. The rotation error cumulates the effect of deformations and the errors of the teeth, providing complete indications on the mechanism of the excitation. Concerning the exploitation parameters, experimental research has shown that the noise and vibration levels increase at the same time as the load and angular speed. Doubling the loading moment has the effect of increasing the noise level by 3 to 4 dB. On the other hand, the doubling of the rpm produces an increase of 6 to 7 dB, at the same loading. The influence of the oil viscosity on the vibroacoustic behavior of gears is negligible [106].

The analysis in the frequency domain is the most adequate technique for processing the vibroacoustic signal coming from the gearing, because the modifications of some spectral components correlated to the evolution of damages that do not sensibly affect the global vibration level are detectable in the frequency spectrum, and the modifications of the spectrum provide important information concerning the causes of the excitation.
Chapter 2

of the damage. Usually, the frequency spectrum of the noise and vibration from gearing presents peaks at: (a) the gearing frequency and its harmonics, (b) secondary components, (c) lateral bands, and (d) low harmonics of the rotary frequency.

(a) The harmonics of the gearing frequency: the gearing frequency can be calculated as the multiplication between the rotation frequency of the shaft ($f = n/60$) and the number of teeth of the wheel $z$, so $a = f \times z$. The spectrum peaks corresponding to the gearing frequency and its harmonics are caused by the shocks, which arise in gearing because of the deviations from the ideal profile (Fig. 2.9). These deviations occur either during manufacturing or by the nonuniform wear of the flanks, which is larger on both sides of the rolling circle. The wear presence is more evident to the superior harmonics.

(b) The secondary components (accidental) occur in the same conditions as the gearing frequency and its harmonics, but correspond to a different number of teeth, and these secondary components are due to kinematic errors of the generating kinematic chains of the gear-tooth cutting machine. The most important of these errors is the gear-tooth cutting error on the rotation of the gear-tooth cutting table. If the wheel has anumber of $N$teeth on the functioning of the gear wheel on the table activated by it, a frequency will appear corresponding to $N$, as the harmonic integer multiple of the rotation frequency. This component is easily recognized because of its property of being independent by the increase of the load.
The lateral bands around the gearing frequency and its harmonics can be explained by the amplitude modulation or the nonuniform vibration frequency of the gearing, caused by some local damage. For example, the radial runout of the gear or the eccentricity of the gear wheels' sustaining shafts make the division circles of the two gearing wheels not remain tangent during the whole gearing time. Because of this radial runout, the low frequency corresponding to the rotational movement with $f_i$ frequency superimposes a relatively high frequency vibration corresponding to the gearing process $f_a$, resulting in a vibration modulated in amplitude. In the limit case of a 100% modulation, the $f_i$ component disappears, and the lateral frequencies characteristic to modulation remain:

$$f_{1\inf} = f_a + f_1$$
$$f_{1\sup} = f_a + f_1$$

Because the modulation process is distorted by manufacturing errors and 100% modulation is not realized, peaks arise in the spectrum for frequencies $f_{j\inf} = f_a - j \ast f_1$ and $f_{j\sup} = f_a + j \ast f_1$, with $j = 2, 3, 4, ...$

Also, every fluctuation in the tooth load will have the tendency to generate a variation of the vibration amplitude, so an amplitude modulation appears. At the same time, those fluctuations also determine fluctuations of angular speed, so a frequency modulation appears. The two modulations determine an increase of the lateral bands of frequency amplitude, their distance in the spectrum being equal to the modulation frequency. This contains important information on the source of the modulation effect. Each modulation with a pure frequency tends to give a family of lateral bands, and in the case where the modulation is not pronounced, this can be represented by two or three groups of lateral bands. Under these conditions, an additional effect is to increase the number of lateral bands.

The low harmonics of the rotation frequency correspond to the cumulated impulses that repeat with each rotation of the wheel. The modulation in amplitude or frequency has the tendency to give symmetric signals. Any asymmetry of the signal can be interpreted as an additive signal that also gives a number of harmonics of the respective frequency.

In addition to the mentioned frequencies, other significant components may appear in the spectrum, independent of rotation, corresponding to some self-modes of vibrations for the gearing, shafts, gear box, and the like. Also, the variation function of time of the rigidity of the tooth gearing has a specific action. The parametric vibrations of the gearing are characterized in this case by the existence of many domains of instability to frequencies equal to rational fractions, multiples, or submultiples of the self-frequencies of the system. A resonance phenomenon can appear.
for the same reason, when the excitation frequency \( f \) corresponds to one of the first subharmonics of the fundamental self-frequency \( f_i \).

In conclusion, the frequency spectrum of the gearing transmission permits an evaluation of the mechanical state of the transmission to be made. In order to identify the sources of noise and vibration, a correlation of the frequencies corresponding to the maximums of the spectrograms with the frequencies of the possible sources from transmission is made, calculated on the basis of their constructive and functional parameters.

Cepstrum analysis is a powerful and useful instrument of investigation for gear transmissions. It allows detection of periodicity of the spectrum and the precise determination of the frequency of the signal modulation. In the gear diagnosis domain, the Danish company Brüel & Kjær has had notable results beginning in the 1980s. An excellent example is the diagnosis of some problems that occur in the differential mechanisms in trucks produced by Raba (Hungary) in collaboration with Brüel & Kjær.

The test consists of rolling the differential mechanism on a stand until the damage occurs, simulating diverse loading (resistant moments). The gear vibrations are permanently monitored, making it possible to stop the test at any moment in order to study the damaging mechanisms before the progress of the damage makes it impossible to recognize the source. The initiation of the damage is recognized by the increase of the characteristic frequencies and of the lateral bands around these characteristic frequencies (the Cepstrum analysis method) [14].

The gearing frequency is sufficiently low, so many harmonics of this frequency are included in a spectrum of 2 kHz. The monitoring of this zone has indicated the increase of the second and third harmonics' amplitude because of the debut of the pitting phenomenon to the gear teeth. As the phenomenon progresses, the lateral bands around these harmonics increase. Figure 2.10 presents recordings obtained after the damage due to pitting has put gear functioning into danger. In Figure 2.10a, the gearing frequency and its harmonics are evident, and a magnification in the zone of interest (the second harmonic, Fig. 2.10b) shows an excessive increase in the lateral bands, at a distance of 12.05 Hz. The point of occurrence of the lateral bands can not be exactly predicted but mathematical modeling of the damages and the perturbations introduced by these damages allows prediction.

By processing the signal by Cepstrum analysis (Fig. 2.10c), the periodicities become evident, cumulated in a single band that corresponds to the frequency of 12.05 Hz. The analysis also indicates the occurrence...
FIGURE 2.10
Recordings obtained after damage due to pitting that puts a gear function into danger: (a) gearing frequency and its harmonics; (b) magnification of interest zone; (c) Cepstrum analysis; (d) occurrence of wear and periodicities of the lateral bands.
Chapter 2

of wear for the gear crown, and, in this case, the periodicities of the lateral bands are grouped to 1.7 Hz (Fig. 2.10d). This highlights the fact that diagnosis of gear damage is possible by correctly processing the vibration signal, using methods from the domain of frequency analysis.

The Department of Machine Parts and Mechanisms of the Polytechnic Institute of Iasi has developed some original research on the noise and diagnosis of gearing. V. Merticaru (1971) tackled the problem of dependence of the cylindrical gear wheels on manufacturing and working conditions [106]. In his doctoral thesis (1987), B. Dragan continued this research with his contribution to noise and vibration reduction in the gearbox of machine tools. His research focused on identification of critical natural frequencies and of different kinds of damage in the gearbox of a milling machine, the kinematic scheme of which is presented in Figure 2.11 [39].

To diagnose damage, the determination of natural frequencies, modulation frequencies, and periodicities from the frequency spectrum has necessitated the building of a complex schema for analysis of the vibroacoustic signal, an analogue type schema having compression possibilities, Zoom analysis, and Cepstrum analysis (Figure 2.12).
FIGURE 2.12 Zoom analysis and Cepstrum analysis.

Initially, reference spectra and “Cepstrums” for the gearbox, accepted as functioning in good condition, have been recorded. Modifications of the spectrum on the gearing frequency and its harmonics have been observed by introducing a damaged gear wheel into the gearbox (position 4 in the kinematic schema); in addition, the global noise level increased by 3 dB. Using Cepstrum analysis, an increase of approximately three times over the reference level of the first harmonic, corresponding to the rotational frequency of the fault wheel (radial runout) was observed. Thus the advantages of Cepstrum analysis were high.
44 Chapter 2

lighted, advantages related to a special sensibility and a simplification of data interpretation, because in cepstru the periodical peaks from the frequency spectrum are cumulated.

2.4 DIAGNOSIS OF BELT TRANSMISSIONS

Belt transmissions generally produce a reduced noise and they even have the quality of attenuating the vibrations produced by other sources from the kinematic chains. The three main causes that lead to the occurrence of vibroacoustic phenomena in this case are: the variation of the friction forces on the relative slipping of the belt on the wheel, some aerodynamic phenomena, or imperfections on the belt joint. In order to decrease the intensity of such phenomena, the following are recommended:

- Use of plastic or rubber plated belts.
- Belt stretching has to be optimum.
- Belt pulleys have to be made from nonmetallic materials with high damping capacity.
- Use of trapezoidal belts instead of flat ones.

The damaged driving wheels produce in spectrum components to the rotation frequency and its harmonics, and damaged belts generate spectral peaks on the frequencies, where \( f_c = \frac{v}{x/L} \), where \( v \) is the speed of the belt, \( x \) is the number of belt wheels, and \( L \) is the length of the belt. The belt damage can be located with the aid of a stroboscope, fixing the image by synchronizing at the \( f_c \) frequency.

2.5 DIAGNOSIS OF DRIVING ELECTRICAL MOTORS

The driving of the kinematic chains of machine tools is mainly realized by asynchrony or direct current electric motors. This section deals with driving by asynchronous triphased motors. Their functioning in a stationary regime is accompanied by phenomena that are constituted of forced vibrations and noise, influencing the elastic system of the driven kinematic chain.

2.5.1 Vibroacoustic Phenomena of Mechanical Nature

These phenomena are determined by the imbalance of the rotational parts, by the dynamic efforts variable in time (raised due to an incorrect...
execution and/or mounting), by the vibration of the brushes on the alternator, and so on. For example, the brush noise depends on their quality and on the quality of the sliding surfaces, on the holders' guiding way, and on the contact pressure. The noise increases at the same time as the rpm \( n \) of the rotor and as the number \( z \) of the collecting lamella increase. In spectra, the brushes' noise occurs to the frequency and superior harmonics.

In order to identify mechanical noise, which is always combined with magnetic noise, the motor is disconnected from the power source; the electrical components of the noise disappear immediately, allowing study of the mechanical ones. The mechanical noise can be reduced by a static and dynamic equilibration of the rotor, using the slipping bearings instead of rolling bearings by the optimization of the brushes/collector pressure [4, 11].

2.5.2 Vibroacoustic Phenomena of Magnetic Nature

Magnetic noise of electrical engines is due to the periodic magnetic forces from the air gap of the dynamo, the magneto-driving forces, or parasite magnetic fields. In the case of asynchronous motors, the angular frequency of the parasite magnetic fields is superimposed on the harmonics of the main field, which leads to an important increase of the magnetic noise level. The parasite alternative magnetic forces arise when the stator is not circular, the rotor has no axial symmetry, or is not centered. The notches of the rotor and stator distort the magnetic field by concentrating the lines of the flux density in the air gaps from the teeth (Fig. 2.13). Under these conditions, a complex vibration is born, whose frequency is given by the equation:

\[
\frac{f_m}{\omega} = \left(\frac{nR_s \pm ke}{s \pm k_1}\right)
\]

where \( \omega \) is the frequency of the electrical network (50 Hz), \( R_s \) is the rotor notch number, \( ke \) represents electricity coefficient (0 for static eccentricity, and 1, 2, 3 for dynamic eccentricity), \( s \) represents the slip, and \( p \) represents the number of pairs of poles, \( n = 1, 2, 3, \ldots, k_1 = 0, 2, 4, 6, \ldots \). Reduction of magnetic noise can be obtained by the inclination of the rotor notches or even by using rotors with double-inclined notches, executing some symmetrical electric reeling, and by reducing the air gap. The reduction of the magnetic field intensity by decreasing the excitation
Figure 2.13: Magnetic flux in an electric motor.

Current leads to substantial reduction of noise; however, this measure is disadvantageous because it implies a substantial increase of motor size, for the same power.

Analysis in the frequency domain and also cepstrum analysis allow for the detection of mechanical and magnetic damage, which occur during the functioning of the asynchronous motor. Figure 2.14 (left) presents a recorded example of the base spectrum (low frequency) of the functioning of a mechanical damaged motor (rupture in the motor). The effect becomes evident by the amplitude increase to the rotation frequency;
FIGURE 2.14
Detection of mechanic and magnetic damages: (left) analysis in frequency domain; (right) Cepstrum analysis.
<table>
<thead>
<tr>
<th>Vibrations cause: frequency</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radial Unbalanced type can be established analyzing signal phase (static $0^\circ$; couple $180^\circ$; dynamic $0-180^\circ$)</td>
<td></td>
</tr>
<tr>
<td>Bent shaft or angular unaligned $1 \times f$, $2 \times f$, $3 \times f$, $4 \times f$, ... and $0.5 \times f$, $1.5 \times f$, ...</td>
<td></td>
</tr>
<tr>
<td>Parallelism error $1 \times f$, $2 \times f$, $3 \times f$, $4 \times f$, ... and $0.5 \times f$, $1.5 \times f$, ... and $0.5 \times f$, $1.5 \times f$, ...</td>
<td></td>
</tr>
<tr>
<td>Radial Large number of harmonics and half harmonics</td>
<td></td>
</tr>
<tr>
<td>Damages of rolling bearings Wide frequency domain (1 to 20 kHz) — Resonance frequencies are excited by impact with local damages from rolling paths</td>
<td></td>
</tr>
<tr>
<td>Incorrect lubrication (shocks) of slipping shafts $0.43 \div 0.48 \times f$</td>
<td></td>
</tr>
<tr>
<td>Nonrigidity of stator holder, nonequilibration of phase reels' resistance, stator exfoliation $2 \times f$, $3 \times f$, $4 \times f$, ... and $0.5 \times f$, $1.5 \times f$, ...</td>
<td></td>
</tr>
<tr>
<td>Dynamical eccentricity, fissured or broken stator bars $1 \times f$ and $2 \times f$</td>
<td></td>
</tr>
<tr>
<td>Bent, worn-out, or deformed rotor by local heating</td>
<td></td>
</tr>
</tbody>
</table>

*a* $f$ represents the rotor rotation frequency; $f_R$ represents the electrical network frequency; $f_a$ represents the slipping frequency.
at the same time, lateral bands arise around this amplitude, produced by the increase of magnetic noise due to the slipping increase. Cepstrum analysis [Fig. 2.14 (right)] confirms the vibroacoustic phenomenon observed in the frequency domain.

2.5.3 Vibroacoustic Phenomena of Aerodynamic Nature

The aerodynamic noise is caused by the forced circulation of the cooling air from inside the electric machine, and also by the resonance of the air from the gaps and orifices of the rotor and stator. These phenomena have a harmonic character and can be identified in the spectrum on the frequencies

\[ f_a = k \times n \times \frac{z}{60}, \]

where \( z \) is the number of pallets of the fan (for the noise of the air of forced cooling) or the number of rotor notches (for the rotor noise), and \( n \) is the motor rpm, \( k = 1, 2, 3, \ldots \).

Decreasing the aerodynamic resistance of the ventilation network can reduce the aerodynamic noise. Thus, aerodynamic shapes must be designed for the ventilation radial orifices of the stator and rotor; the fans must be built with aerodynamic pallets; and parts to direct the air must be designed in order to avoid the bends and narrowing of the cooling air jet. In order to avoid formation of the acoustic resonators, the existing gaps and orifices in the rotor and stator of the electric machine should be filled with phonoabsorbing material. For high rpm motors, noise attenuators for air admission and evacuation channels can be used.

Table 2.4 represents a synthesis of research in the domain of direct current and asynchronous motor diagnosis currently used in industrial drives. The superimposing of all the excitation sources presented leads to the occurrence of numerous spectral peaks. The experimental research on the vibroacoustic behavior of the usual triphase asynchronous motors (0.6 to 7.5 kW) has shown that the zone of interest of the frequency spectrum is between 16 and 530 Hz. The same domain is significant also in the case of direct current motors that are used to drive the machines and equipment.
tered on machine tools and equipment. They become more and more destructive with the increase of the machining rpm. The causes of these deviations can be execution and/or mounting errors, nonhomogeneity of the materials used (inclusions on the cast parts or density variations on the cast or forged parts), the asymmetrical configuration of some pieces, hydro- or aerodynamic phenomena, wear phenomena, and so on.

2.6.1 Imbalance (Lack of Poise)

Imbalance, or lack of poise, arises when the rotational and mass centers of a rotational part are not coincidental. If imbalance can be separated into a single plan, this is denominated static imbalance, and if this arises in many more planes, dynamical imbalance results.

In the case of static equilibration the two centers are made to coincide by adding or eliminating a mass on the rotational plane [the case of the grinding wheels, flying, and belt pulleys as presented in Figure 2.15 (left)]. In the case of dynamic equilibration, not only the centrifugal forces but also the coupling of these forces must be taken into consideration; this coupling produces an angular movement of the main inertial axis compared to the rotational axis. By equilibration, these two axes must be brought into coincidence [the case of rotors, Fig. 2.15 (right)].

Because of the centrifugal forces created by the unbalanced masses the following occur: dynamic forces appear in bearings formed from a primary component due to the nonequilibrated mass of the bearing plane and a secondary component due to the unbalanced coupling. The imbalance on the bearing level can be defined with the help of a turning vector whose magnitude is given by the magnitude of the resultant force.
Vibroacoustic Machine Tool Diagnosis Research

The imbalance of the rotational parts produces vibrations on the rotation frequency \( f_i = \frac{n}{60} \) and on the superior harmonics of this frequency, having high amplitudes especially in the radial direction. The amplitude of these vibrations increases at the same time with the increase of rpm. The imbalance also can be detected by measuring the vibration movement phase: the perturbation force is a rotational vector, so the phase will be dependent on the transducer's location, as the amplitude of the movement will practically remain constant.

2.6.2 Axial Imbalances

The vibrations produced by axial imbalance are characterized in the spectrum by the existence of some significant peaks of the rotational frequency and especially of its second harmonic (\( 2f \)). The ratio between the amplitudes of the two components gives information on the degree of axial imbalance. The axial imbalance produces some high-level axial vibrations that can be perceived at both ends of the shaft with a dephasing of 180°, making them different from those produced by lack of poise, also located at the ends of the shaft.

2.6.3 Dimensional and Shape Deviations

These errors become significant on machine parts that have rolling contact (gears, bearings, ball screws, roller guidings, etc.). In the case of gear transmission, when the leading wheel has constant angular speed, it can be observed that the angular speed of the driven wheel is influenced by the transmission errors cumulated from the dimensional and shape errors of the gear geometry. As the transmission error is a function dependent on time, each spectral component of this error will be determined by the force of interaction between the two wheels.

The shape errors of the profile (\( E_{fp} \)) lead to an increase of up to 20 dB in the noise level of the gearing (Fig. 2.16), because their frequencies are high and can coincide with the natural transmission frequencies. These errors are signaled in the spectrum as harmonics of the gearing frequency and low harmonics of the rotation frequency [46].
2.6.4 Mechanical Plays

The existence of the mechanical plays is highlighted by the presence of some strong directional vibrations, a characteristic that permits their separation from those produced by lack of poise and axial imbalance. If a harmonic load stresses an assemblage with plays, the answer of the structure is no longer harmonic, even though the frequency remains periodic (Fig. 2.17). The detection of the mechanical plays from the joints and kinematic couplings of the machine tools, even in the incipient phase, is very important because their influence on the shape and dimensional precision and quality of the part surfaces is of first rank importance.

2.7 DIAGNOSIS OF THE TOOL AND CUTTING PROCESS

2.7.1 Diagnosis of the Cutting Tool

Classifying criteria for evaluation of the integrity and wear of cutting tools have been chosen: (a) the moment of control, divided into offline...
FIGURE 2.17

Methods or evaluation methods outside the cutting process, and online methods or evaluation methods during the cutting process; and (b) the manner of measurement, also divided into groups: direct methods, including measurement of the cutting tool (the width of wear on the main and secondary clearance faces, the width of wear on the transverse edge, the depth of the wear crater on the rack face, and the width of the crater); and indirect methods that evaluate the wear characteristics of the tool by wear, fissuring, and breaking effects on the part or on the variation in time of some correlate measures with the cutting process.

The offline evaluation of the tool state by direct methods is usually achieved by the tool's movement in numerical command to a point whose coordinates are known, followed by the cutting edge, rack, and clearance face's palpation. The disadvantage of this method is that the tactile feelers can not perceive the integrity or the wear but only the palpation direction.

Many more direct methods without contact used to evaluate tool status exist:

- Perception of the integrity of the cutting edge (drills, taps), using pneumatic transducers [142]
- Supervising the level of radioactivity of the tool cutting edge, previously bombarded with hard particles [73]
- Wear and cracking evaluation using ultrasound sources
- Digitization of the wear surface image of the nonworn tool and its comparison, at time equal intervals, with the image of the real wear, calculating the distribution of the wear surface [97, 167]
Chapter 2

Present online methods for evaluation of the tool state cover over 60% of total investigation techniques. They are less precise in determining the amount of wear, but they can perceive the fissure and the crack of the cutting edge and do not interrupt the manufacturing process. The most frequently used methods are discussed in the following.

2.7.1.1 Wear Control

Used on the basis of processing time, it considers the estimated durability of the tool.

2.7.1.2 Load Characteristics Evaluation of the Tool State

The Skandvik Company produces tensometric jacks that must be used in the bearing of the lead screw, because of the special sensibility of the force on the lead direction, comparative to the tool wearing. The Prometec Company, Germany, produces special bearings for the main shaft, bearings containing tensometric marks mounted in special channels of the external ring. The signal amplitude captured in this manner is proportional to the shaft load, implicit in the cutting tool. Figure 2.18 schematically presents the formation of the signal for comparison and evaluation of wear and fracture of the tool in the cylinder bore manufacturing process, using the Prometec technique (where $P_0$ represents the...
Vibroacoustic Machine Tool Diagnosis Research

2.7.1.3 Acoustical Emission (AE) Evaluation of the Tool State

The acoustical emission signal can be correlated with specific cutting tool wear criteria. These criteria are multiple and depend on the processing type (roughing and finishing) and on the used tool. The most used criteria are wear on the clearance and/or rack face, the dimensional deviations of the part, and the roughness of the processed part.

The characteristics of the AE signal modify at the same time as the wear; an important modification of the effective value of this signal indicates the reach of the wear limit. It is interesting to note that the cutting process can be usually continued, without rupture, but in very bad conditions of geometrical shape and quality of the surface.

During the cutting process, the effective value of the AE signal has a specific evolution: progressive increase, followed by a substantial increase in the vicinity of the catastrophic wear phase (this is much more evident on tools equipped with metallic carbide plates), then an accentuated decrease until the moment of the cutting edge destruction. The same behavior is found both in the roughness and finishing cases.

Figure 2.19 presents a recording of the effective value of the acoustic emission signal on a milling machine with a mill having a single tooth, in three successive passes. The passes are separated by two zones of absence of the AE signal; during the third pass the tooth has broken, a fact highlighted by a peak, and then an abrupt decrease of the effective value of the signal.

Concerning the break of the cutting tool, the most frequent causes are the mechanical shock when meeting some hard inclusions in the material to be processed or successive mechanical shocks (on the turning of some polygonal and grooved parts), or the thermal shock as a result of interruption of the cooling liquid. Tool break is easily highlighted by supervising the effective value of the AE signal because of the transitory energy jump. A typical example of tool breaking, hard to highlight by other methods, is the breaking of the auger when boring (Fig. 2.20). The tool-part contact is well detected by supervising the effective value of the AE signal and is clearly separated from the breaking zone (between the dashed lines) and from the zone of ulterior rack of the tool.
FIGURE 2.19  Recording of the effective value of the acoustic emission signal on a milling machine with a mill having a single tooth, in three successive passes.

In conclusion, the AE method is applicable and already widely used for the detection of tool breakage, but monitoring tool wear in the same manner is a more complicated problem because of many factors.

FIGURE 2.20  A typical example of tool breaking.
finishing operations in the case of different cutting processes remains another experimental study problem and requires the accumulation of an important database.

2.7.1.4 Electrical Resistance Monitoring

This monitors the tool-part contact or the thermoelectromotoric tension that arises during processing. The contact resistance in the tool-part zone is of $10^{-4}$ to $10^{-2}$ Ω compared to $10^2$ to $10^3$ Ω, the resistance of the bearings and $10$ to $10^{2}$ Ω, the electrical resistance due to the cooling–lubricating fluid. The fissure or fracture of the cutting edge produces an increase of up to 30% and then an abrupt decrease to zero of the voltage in the measuring circuit [122].

H. Wiele and P. Metz [165] highlighted the possibility of supervising tool wear by estimating the thermal gradient. Placing two thermocouples under the cutting plate, they discovered that the difference between the contraelectromotor voltages of the two controlled points is proportional to the wear on the clearance face. The disadvantages of these two methods consist of the difficult emplacement of the transducers, and also on the sensibility of the thermoelectromotor voltage on the variations of the tool geometry and of the parameters of the cutting regime.

Recently, Romanian researchers have grappled with the domain of diagnosis of the cutting tool state in their doctoral theses. E. Carata [23] brought important contributions on the elaboration of a research methodology in order to determine online the tool wear on boring, by vibroacoustic methods. L. Bogdan [12] correlated the information on three parameters (noise, vibration, and temperature) in order to evaluate the state of the cutting tool.

2.7.2 Diagnosis of the Cutting Process

The cutting process generates elastic waves that transmit to the working piece and the tool and its support. An acoustical emission transducer, placed in the vicinity of the cutting zone, can detect them, and the perceived signal is a “signature” characteristic of the cutting conditions. At the beginning of the 1990s, T. Moriwaki [110, 111] proposed a supervising scheme of the acoustical signal in cutting, which today is widely accepted (Fig. 2.21). The inferior cutting frequency of the filter set used is 100 kHz, in order to avoid the vibroacoustic signals associated with the system machine tool–clamping device–tool–part. The superior cutting frequency is 10 Mhz, in order to avoid electrical noise; the
natural nominal frequency of the transducer of acoustical emission can be approximately 500 kHz. This scheme has provided an identification method for acoustical emission sources specific to the cutting process; in addition, this scheme allows the determination of the characteristic frequencies and the realization of a correlation between the development of the cutting process and magnitudes characteristic of the acoustical emission signal.

The main sources of acoustical emission in the cutting process are (according to Souquet, Weber, and Dornfeld; Fig. 2.22):

- Plastic deformation in the shearing zone
- Friction of the chip on the rack face of the cutting tool
- Cutting edge deposits
- Friction between tool and processing part
- Collision and friction between chip and part
- Fragmentation of the chip
- Friction of the chip on the chip breaker
FIGURE 2.22 Main sources of acoustical emission in the cutting process.

The analysis of the signals of these sources provided data for a mathematical model that connected the effective value of the AE signal (AE\text{RMS}) with the parameters of the cutting regime (cutting speed, cutting depth). Experimental research on turning and boring has confirmed the validity of the model for orthogonal cutting. In the milling case, difficulties occur because of the presence of shocks when each tooth touches the part.

The proposed mathematical model has proved efficient both for supervising the evolution of the cutting tool wear and to detect its breakage, especially where the cutting conditions do not allow visualization of the tool (boring):

$$AE_{\text{RMS}} = C \sin \alpha \left[ \tau_k b l V (t_l \cos \alpha \sin \phi \cos (\phi \alpha) + 1) \right]^{1/2}$$

where $C$ is an experimental constant, $\alpha$ is the tool's attack angle, $\phi$ is the cutting angle, $\tau_k$ is the cutting stress, $b l$ is the cutting length, $t_l$ is the chip–tool contact length, and $V$ is the tangential cutting speed.

The acoustical emission signal (AE\text{RMS}) converted in the frequency domain can look different depending upon the emplacement...
Supervising the acoustical emission has imposed the grouping of the influence factors into three categories: parameters bound to the nature of the processed material (hardness, the capacity of being processed); parameters connected to the material and geometry of the cutting tool; and parameters of the working regime (the speed and depth of cut and feed). Concerning the factors from the first category, it has been observed that the level of acoustical emission varies proportionally with the material hardness, and the differences of the capacity of being processed modify only slightly the characteristics of the AE signal. For example, for an increase of hardness with 300 Brinell units, the level of acoustical emission can increase by approximately 15 dB. As to the factors in the second category, the estimation is that not the nature of the tool material but the way that materials are preponderantly degrading (abrasion, fissure, chemical diffusion) affects the acoustical emission signal. The modification of the cutting tool geometry has a significant effect on the energy of the acoustical emission signal. From this point of view, the most important parameter is the rack angle; experimental research (Kannatey-Asibu and Dornfeld) has shown that the medium of the acoustical emission signal energy sensibly modifies on the increase of the rack angle (Fig. 2.24). One of the effects of the rack angle increase
Chapter 2

is the increase of the contact length chip–tool; consequently, a similar dependency will be observed also between this rack angle and the energy of the acoustical emission signal. Systematic tests (Moriwaki, Souquet, Deschamps, Weber, Herberger, Diei, and Dornfeld) concerning the influence of the cutting regime parameters on the acoustical emission level have shown that the effective value of the acoustical emission signal is proportional to the square of the cutting speed (Fig. 2.25a) and also to the square of the depth of cut (Fig. 2.25b). The influence of the feed magnitude on the AE signal is negligible [32, 33]. During experimental research, it has been noticed that the use of cooling–lubricating liquids decreases the effective value (RMS) of the acoustical emission signal.

FIGURE 2.25 Influence of cutting regime parameters on acoustical emission level; acoustical emission signal is proportional to: (a) the square of the cutting speed; (b) the square of the depth of cut.
2.8 TECHNICAL DIAGNOSIS IN FLEXIBLE PROCESSING SYSTEMS

Modern machine tools are integrated in flexible production systems that include parts and/or tool feeding systems, parts and/or tool store systems, numerical or computer-assisted control systems, systems of adaptive or optimal control, and so on, and each component of the system develops specific actions. From this point of view, a matrix representation of the production system (Fig. 2.26) leads to a better understanding of its problems; one of these problems may be, for example, the prediction and diagnosis of the machine tool and/or cutting tools destined to fail [145, 35].

The normal functioning state of the flexible cutting systems supposes the optimal and simultaneous accomplishment of many fundamental functions:

- Automatic processing
- Automation of the flows (materials, tools, parts)
- Control, supervisory, diagnostic, and automatic maintenance
- Informational integration

FIGURE 2.26
Matrix representation of a production system.
The laboratory of Machine Tools of the University of Aachen has devised an expert system for the direction of flexible manufacturing systems. In its frame, the diagnostic function appears on the most complex level, and the monitoring has a permanent character. Accomplishing the diagnostic function involves a rapid and correct evaluation of the damage messages and deduction of the reasons for these damages, possible or existent. In this respect, an important amount of information is processed, considering that damage may also have many different causes. A correct diagnosis most often requires an oriented request of supplementary information; statistical and heuristic data are requested and the system must have the capacity to adapt to the new experiments and accumulations. This is not possible using conventional programming methods because the combinations (message of damage, the cause) are practically infinite; that is why the expert system does not describe the problems as sequential algorithms, but as relations and functional dependencies.

The presented expert system also has the capacity to recommend and even to execute a series of corrective actions as a result of establishing the technical diagnosis. The reaction time is very short, the information processing usually being done in real-time.

2.9 CONCLUSIONS: THEORETICAL AND EXPERIMENTAL RESEARCH PERSPECTIVES

Supervision of the functional state of machine tools and of the manufacturing processes developed by them have become subjects of wide interest in the last decade. The most important reasons for this phenomenon are:

- Unexpected stops of machines produce significant financial loss to companies, especially in those plants that use optimized plans for their production.
- Monitoring and diagnosis lead to the increase of the machines' autonomy, allowing their intensive use in two or three shifts.
- Monitoring and diagnosis lead to increases in productivity and production quality.
Chapter 2

The cost of installation and maintenance of the monitoring and diagnostic systems is decreasing continuously, and at the same time the cost of the machine tools is increasing because of the increase of their complexity.

By analysis of some technical parameters that correlate with the functional state of the machine tool (mechanical vibrations, noise and acoustical emission, temperature, force, cutting moment, etc.), a series of monitoring and diagnosis methods has been identified. Two classification systems of diagnosis exist: diagnosis methods of surface, which indicate only the functioning state and/or the existence of damage; and diagnosis methods of profoundness, which allow for the appreciation of the nature, location of damage, and time until the machine stops.

Not all acquisitioned signals from the functioning machine tool contain useful diagnostic information. An example of this is the forced vibrations coming from a discontinuous cutting process, vibrations that provoke fluctuations of the cutting forces, and the mechanical resonance of the machine. Another example is the trepidation phenomenon (chatter) that induces vibrations in the entire machine level. Both examples present structural vibrations but they are regarded as major damage by an inadequate monitoring and diagnosis system.

The literature has shown that relevant research exists concerning diagnosis of some elements of machine tool structure which are common to other types of machines and equipment (bearings, gearing, and belt transmissions). The diagnosis of cutting tools and the cutting process is an intensively investigated domain. The methods used in diagnosis are very diverse, and dependent upon the university or researcher who investigates them; often they do not have a systemic character or can not be reproduced. Considering these aspects, this research endorses the systemic approach of the diagnostic methods useful in the machine tool domain and their application on the kinematic chain level, especially for the feed kinematic chain, where the diagnostic information is missing. This work proposes the theoretical and experimental verification of the physical model of the investigated feed kinematic chain, in order to remove the possibilities of false diagnostics provoked by an inadequate structural behavior.

Theoretical and experimental research should be oriented to the determination by calculation of the characteristic frequencies of the functioning of the specific feed kinematic chains (bearings, ball screws, roll cam follower, lug) because of their role in identifying mechanical damage.
Cognizant of the recent performance of computing systems, this work proposes the introduction of virtual instrumentation in the vibroacoustic diagnosis of machine tools, by elaborating and providing users with virtual diagnosis apparatus that has increased performance capacity compared with traditional investigation equipment.

Last but not least, the role of this work is to create a databank based on the findings of technical diagnosis by vibroacoustic methods so that further developments of machine tool diagnosis on the level of expert systems can be realized.
3.1 THEORETICAL METHODS TO ESTABLISH TECHNICAL DIAGNOSTICS

By clearly establishing the relations between the level of the supervised parameter or parameters and the functioning state of the technical system, pertinent methods of study have been obtained.

Theoretical research uses statistical and/or probabilistic evaluation methods, mono- or multiparametric. The purpose of these methods is either to establish a series of decision algorithms on the basis of analysis of the possible state of the technical system, or to evaluate the influence of not mentioning the state of the technical system on the global cost of operation.

3.1.1 Statistical Methods

Statistical methods start from the evaluation of the minimum risk of spoilage. A limit level $x_0$ is adopted for the supervised parameter $x$ and the repartitions of this parameter in both its states are supposed to be known: $f_1(x)$ for the normal state $D_1$, and $f_2(x)$ for the wrong state $D_2$, as presented in Figure 3.1. It can be observed that adopting the limit
level implies a certain level of risk in decision making, illustrated by the hatched zones from the $D_1$ and $D_2$ domains, under the repartition functions. Two types of risk occurred: $\alpha$, the risk of false alarm or the producer's risk, and $\beta$, the risk of not accomplishing the goal or the beneficiary's risk.

The Neyman–Pherson method is a statistical method that can be applied to technical systems with a single characteristic parameter. The method consists of establishing an $a$ level, the maximum level allowed for the false alarm probability:

$$\int_{x_0}^{\infty} f_1(x) \, dx = a \quad (3.1)$$

From this $a$ level, the risk value of the $x_0$ parameter is deduced. The same value may also result from the maximum $b$ allowed level ($b < 0.05$) in the case of an unaccomplished purpose:

$$\int_{x_0}^{-\infty} f_2(x) \, dx = b \quad (3.2)$$

When establishing the two levels ($a$ and $b$), the number of technical systems drawn out from operation must be higher than the number of those technical systems for which a spoilage is to be expected as a result of the inevitable errors when specifying the functioning state.

If the probabilities that the system is in its normal state $P(D_1)$ or in its incorrect state $P(D_2)$ are established and $C_{21}$ equals the cost implied by a false alarm, $C_{12}$ equals the cost implied by nonaccomplishment of purpose, and $C_0$ equals the cost of nondetermination.
Vibroacoustic Methods Package 71

of the functioning state, the cost of the global risk is given by the relation:

\[ C = C_{21} P(D_1) \int_{\infty}^{x_b} f_1(x) \, dx + C_{12} P(D_2) \int_{x_a}^{-\infty} f_2(x) \, dx + c_0 \left[ P(D_1) \int_{x_a}^{x_b} f_1(x) \, dx + P(D_2) \int_{x_a}^{x_b} f_2(x) \, dx \right] \]

(3.3)

Deriving the expression function of \( x_a \) and \( x_b \) values of the parameter, the minimizing conditions of the global cost are determined as

\[ f_1(x_a) f_2(x_a) = (C_{12} - C_0) P(D_2) \]

\[ f_1(x_b) f_2(x_b) = C_0 P(D_2) (C_{21} - C_0) P(D_1) \]

(3.4)

This method is used in cases where the costs of nonrealization of the goal or a false alarm are high. In this case, the existence of the nondetermined zone situated between the \( x_a \) and \( x_b \) values of the supervised parameter \( x \) is admitted.

3.1.2 Probabilistic Methods

Probabilistic methods allow the establishment of each state characterized by a number of parameters with discrete or continuum repartitions, using a diagram of a number of states of the technical system. On the basis of this correlation of state parameters, decision rules or parameters can be established.

The Bayes method is a multiparametric probabilistic method that allows determination of the most significant diagnostic, by evaluating the state combinations of the significant parameters. If in order to determine the diagnostic, the functioning state is noted \( D_i \), simple parameter, and if \( P(D_i/x_j) \) is the probability of the \( D_i \) diagnostic in the known conditions of the influence of the \( x_j \) parameter on the system, and \( P(x_j/D_i) \) is the probability that the \( x_j \) parameter manifests in the \( D_i \) state, then the probability that both events manifest \((D_i,x_j)\) is given by the following equation.

\[ P(D_i,x_j) = P(D_i) P(x_j/D_i) = P(x_j) P(D_i/x_j) \]

(3.5)
At a certain moment the diagnosed system can be in a unique state so the following relation is true.

\[ \sum_{i=1}^{n} P(D_i) = 1 \quad (3.6) \]

If a concrete realization \( X \) is considered in the group of \( x_1, x_2, \ldots, x_j \) parameters, then the Bayes relation becomes:

\[ P(D_i | X) = \frac{P(D_i) P(X | D_i)}{\sum_{i=1}^{n} P(D_i) P(X | D_i)} \quad (3.7) \]

It is considered that the \( x_j \) parameters are usually independent, which leads to the simplification:

\[ P(X/D_i) = P(X_1/D_i) P(X_2/D_i) \ldots P(X_n/D_i) \quad (3.8) \]

This simplification is used many times in practice, despite some inevitable interdependencies.

In order to simplify Bayesian analysis, diagnostic matrices can be made. In these matrices are inscribed the following probabilities determined by statistical research: \( P(D/x) \), the probability of the \( x \) parameter manifesting in \( D \) state and \( P(D) \), the probability of finding \( D \) state. The most significant factor is recognized in matrix making \( P(D/X) = \max. \)

Considering the following equation,

\[ \sum_{i=1}^{n} P(D_i | X) = 1 \quad (3.9) \]

the basis of the estimation calculus of the technical diagnosis must be reevaluated if the probabilities \( P(D/x) \) are under (0.4...0.5).

Observations:

1. The complex of \( X \) parameters, which were theoretically or experimentally determined, may define a \( D_i \) state if \( P(D_i/X) > P_i \), where \( P_i \) is the limit probability for the \( D_i \) state (\( P_i \approx 0.9 \) is recommended).

2. The analysis' volume increases exponentially with the number of functioning states and parameters considered significant for these states.
3. The application of some rigorously controlled selection criteria leads to reduction of the number of significant values of $X$ parameters.

3.2 EXPERIMENTAL METHODS TO ESTABLISH TECHNICAL DIAGNOSTICS

The functioning state of a machine tool may be correlated with diverse parameters such as: (a) vibrations, (b) noise and acoustic emission, (c) temperature, and (d) cutting force and moment. Diagnostic methods based on the use of the first two parameters are presently the most widespread.

The acoustic or vibrator signal, captured by adequate transducers and used for diagnostic purposes, may be processed in many ways. The directly recorded vibration or acoustic signal is very rarely used in its primary form; usually the important elements used for analysis are the effective value or the power spectrum, thus the signal's energy. The advantage of methods based on the energy of the vibratory signal is that it allows the use of a common inexpensive instrumentation. The inexpensive quality recommends these methods for research laboratories and production technical systems. More elaborate procedures use the phase of the captured signal.

Use of the acoustic signal in diagnosis aims to create an ambient system that allows a correct acoustic measurement of the sound emitted by a machine tool, which is why measurements are done in an anechoic or reverberant room, well isolated from environmental sound. These conditions are hard to realize in a plant environment, but they may be produced in research laboratories.

Another major disadvantage of using the acoustic signal is its incapacity to identify the diverse noise sources of the machine, and because of this disadvantage, if the machine does not pass the noise test, other diagnostic procedures will be used in order to determine the source and the time until repairing. This disadvantage may be used to correlate the vibration tests with the noise tests. It is possible to locate an accelerometer in the immediate vicinity of a noise source in a variety of locations on a machine, to determine if this source is a problem for the machine. Precise information necessary to diminish the noise level is also obtained.

Use of the vibration signal for diagnostic purposes has proved to be very advantageous. The isolation of the machine from the vibrations of the plant environment is simpler and more efficient: a rubber or polyurethane foam carpet can serve as an excellent isolator as
the environmental vibrations are of low frequency. From this point of view, it must be noted that machine tools need foundations that ensure antivibration isolation or at least use dampening pads for leaning. Environment-radiated noise in machine tools produces structural vibrations of incomparably smaller amplitude than those of the internal mechanisms; these vibrations can be ignored. The main advantages of vibration measurements are twofold: the possibility of fault detection and the possibility of locating the source of these faults, that make vibration the main signal for diagnostic study.

There are major differences among diagnosis methods depending on their capacity to reach the imposed goal, identify the fault, and establish the technical diagnostic. In this respect there are methods that indicate the functioning state and/or the existence of a fault, called basic diagnosis methods, and methods that estimate the fault kind, location, and time until spoilage, called profoundness diagnosis methods. A comparative study of the two types of methods highlights the fact that the same physical effects and, many times, the same vibroacoustic signals, but treated with different mathematical algorithms, are differently valorized depending on the desired precision degree of the diagnosis.

3.2.1 Specific Parameters Common to Vibroacoustic Methods of Diagnosis

In order to process the vibration signal in the time domain (Fig. 3.2), some parameters specific to the analysis of the vibroacoustic signals are introduced:

The medium value (arithmetic) of the signal:

$$x = \frac{1}{T} \int_{T_0}^{T} x(t) \, dt = \frac{1}{N} \sum_{i=1}^{N} x_i$$

The effective value (effective of the root mean square, RMS):

$$x_{ef} = \sqrt{\frac{1}{T} \int_{T_0}^{T} x^2(t) \, dt} = \frac{1}{N} \sum_{i=1}^{N} x_i^2$$

The peak value of the signal:

- positive peak: $$x_v^+ = \max . x(t)$$
- negative peak: $$x_v^- = \min . x(t)$$
The signal's dispersion ($\sigma$ - standard deviation of the same signal):

$$\sigma^2 = \lim_{T \to \infty} \frac{1}{T} \int_0^T (x(t) - x_0)^2 \, dt$$

(3.12)

The function of amplitude distribution [the probability that the vibration amplitude is inferior to a given value $x$; see also Fig. 3.3 (left)]:

$$P(x) = \lim_{T \to \infty} \frac{1}{\Delta t} \sum_{i=0}^{\Delta t T} (x_i - x_0)^2$$

(3.13)
Chapter 3

The function density of probability of the amplitude (the probability that the instant amplitude of the vibrator signal will be in a given interval; Fig. 3.3 (right)):

\[ p(x) = \lim_{\Delta x \to 0} \frac{P(x) - P(x + \Delta x)}{\Delta x} \]  
(3.14)

It can be deduced from the last definition that between the function of amplitude distribution and the function density of probability of the amplitude exists the relation:

\[ p(x) = P(x) \, dx \]

or

\[ P(x) = \int_{-\infty}^{\infty} p(x) \, dx \]  
(3.15)

The autocorrelation function (estimation if the vibrator signal remains similar to itself):

\[ C_x(\tau) = \frac{1}{T} \int_{-T}^{T} x(t) x(t + \tau) \, dt = \frac{1}{N} N \sum_{i=1}^{N} (x_i + x_k) \]  
(3.16)

Another parameter is added to those above in order to estimate the signal in the frequency domain:

The spectral density of power (the amplitude density in the power spectrum):

\[ S_x(f) = \frac{1}{2T} \int_{-T}^{T} x(t) e^{-2\pi jft} \, dt \]  
(3.17)

This function is in fact the Fourier transform of the autocorrelation function from the time domain. With this function's help the total power of the signal is obtained by integrating the partial powers of the spectral components:

\[ P = \int_{0}^{\infty} S_x(f) \, df \]  
(3.18)
3.2.2 Diagnostic Surface Methods

3.2.2.1 Peak Factor Method

This method evaluates the vibroacoustic signal in the time basis by recording the peak value and the effective value, followed by the calculus of the peak factor:

\[ F_v = \hat{x} / x_{ef} \]  

(3.19)

On the occurrence and development of a fault in a bearing, the shocks generated while rolling over the fault make the peak value increase substantially, but the shocks have a very small influence on the effective value of the vibrator signal. In consequence, the value of the peak factor increases and this tendency has to be supervised.

In the technical literature, on the basis of numerous tests, the following characteristic values are given for the peak factor.

- \( F_v < 10 \): good bearing;
- \( F_v = 10, \ldots, 20 \): fault conditions occur;
- \( F_v = 20, \ldots, 25 \): incipient fault;
- \( F_v > 25 \): fault bearing.

The effective value of the vibrator signal increases even as the shock's amplitude from individual faults remains constant, as the bearing is deteriorating and more and more faults occur. This phenomenon makes the peak factor "fall" to the initial value, toward the end of the bearing life cycle, making a deteriorated bearing appear in good condition. Such behavior will trick an uninformed user of this diagnostic technique.

The peak factor method is simple and easy to use. It is especially useful in the case of monitoring a large number of measuring points when an early warning is not required, and the consequences of spoilage are not too great. In particular situations, the method can be completed by another diagnosis method in profoundness, for example, Cepstrum analysis.

3.2.2.2 Diagnostic Index Method

This method has its basis in the use of normalized values of the effective and peak parameters of the vibrator signal.
Normalization aims to report the value of parameters characteristic of the analyzed signal, measured at a certain moment \( t \), to a reference value for that parameter. For diagnosis, it is useful for the reference value of the normalized parameter to be the value measured in the perfect operating state of the supervised system.

Use of the normalization method allows the estimation of the functioning state of simple mechanical systems (e.g., bearings) and only by use of the normalized effective values or peak values of the vibration signal. For example, the fatigue of the radial ball or roller bearings can be correlated with the effective value of the signal acceleration as follows.

\[
\begin{align*}
x_{\text{ef}} &= 20 \text{ [mm/s}^2]\text{]: normal function;} \\
x_{\text{ef}} &= 20, \ldots, 45 \text{ [mm/s}^2]\text{]: slight traces of light settling;} \\
x_{\text{ef}} &= 45, \ldots, 90 \text{ [mm/s}^2]\text{]: strong settling until visible faults;} \\
x_{\text{ef}} &= 90, \ldots, 150 \text{ [mm/s}^2]\text{]: major faults;} \\
x_{\text{ef}} &> 150 \text{ [mm/s}^2]\text{: out of operation.}
\end{align*}
\]

The diagnostic error by this method is approximately 50\% (see Table 3.1), and decreases to under 30\% by normalization of the effective value indicator.

The diagnostic index can be defined with the relation

\[
K(t) = \frac{x_{\text{ef}}(0)}{x_{\text{ef}}(t)} \quad \text{(3.20)}
\]
so it has a value between 0 and 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Without Error</th>
<th>With Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective value, ( x_{\text{ef}} )</td>
<td>( x_{\text{ef}}(t) &lt; 50 )</td>
<td>( x_{\text{ef}}(0) &lt; 30 )</td>
</tr>
<tr>
<td>Peak value, ( x_v )</td>
<td>( x_v(t) &lt; 50 )</td>
<td>( x_v(0) &lt; 35 )</td>
</tr>
<tr>
<td>Diagnostic index, ( K )</td>
<td>( x_{\text{ef}}(t) &lt; 35 )</td>
<td>( x_{\text{ef}}(0) &lt; 25 )</td>
</tr>
</tbody>
</table>

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The value of the diagnostic index correlates very well with the functioning state of the machine parts containing rolling elements:

\[ K(t) = 1, \ldots, 0.5: \text{good functioning characteristics;} \]

\[ K(t) = 0, 0.5, \ldots, 0, 2: \text{appearance of accelerating factors of damaging phenomena;} \]

\[ K(t) = 0, 2, \ldots, 0, 02: \text{effects of damaging phenomena occur;} \]

\[ K(t) < 0, 02: \text{risk of immediate work stoppage by spoilage.} \]

In the technical literature this method is quoted with an error range of 25%, as presented in Table 3.1.

### 3.2.2.3 Kurtosis Method

The Kurtosis method is a probabilistic diagnostic method that uses the acceleration of the vibrator signal. The amplitude of this signal may be represented by the function density of probability [relation (3.14)].

A bearing in good functioning condition is the source of some stochastic vibration that respects a normal (Gauss) distribution of the amplitude. The injurious processes are the cause of the occurrence of some supplemental components that change the initial character of the signal and implicitly modify the probability density function of the signal. Thus, deviations from the normal (Gauss) distribution are born, and they can be quantified using the statistic moments of superior order.

The Kurtosis factor is a fourth-order moment expressed as

\[ \beta_2 = \frac{1}{\sigma^4} \int_{\infty}^{\infty} (x - \bar{x})^4 p(x) \, dx \quad (3.21) \]

where \( \bar{x} \) is the arithmetic mean of the signal, \( p(x) \) is the density of probability of the same signal, and \( \sigma \) is the standard deviation. The value of the Kurtosis index for a Gaussian distribution of a signal is \( \beta_2 = 3 \), in a large band of frequency (2.5 ÷ 80 kHz) and with a maximum deviation of 8%. The increase of this index indicates the debut (\( \beta_2 = 4 \ldots 6 \)) and the existence (\( \beta_2 > 6 \)) of a mechanical fault, respectively. For higher values of the index (\( \beta_2 = 9 \ldots 10 \)), the machine has to be stopped and the faulty spare part changed.

This method has been applied with good results in supervising the rolling bearings. Figure 3.4 presents the basic electronic circuit for the calculus of the Kurtosis index starting from the measured vibration signal on the box of a bearing. The role and type of each electronic block can be observed and also the successive transformations of the initial signal. The advantage of this method lies in renouncing the use of...
some comparative values that make the method useful without previous preparation. The Kurtosis method is quoted as one of the most precise surface diagnosis methods with an error range of 20 to 25%, according to the technical literature.

3.2.2.4 Shock Impulse Methods

Specific faults occur in the functioning of mechanisms that replace the slipping friction with the rolling friction such as some irregularities. The irregularities of rolling surfaces and bodies, which are due to mounting faults and/or wear damage, disturb the process of uniform rolling and lead to the occurrence of mechanical shocks. Thus, a wave of mechanical pressure occurs (shock impulse), which diffuses in the material as a spherical wave, with a speed specific to the bearing's material. The residual arrow dampens very slowly compared to the process of acceleration by shock (Fig. 3.5). The maximum value of the amplitude of these large band sonic waves is dependent on the kinetic energy transferred and by the square of the shock speed. At constant rpm, the shock speed modifies proportionally with the body mass and the depth to which the rolling body penetrates.

The magnitude of the damages can be established by measuring the shock impulses and by counting the sizes of the bearing (internal diameter $D$) and the rpm $n$. The level of maximal values $dB_M$ and the white noise level $dB_C$ determine the logarithmic value $dB_{sv}$ (decibel shock value). The reference value is the initial value $dB_I$, representing...
the level of shock impulses of the new bearing perfectly mounted and
greased. The reference value can be also established empirically using
the relation:

\[
\text{dB} = 20 \log(n + 0.6\log D - \log 2150) \quad (3.22)
\]

The normal value of shock impulses \(\text{dB}_N\) is taken as the basis in order
to evaluate the functioning state of the bearing:

\[
\text{dB}_N = \text{dB}_{SV} - \text{dB}_I \quad (3.23)
\]

and the correlation is as follows.

\[
\text{dB}_N = \ldots 20: \text{good functioning state; } \\
\text{dB}_N = 20 \ldots 35: \text{functioning state to the limit, because of the lack}
of grease, some mounting errors, or the appearance of the pitting
phenomenon; \\
\text{dB}_N = 35 \ldots 60: \text{critical state, risk of “out of operation.”}
\]

The working principle of the method is illustrated in Fig. 3.6. The shock
wave, which is captured by an acoustic emission transducer, is introduced
in a narrow band-pass filter. The filtered signal is transformed by an
impulse generator in an amplitude impulse proportional to the shock
speed.

The SPM diagnosis method has a statistic character and the diag-
nostic error is under 10%. This method especially highlights faults due
to pitting, material fatigue, and mounting errors. The use of this method
has the following advantages.
The results of measurements are not influenced by machine tool or other equipment vibrations. The level of the shock impulses of a damaged bearing, compared to a new bearing, may increase by a factor of 1000 (60dB). The results of measurements of neighboring bearings can be separated as a result of dampening the high frequency vibrations.

Figure 3.7 presents typical shock impulse diagrams drawn by the SPM method: (a) a bearing in good functioning shape; (b) impure viscous grease; (c) fault or insufficient grease; (d) bearing not greased; (e) phenomenon of friction synchronized with rpm; (f) rhythmic functioning perturbations.
cous grease, (c) a mounting fault or insufficient grease, (d) bearing not greased, (e) phenomenon of friction synchronized with rpm, and (f) rhythmic functioning perturbations, for example, by load shocks or pressure shocks.

3.2.3 Profoundness Diagnosis Methods

3.2.3.1 Spectrum Comparison Method

Analysis in the frequency domain is based on obtaining the frequencies spectrum using the Fourier transform:

$$G(f) = \int_{-\infty}^{\infty} g(t) e^{-j2\pi ft} dt$$

$$g(t) = \int_{-\infty}^{\infty} G(f) e^{j2\pi ft} dt$$

(3.24)

Spectrum comparison is a frequency method that, on the basis of automatic comparison of the spectra coming from the same measuring point, but at different times, recognition of some faults and also, through tendency analysis, permits estimation of the time until final damage (out of use).

The method is applied in the following steps.

1. Obtaining the reference pattern. With the machine in perfect functioning state, more frequency spectra are recorded in the domain $2\text{Hz}...20\text{kHz}$, depending on the memory of the analyzer. The reference spectrum is obtained from the mean of the recorded spectra (represented as darker shading in Fig. 3.8a), and is kept as it is. The reference pattern results as an evolute of the reference spectrum, by widening the frequency peaks (represented by the thick line in Fig. 3.8a). This widening of peaks is made to avoid the false signals that can occur on the translation of whole spectrum at small rpm fluctuations of the monitored element.

2. Definition of the limiting profiles. Two other profiles are defined related to the reference pattern: the tolerance pattern (of the admissible levels) and the alarm pattern (of maximum levels where the intervention for readjustment is compulsory). These profiles are obtained either adding a tolerance of the amplitude, on short frequency domains to the reference pattern, or translating the whole reference pattern to a preestablished level. Usually, in order to obtain the tolerance pattern,
FIGURE 3.8

Steps of the spectrum comparison method: (a) reference spectrum and pattern spectrum, (b) tolerance pattern and alarm pattern, (c) current spectrum, (d) tendency chart.

the translation is made vertical to the "2 × reference pattern" (represented by the dash–dot line in Fig. 3.8b), and for alarm pattern to "10 × reference pattern" (represented by the thin line in Fig. 3.8b).

3. Comparison of spectra. The current spectrum (black in Fig. 3.8c), captured in the respective measuring point after a time interval or with a rhythm on the user latitude, is compared by superimposing on the tolerance pattern. After comparison, the frequencies that have surpassed this pattern and the value of the overages are highlighted in a chart. It is necessary to stop the machine when the alarm pattern has been surpassed, in order to find and fix the damage.

4. Drawing the tendency diagrams. Evolution of the frequencies that surpass the tolerance pattern can be analyzed on the basis of some successive comparisons for predetermined intervals. A diagram of the increase of the amplitude difference between the current spectrum and
the tolerance spectrum can thus be drawn by points, a diagram which is usually linear (Fig. 3.8d). The point whose abscissa indicates the moment of intervention \( t_i \) for reestablishment is at the intersection of this line with the horizontal line representing the maximum admissible value for the analyzed frequency (value taken from the alarm pattern). The difference between this moment and the time when the last current spectrum was drawn represents the interval for which the machine can still be used in limited operation conditions.

3.2.3.2 Evolute Method

The characteristics of part vibrations change while a fault begins to develop in a part that has rolling elements. Each time a rolling element meets a discontinuity on the rolling path, an impulse occurs. This impulse periodically repeats with a rate determined by the location of discontinuity, the geometry of the part, and the rpm of the driving element. These repetition frequencies are characteristic frequencies; they are not always easy to find in a standard frequency spectrum because they are mixed with vibratory components of a much higher level.

The impulses resulting from the concussion of the rolling elements appear as an increase of the wide band in the domain of the superior frequencies of the vibratory signal. In consequence, separating this frequency domain using the Zoom function and the Fourier analyzers, or using a band-pass filter, a signal that contains these impulses is obtained. This signal is leveled in order to find the evolute of impulses in the time domain; then the signal is passed in the frequency domain and the evolute spectrum results. This spectrum has maximums at the impact frequency, thus the nature of the fault and also the element that has the fault can be recognized. This information is usually the key to the time approximation until stoppage due to damage. The absolute value of the peaks from the spectrum depends a great deal on filtration and on the excited resonance frequencies, and does not present interest for diagnosis.

The maximums indicated by the occurrence and the evolution of the mentioned faults are not usually perceptible in the raw spectrum of the vibrator signal because their modular frequency manifests as lateral bands around the natural frequencies.

If the periodic modulation function is also a harmonic oscillation then it can be written:

\[
f_p(t) = A_T + A_M \cos \omega_M t,
\]

(3.25)
where $A_T$ is the amplitude of the carrier frequency, $A_M$ is the amplitude of the frequency of modulation, and $\omega_M$ is the modulating pulsation.

The following relation is deducted from the previous relation.

$$x(t) = A_T \cos(\omega_T t) + A_M [\cos(\omega_T + \omega_M) t + \cos(\omega_T - \omega_M) t] \quad (3.26)$$

where $\omega_T$ is the pulsation of the carrying signal.

The lateral bands that appear are visible in the real signal spectra only in very rare cases. Most frequently, they are superposed with neighboring components of the frequency. The classical models for signal analysis can not draw sure conclusions from the analysis of such a spectrum, and that is why the extraction of the evolute curve is used. In order to extract this evolute curve, a modality to "positivate" the signal in the time domain must be found; this may be done using one of these methods:

- Forming the mean value of short time
- Forming the effective value of short time
- Directing and filtering of the signal
- Using the Hilbert transform
- Passing directly to Cepstrum analysis (Fig. 3.9)

The mean value of short time can be calculated as

$$m(t) = \frac{1}{T} \int_{t-T}^{t} x(t) \, dt$$

where $x(t) = 0 \text{ if } x(t) < 0$

and

$$m(t) = x(t) \text{ if } x(t) \geq 0 \quad (3.27)$$

or

$$m(n) = \frac{1}{N} \sum_{i=nN}^{N} x_i, n=1, 2, 3, \ldots$$

where $x_i = 0 \text{ if } x_i < 0$

and

$$x_i = x_i \text{ if } x_i \geq 0 \quad (3.28)$$
The effective value of short time can be calculated as
\[ e(t) = \sqrt{\frac{1}{T} \int_{t}^{T} x(t)^2 \, dt} \] (3.29)
or
\[ e(n) = \sum_{n=N}^{\infty} \sqrt{\frac{1}{N} \sum_{i=n}^{N} x_i^2}, n = 1, 2, 3, \ldots \] (3.30)

The length of the time interval has a special importance; usually the following relation must be respected,
\[ f_T > \frac{1}{T} \geq f_M \] (3.31)
where \( f_T \) is the carrying frequency and \( f_M \) is the modulation frequency.

It can be mentioned in conclusion that the time interval \( T \) must be at least as large as the period of the carrying vibration having the smallest frequency.

The most exact method of extraction of the evolute is the application of the Hilbert transform of the time domain signal:
\[ H\{x(t)\} = \frac{1}{\pi} x(t) \ast \left( \frac{1}{t} \right) \] (3.32)

When passing in the frequency domain applying the Fourier transform, the following relation is obtained,
\[ F\{H\{x(t)\}\} = X(f)(-j \text{sign}(f)) \] (3.33)

Thus, using Fourier analyzers, changing the phase in the frequency domain is simple to realize; this change corresponds to a 90° rotation in the complex space.

If we consider the original signal and the Hilbert transform of this signal as real and imaginary parts of a complex function \( x_H(t) \); then this is the evolute of the time signal:
\[ x_H(t) = x(t) + jH\{x(t)\} \] (3.34)

If the frequency analyzer does not possess the algorithm needed to obtain the Hilbert transform, the method of signal directioning and filtering can provide very good results. The signal captured by the accelerometer contains, as specified above, lateral bands of the fault frequency and...
90 Chapter 3

of the rotation frequency around each characteristic frequency. In other words, the carrying signal containing the whole characteristic frequency is modulated by a signal containing the fault frequency \( f_d \), the rotation frequency \( f_r \), and their subharmonics.

The reduction of the frequency content of the signal is realized when passing through a band-pass filter centered on one of the characteristic frequencies. The bandwidth of this filter is taken in such a way that the lateral frequencies induced by the fault can also pass. To make this possible, the largest value of the fault frequency \( f_{md} \), and the bandwidth \( l_b > \pm f_{md} \) (usually \( \pm 2f_{md} \)) must be approximated. Consequently, when leaving the filter, the signal will contain the characteristic frequency and its lateral frequencies \( f_d(2f_d) \) if \( f_r(2f_r) \). The signal is then demodulated and passed through a low-pass filter to eliminate the eventual lateral frequencies that are around the first superior harmonic of the central characteristic frequency.

Processed in the manner outlined above, the signal is then passed in the frequency domain by a Fourier analyzer, and the evolute spectrum is obtained, a spectrum that contains all the mentioned frequencies, including the frequency specific to the damage.

Separation of fault damage is realized using a "normalization method" similar to that presented in the diagnostic index method. This separation will be possible if previously a spectrum of evolute in a perfect functioning state of the machine was obtained. Normalization consists of the distribution of amplitude values of the corresponding frequencies, frequency with frequency, between the spectrum with fault and the spectrum without fault, using a relation such as

\[
R(f) = \max\{A_d(i)\}/\max\{A_b(i)\}
\]

where \( A(i) \) is the amplitude of the frequency \( i \), and the indices \( d \) and \( b \) have the meaning "fault" and "good."

3.2.3.3 Cepstrum Analysis Method

Cepstrum was first proposed in 1963, and it was defined then as the "power spectrum of the power spectrum logarithm." The reason for this definition is not entirely clear because even in the original work it is compared with the autocorrelation function that cannot be obtained as an inverse of the Fourier transform of the power spectrum. Later, Cepstrum was defined as the "inverse of the Fourier transform of the"
Vibroacoustic Methods Package 91

A logarithmic power spectrum, clarifying the link with the autocorrelation function. At the same time, a function similar to Cepstrum has been defined as the "inverse of the Fourier transform of the complex logarithm of the complex spectrum," and, in order to distinguish the Cepstrum defined above, it was named complex Cepstrum, and the first was renamed power Cepstrum.

The Cepstru denomination is paraphrased from the word spectrum; in the same mode a series of other terms is introduced: quefrency from frequency, ramonic from harmonic, gamnitude from magnitude (amplitude), lifter from filter, and others.

Theoretical Basis of Cepstrum Analysis.

Using the $\mathcal{F}$ symbol to indicate the Fourier transform of the quantity in parentheses, the definition used for the power Cepstrum is

$$c_p(\tau) = \mathcal{F}^{-1}\{\log \mathcal{F}_{xx}(f)\}$$

(3.36)

and for the complex Cepstrum is

$$c_c(\tau) = \mathcal{F}^{-1}\{\log \mathcal{F}_x(f)\}$$

(3.37)

where $\mathcal{F}_{xx}(f)$ is the power spectrum of the time signal $f(t)$,

$$\mathcal{F}_{xx}(f) = |\mathcal{F}\{f_x(t)\}|^2$$

(3.38)

and $\mathcal{F}_x(f)$ is the complex Cepstrum of $f_x(t)$.

Expressed in real and imaginary components, respectively, in amplitude and phases, with $f_x(t)$ real. From the previous relation, the complex logarithm of $\mathcal{F}_x(f)$ results in

$$\log \mathcal{F}_x(f) = \log A_x(f) + i\phi_x(f)$$

(3.40)

The Cepstrum analysis applications imply the detection of periodic structures from the spectrum (harmonics, lateral bands, echoes, reflections), followed by the separation of source from effects of the transmission path of the signal. The fundamental characteristic of this procedure is the representation, for any physical system, of output signal $y(t)$ as a convolute of input signal $x(t)$ with the system response in frequency function $h(t)$:

$$y(t) = x(t) * h(t)$$

(3.41)
Applying the convolution theorem, this relation transforms itself in a multiplication in the frequency domain, and applying the logarithm the relation becomes additive:

\[ Y(f) = X(f) \times H(f) \]

\[ \log Y(f) = \log X(f) + \log H(f) \]  

(3.42)

This additive relation maintains itself also in cepstrum because of the linearity of the Fourier transform; so here, the effects of the source and transmission are additive:

\[ F^{-1}\{ \log Y \} = F^{-1}\{ \log X \} + F^{-1}\{ \log H \} \]  

(3.43)

The power Cepstrum and the complex Cepstrum offer the possibility of separating the components because of the excitation from the components due to the dynamic characteristics of the structure (the way covered by the signal), because of the logarithm properties. In addition, the power Cepstrum and the complex Cepstrum offer the advantages of the possibility of eliminating the last-mentioned components and reconstituting on this basis the excitation. At the same time, Cepstrum is less sensible to these dynamic characteristics of structure: for the same excitation, the spectrum of frequencies depends more on the point where the transducer is mounted on a structure, as Cepstrum is less influenced by the choice of the measuring point.

Another important advantage of Cepstrum analysis is the fact that all the lateral bands of a certain frequency are mainly grouped in a single line (ramonica), this line containing significant information concerning the medium height of the lateral band. The use of Cepstrum analysis for machine tool diagnosis is based on the analysis ability to detect the periodicities from spectra (families of harmonics and lateral bands), and also on the insensibility of the analysis related to the path from the internal source to external measuring point. These advantages have imposed the use of Cepstrum analysis for diagnosis of mechanical systems, especially for gearing transmissions (reduction gears, gearboxes, etc.) and for bearings.

### 3.2.3.4 Acoustic Emission Method

Acoustic emission is defined as the succession of elastic waves generated by the liberation of the internal energy stored in a structure. The acoustic emission manifests in the high frequency domain (\( f > 100 \text{ kHz} \)) by elastic waves detectable as vibrations on the supervised structure.
A working method, acoustic emission represents a nondestructive technique, capable of detecting when and where a fissure or crack occurs. The nature and the causes of these faults are then investigated by complementary methods. Four main sources of acoustical emission exist: structural dislocation movements, phase transformation, friction mechanisms (microfrictions, microconcussions), and fissure forming and extension.

In the case of dislocations (i.e., displacement of an imperfection of line in a crystalline network), that occur as an avalanche, the detected signal is of the continuum type, as for the phase transformations (i.e., forming of martensite in carbon steel), the signal is of the impulse type and can be detected for each transformed grit.

The fissures occur in the material nodes and points where the local effort surpasses the fracture stress. Thus, new surfaces are formed and energy is released, energy that is partially converted in acoustic emission. The signal is of impulse type and high frequency. At the same time, the friction mechanisms entered in action also emit impulse type acoustic signals.

In acoustic emission the signal amplitudes cover a wide domain; in relative units, these amplitudes are: 1 to 10 for structural movements, 5 to 1000 for phase transformations, and 20 to 1000 for fissures.

The propagation of acoustical emission is similar to that of radio waves. The source emits packages of spherical waves that are immediately affected by the numerous intersected surfaces that create reflections and surface waves (Fig. 3.10). The nonhomogeneity of the propagation environment also distorts the wavefronts. In consequence, the mathematical relations that describe the real propagation phenomenon are very complicated, and they introduce serious difficulties in sources and effect localization and measurement. This fact limits the usable domain of methods based on acoustical emission for large structures made of steel, where a specific incertitude coefficient can be tolerated.

Many types of treatment of the detected signal are available for the acoustic emission study; that is why at all times a general evaluation must be done first.

Counting of impulses is necessary in impulse type signal treatment. This method supposes an evaluation of the number of impulses that pass over a previously established limit value. In order to do this evaluation, the measuring chain contains a discrimination device for the impulse amplitude level, followed by an impulse counter (per total or per time unit). The simple count of impulses (Fig. 3.11c) can be improved by an evaluation of the impulse area (Fig. 3.11a), which also takes into
consideration the duration of the impulse, eventually by introducing a combination of limits (Fig. 3.11b).

The meaning in amplitude of the impulses is realized in cases when the acoustical emission manifests itself by signals of the continuum type. Calculation of the effective value (RMS) is significant because it is proportional to the power/energy of the signal. This method is encountered sometimes under the name of energetic analysis of the impulse.

It is useful to locate the source of the information provided concerning the source's and the wave trajectory's characteristics and modifications, localization of the primary faults, and the reduction of the times of re-putting into function. In order to locate the source, some controlled elastic waves are created from ultrasonic sources. The ultrasonic wavetrain is characterized by a factor of the simultaneous wave that depends on the frequency of the impulse succession, duration, and number of peaks that surpass a certain limit. In this way, breaking zones can be located with an anticipation in materials.

In order to locate a source, three transducers are used. The time difference between the moments when the signal arrives at two transducers determines a plain hyperbola, if the propagation speed in environment is known. The intersection of obtained hyperbolas from the pair of transducers (1;2), (1;3), (2;3) defines the correct position of the source.

3.3 RECOMMENDATIONS CONCERNING THE USE OF DIAGNOSIS METHODS FOR MACHINE TOOLS

The multitude of noise and vibration sources produced by the complex dynamic structure of machine tools provides serious problems for diagnosticians. However, it is expected that noise and vibrations, coming from functioning machines, are generated by the characteristics of the component mechanisms and subassemblies of the machine tool. At the same time, the working regime parameters and the characteristics of the processed materials have a great influence on these phenomena.

In order to apply vibroacoustic diagnosis to machine tools, the natural sources of noise and vibrations must be identified, and also the parameters that best correlate with the functioning state of the machine tool or its subassemblies and elements. It is indicated that the monitoring of the machine tool functioning state or its component elements may be realized using working techniques in the time domain.
Vibroacoustic Methods Package 97

establishment of the technical diagnostic, using the method of analysis in the frequency domain.

Very good results have been obtained using the Kurtosis method, which has the advantage of immediate application, without knowing the machine history. In the appendices to this book the use of this method of diagnosis of the functioning state for the majority of the components of feed kinematic chain physical models is illustrated.

Concerning the profoundness diagnosis, the best results are obtained by the method of spectrum comparison that, besides indication of nature and place of fault, can also estimate the remaining time until a machine fails because of damage.
4.1 INTRODUCTION TO MECHANICAL SYSTEMS ANALYSIS

The dynamic study of a mechanical system has as its goal the knowledge and, sometimes, the prediction of the dynamic behavior, in order to understand which way the modifications made to a system or to the disturbing sources affect the dynamic behavior of this system. Physical or mathematical models must be created in this respect, models that can approximate as well as possible the behavior of the real system.

The creation of a system model usually supposes the use of an adequate combination of theoretical and experimental methods whose succession is determined by the goals of the research and the characteristics of the system. Theoretical analysis of the system is carried out to determine the dynamic properties of the system and is based on equations that characterize the system, also known as "model construction equations." The theoretical analysis implies certain steps that must be followed:

1. Establishing some simplifying hypothesis for the system in order to reduce the analysis effort.
2. Establishing the sum equations for the masses, the energies, and/or the impulses that occur in the system

3. Establishing the phenomenological equations in the case of irreversible processes (i.e., heat propagation)

Generally, a system of ordinary differential and/or partial derivative equations is obtained, and these equations represent the theoretical model of the system of given structure and parameters. This model is frequently very complex and cannot be used as it is. Model simplification is necessary and can be accomplished by

- Linearization of partial derivative equations
- Approximation by ordinary differential equations of the partial derivative equations
- Reduction of the order of ordinary differential equations

The resulting theoretical model contains the functional link between the physical data of the system and its parameters. The theoretical model is recommended only if sufficient elements are known (elements that are connected to the laws that characterize the system's dynamic behavior), or if the theoretical model's behavior must be simulated. It must be stressed that theoretical analysis enables the researcher to establish equations that describe the dynamics of the modeled system even when the system is in the state of design, not available for experiments.

Experimental analysis of a system, a method also known as "identification of the system," proposes to determine the mathematical model on the basis of measurements of variables that characterize its evolution in a certain regime. In this situation, we always start from knowledge about the system gathered through previous theoretical or other analysis. Then, the input and output of the system are measured and evaluated using an adequate method for identification, which is the link between the measured variables. It should be noted that the input magnitudes can be signaled by the normal function of the system or can be artificially introduced signals. The experimental model contains numerical values as parameters whose functional connection with the physical data remains unknown. This model, which generally describes the momentary dynamic behavior of the system, is obtained with minimal effort, and can be used to lead or predict certain variables.

Theoretical analysis can use the results of the experimental analysis to verify the precision of the theoretical model or to determine the parameters of the model that cannot be determined otherwise.
experimental analysis can use the results of the theoretical analysis especially for the model structure. The models that result from the two types of analysis can be compared. Reexecuting certain steps of the analysis can eliminate the eventual nonconcordances. In conclusion, it is evident that the correct model of a system is necessary to perform an adequate combination of theoretical and experimental methods. One of the possible combinations of the two types of analysis is presented in Figure 4.1. The analysis steps and their succession are influenced during the procedure.

4.2 THE EXPERIMENTAL STAND

The kinematic feed chain ensures the cyclical positioning on one of the generating trajectories ($G, D$) of the generator element ($D, E$ or $G, E$). The classical structure of the kinematic feed chains is presented in Figure 4.2, where the notations represent the following.

- OP represents the start/stop of machine movement.
- I is the reverse for the feed movement direction.
- $K_s$ is the mechanism of periodic transmission of the movement (if the advance is intermittent).
- $M_R$ is the mechanism of feed magnitude adjustment.
- $S$ is the safety mechanism (protection to overloads).
- $M_T$ is the mechanism that transforms the rotation movement into translation movement.

In the most recently proposed structures of the feed kinematic chains some of the above-presented mechanisms have disappeared, their roles being taken by the driving element which is usually a continuous current motor with a large domain for rpm adjustment.

The problem of establishing the technical diagnostic in the kinematic feed chains of modern machine tools necessitated building an adequate testing stand, one that contained all the necessary elements. Figure 4.3 presents the structural kinematic schema of the studied kinematic feed chain.

The driving element is a direct current motor, type SMUC-35, having the characteristics:

- The actual moment, $M_n = 35 \text{N m}$
- The nominal intensity of current, $I_n = 2.8 \text{A}$
- The couple with the ampere coefficient, $K_T = 13 \text{Nm/A}$
- The inertial moment, $j = 0.065 \text{kgm}^2$
FIGURE 4.2

Classical structure of a kinematic feed chain.

The leading screw (which has a step of 10 mm and a double nut with balls ($D = 60\, \text{mm}$, $d = 30\, \text{mm}$, $p = 10\, \text{mm}$, $z = 103$ balls, $D_w = 6\, \text{mm}$, and $k_{Rb} = 1.2 \times 10^4 \, \text{daN/mm}$) to compensate the axial play) is fitted in two identical bearing cases that contain a pair of axial bearings 51307-P5 and one pair of radial bearings 6207-P6.

The slide movement along the body's guidings is ensured by the cam followers with rolls type GRT 3 ($L_w = 14\, \text{mm}$, $C_o = 10200 \, \text{daN}$, $f = 1.25 \, \mu\text{m}$ at $1000 \, \text{daN}$, $k_{cr} = 80 \times 10^3 \, \text{daN/mm}$), mounted in "O".

The material used for slide and body is cast iron (Fmn having $E = 1.6 \times 10^4 \, \text{daN/mm}$, $G = 4.5 \times 10^3 \, \text{daN/mm}$, $\gamma = 7.3 \, \text{kg/dm}^3$, $\alpha = 18 \times 10^{-6}$ grad$^{-1}$) and the leading screw is made from alloyed steel (40Cr10 having: $E = 2.1 \times 10^4 \, \text{daN/mm}$, $G = 8.1 \times 10^3 \, \text{daN/mm}$, $\gamma = 8.2 \, \text{kg/dm}^3$, $\alpha = 0.16 \times 10^{-6}$ grad$^{-1}$).

The block schema from Figure 4.4 highlights the main component elements of the mechanic stand.
4.3 THEORETICAL ANALYSIS OF THE KINEMATIC FEED CHAIN MECHANICAL SYSTEM

The numerical analysis method proposes to model the physical phenomena in equations and describes the behavior of the physical systems by equations that express laws of mass, impulse, and shape conservation.

Finite difference methods consist of replacing the differentials from the equations of the model with very small finite differences, with the restriction of the validity only in certain points of the analyzed domain (the points of the discretized network of the model). Because of this method the discretized network will have a rectangular shape, thus for models with curved surfaces the method will be very difficult to apply.

Finite element methods (FEM) are based on local approximation, and on portions or subdomains that also consider the reports of relative dependence between the entire domain and the studied subdomain. The behavior of such a cut-up finite element is formulated by the equation:

\[ k \{d\} = \{q\} \quad (4.1) \]

where \( k \) is the stiffness matrix of the finite element, \( \{d\} \) is the vector of displacements from nodal points, and \( \{q\} \) is the vector of the generalized forces that act on the elements by nodes.
The boundary element method (BEM) supposes that displacements produced by an elastic concentrate force applied at the origin (node) are known. This method is based on the equality between the mechanical work which results from the motion of a force system on the movement coordinates of a second force system and the mechanical work produced by the second system on the movements of the first. By using the relations between forces and displacements the tensor components that actually represent the problem's solution can be determined.

Among these three methods, the finite element method is most preferred because of the following qualities: large domain of applications, liberty to choose the type of discretization and to use simultaneously many more types of finite elements, discretization with variable geometry, and the possibility of performing calculus on substructures. The finite element method represents the "brick" of the discretized physical system, the shape, the type, and its equations being the discretization principles result.

4.3.1 The Method and Images 3D Algorithm

The FEM operates with three types of finite elements that are justified by geometry and number of independent coordinates:

- Unidimensional elements (bar type), that have as ends even the nodes of the discretization network.
- Bidimensional elements (plate type). The IMAGES 3D program includes two elements of this type: membrane (bending stressed only) and plate, which also has the thickness of the plate defined.
- Tridimensional elements (prism, tetrahedral, and hexahedral type). The increase in number of elements leads generally to the increase of the precision degree. However, over a certain value, the error does not decrease, no matter to what degree the number of the discretization elements would increase.

Interpolation functions are used to write the relations concerning the deformation and stress state of the finite element. The most used interpolation function is the Hermite function. For each type of finite element the rigidity matrix is determined (on the basis of the principle of virtual mechanical work), in the local axis system. This rigidity matrix is used to express finite element behavior by the known equation:

\[
\mathbf{k} \cdot \mathbf{u} = \mathbf{r}
\]
The assembling operation of the rigidity matrices and of the nodal force vectors determines the system of equations that characterize the structure: \[ K \textbf{U} = \textbf{R}, \] where the relation's terms represent the result of the aligning of the rigidity matrix and displacement and forces from the local system to the global axis system.

In order to ensure the convergence of solutions to the most exact solution, certain conditions must be followed. The displacement models should be continuous inside the finite element. This condition is accomplished by the use of Gauss polynomial interpolation, which represents continuous functions. The displacements of the finite element should be compatible with the other ones. The displacement compatibility is satisfied only if the displacements of the points from every edge depend only on the displacements of the nodes that delimit the respective edge.

The displacement models should consider the displacements of the entire discretized system and also the constant stress state of elements. This supposes avoidance of a very fine discretization because when constructing the rigidity matrix, the elements of the main diagonal will be of negligible value (zero), which leads to a null determinant and thus to a wrong value of the inverse of this matrix.

4.3.2 Discretization of the Physical Model

The theoretical working model was obtained applying the similitude theory for the physical model presented. The reduction scale for the length was chosen as \( \lambda = 2 \) and the other scales have resulted: \( \lambda_l = \lambda \phi = \lambda \delta = 2 \).

\[ \lambda E = \lambda G = \lambda \sigma = \lambda \mu = 1 \quad (4.2) \]

\[ \lambda F = \lambda^2 = 6 \frac{25}{25} \]

In other words: using the same material, the linear dimensions of the system are multiplied by \( \lambda \), the forces by \( \lambda^2 \), and the elastic constants are multiplied by \( \lambda \) for translation and by \( \lambda^3 \) for rotation, then the amplitudes and the frequencies are multiplied by \( \lambda \), and the efforts remain unchanged.

The following discretization of structure was obtained (Fig. 4.5) based on the principles presented in the previous paragraph. The body
FIGURE 4.5 Structure discretization.

was made with a network of 613 points, the base finite element being the plate (membrane plates bending) under loads of compression and/or bending. The discretization is finer in the bearing zone to better estimate the maximum stress points of the structure.

The body guidings are also plate elements type, but they do not have a median longitudinal point that represents the contact point with the roll cam follower. This point has been connected to the extreme points of the finite element by springs with an increased rigidity compared to the other elements ($k = 10^7$ daN/mm). In this manner, the guiding-rollers contact is better approximated. Finally, for the longitudinal body and its guidings, 463 plates with a thickness between 20 and 40 mm have resulted.

The longitudinal slide (the table) was discretized using a step of 15 mm and 120 elements of plate type have resulted. The table's rolling guidings had been "replaced" by spring type elements having the same rigidity as the elements that define the link between the body and the
guiding plates. The leading screw was discretized in only 23 points because of its homogeneity and its physicomechanical characteristics which are constant in all directions; a bar network that can be loaded to tensile and compression stresses results.

A tubular shaped nut was made using tridimensional finite elements (solids), which were connected to the table slide by means of plates made from the same material.

A special problem was the connection between the body and ground, which was made by springs connected to the ground, having in count the damping and elastic characteristics of the base material.

4.3.3 Statistical Analysis of Physical Model

Static loads were applied in order to determine the deformation mode of the mechanical system, a system designed as an assembly of elements that introduce deformations in a certain proportion for each element, and also to determine the zones of the structure having maximum deformations. In order to find the deformation mode, the load of the model's slide during the cutting process was simulated. The load was made with a static force that cumulated the weight of the semiproduct and the maximum value of the cutting force. The force was applied punctually on the slide decomposed on the following three directions: 1000 daN on OX; 2000 daN on OY; and 3000 daN on OZ. The total deformations of the constitutive elements were supervised on the above-mentioned three directions.

Studying the displacements on the OX axis, it has been observed that the most considerable yield ($\Delta_{xmax}=1.14 \mu m$) is produced in the screw-nut mechanism, as expected. Figure 4.6 presents a cut-through model to visualize the deformations to this mechanism. Less important deformations have resulted on the OY direction until $\Delta_{ymax}=-0.447 \mu m$ value (compression) in the guidings zone.

Hook's law can be applied to the entire model because the loading does not surpass the elastic domain. This law introduces the proportionality relation between the unitary efforts and the deformations. As a result, the tensor of unitary efforts may be calculated and represented using the same algorithm.

As previously mentioned, the deformation state was maximum at the screw-nut mechanism, so the nut stresses have been detailed as the element with the most important yield. Considering the global stress state it can be noticed that a maximum value $\sigma_{max}=4.51 10^{-2}$ daN/mm$^2$ is...
The analysis continued by decomposing the tensor on the main directions ($\sigma_{11}$, $\sigma_{22}$, $\sigma_{33}$ components). $\sigma_{11}$, $\sigma_{22}$ have close values, but $\sigma_{33}$ surpasses them by 150%, being by far most important (the maximum tensile strength: $\sigma_{33,\text{max}} = 3.86 \times 10^{-2}$ daN/mm$^2$).

Figure 4.7 presents the global stress state of the physical model. It is evident that the maximum stresses are in the zone of the movement transform mechanism and the guidings zone; the body appears nonstressed but the table slide is stressed in the rolling guidings zone and at corners.

4.3.4 Modal Analysis of Physical Model

The method of modal analysis follows to determine certain dynamic characteristics by the estimation of the weights matrix, rigidity matrix, and damping matrix. As a result of this analysis the natural pulsations of the structure, the existent damping in the system, and the type of natural vibration modes can be deduced. The first three natural vibration modes and their corresponding natural frequencies were highlighted for the analyzed physical model using the IMAGES 3D program.

The first natural vibration mode (Fig. 4.8) affects the mechanism of movement transformation type screw-nut with balls and corresponds to a natural frequency of 259.6 Hz. High deformation of the free end...
of the nut is observed during the other subassemblies of the model (longitudinal slide, bearings, and body) to remain practically immobile.

The second natural vibration mode appears at 380 Hz frequency (Fig. 4.9), where a sensible deformation of the screw-nut mechanism is recorded, a slightly longitudinal and transversal deformation of guidings occurs, and a little transversal deformation of the body also occurs.

The third natural vibration mode (Fig. 4.10) occurs at 491 Hz and leaves the screw-nut mechanism almost undeformed. However, a powerful deformation of the guidings in a vertical direction and a slight deformation of the table slide are recorded.

The following conclusions can be formulated as a result of theoretical analysis of the mechanical system of the kinematic feed chain.

The most important yield from the kinematic feed chain belongs to the movement transforming mechanism.

The nut represents the most stressed element from the point of view of tension intensity.

The bearings rigidity influences the static and modal behavior of the leading screw.
FIGURE 4.10  
Third natural vibration mode.  
The displacements of the slide–guidings–transforming mechanism ensemble are of major importance on transversal direction and less important on longitudinal direction.

The theoretical model constructed approximates with very good results the real model of the feed kinematic chain of a milling and reaming machine AF 180.

The FEM is susceptible to any factors that contribute to improvement of static and modal behavior of the analyzed structure.

The analysis led to the identification of the elements with maximum stresses in the structure, in order to monitor them during operation.

4.4 EXPERIMENTAL ANALYSIS OF KINEMATIC FEED CHAIN MECHANICAL SYSTEM

The vibration of a mechanical system is caused by external loadings or imposed movements that are variable in time, and are generally called
The response is conditioned both by the excitation parameters and the mechanical characteristics of the system. Solving the vibration problems consists of establishing relations among excitation, response, and mechanical characteristics of the system.

The experimental analysis (identification) of the mechanical system proposes a series of functions of excitation and corresponding functions of response, to facilitate a mathematical description or an analytical model of the system. The relations between excitation and response are experimentally determined; the most frequently used data are the response curves in the frequency of the system obtained by excitation with test signals. On the basis of these curves, the identification of natural frequencies and vibration modes is made, and also of the specific dynamic properties. It is important that during experimentation the influence of other disturbing sources is reduced to a minimum. In addition, the equipment used for structure excitation and response measurement should not modify the utilized mechanical system parameters.

The properties determined under these conditions sometimes differ from those obtained during normal functioning, especially in nonlinear structure cases. Choosing correct types and levels of excitation leads to satisfying results. The dynamic characteristics of a linear system with a single input $x(t)$ and a single output $y(t)$, can be described in the time domain by the proportion function $h(t)$, and in the frequency domain by the response in frequency function $H(i\omega)$ that constitute a pair of Fourier transforms:

$$H(i\omega) = \int_{-\infty}^{\infty} h(t) e^{-i\omega t} dt$$

In the case of determinist excitation, the response is given by the integral of convolution:

$$y(t) = \int_{0}^{t} h(t') x(t - t') dt' = x(t) * h(t)$$

In this case the proportion function $h(t)$ represents the response to an excitation such as unity impulse (Dirac) $x(t) = \delta(t)$. The following relation gives the function response in frequency:

$$H(i\omega) = \frac{Y(i\omega)}{X(i\omega)}$$
where $X$ and $Y$ are the Fourier transforms of excitation and response, which can be written as

$$X(i\omega) = \int_{-\infty}^{\infty} x(t) e^{-i\omega t} dt$$

$$Y(i\omega) = \int_{-\infty}^{\infty} y(t) e^{-i\omega t} dt$$

(4.6)

the inferior limit being zero or the real systems.

If the structure excitation has been made with a force of the harmonic type, the $x(t)$ and $y(t)$ functions will have the expression:

$$x(t) = x v \cos \omega t \quad y(t) = y v \cos (\omega t + \phi)$$

(4.7)

which makes the response in the frequency function become

$$H(i\omega) = y v x v \cos \phi$$

(4.8)

From the above relation a very important conclusion results: the module of response in the frequency function ($|H(i\omega)|$) can be obtained from the amplitude–pulsation characteristic ($y v / x v - \omega$); and $\phi$ is obtained from the phase-pulsation characteristic ($\phi - \omega$). These diagrams can be determined experimentally using the sinusoidal excitation of constant amplitude and variable frequency. The two characteristics can be drawn either dot by dot, making measurements at discrete frequencies in the stationary regime, or continuum, using a frequency scavenging slow enough to permit the establishment of the regime response for each frequency. Using a live frequency analyzer simplifies the gathering of responses, a single excitation signal being sufficient. The structure of frequency analyzers includes an analyzer for functions compartment at whose entrance the signals $x(t) = x v \sin \omega t$, $y(t) = y v \sin (\omega t + \phi)$ are applied and a reference signal $z(t) = z v \cos \omega t$.

This compartment performs the following multiplication,

$$x(t) y(t) = x v y v \cos \phi - x v y v \cos (2 \omega t + \phi)$$

$$z(t) y(t) = x v y v \sin \phi + x v y v \sin (2 \omega t + \phi)$$

(4.9)

where the constant terms represent the real and imaginary parts of the response in frequency function. Elimination of variable terms is made.
Feed Kinematic Chain Mechanical System 115

with down-pass filters, making the mean of the products on an integer number of cycles of excitation.

Processing the signals that correspond to the two components, the analyzer displays the polar (Nyquist) diagram of the response in frequency for the mechanical system (Fig. 4.11). Graphical analysis of these diagrams, as proposed by Kennedy and Pancu [82], remains the most exact method for determination of the dynamic parameters and of the type of natural vibration modes of a complex structure. To do this analysis, each buckle of the diagram is approximated with a circle and calculus relations established for systems with a single degree of freedom are used. Usually the work is done with the hypothesis of a proportional damping and, it is considered that, in the vicinity of no matter what natural frequency, the contribution of the nonresonator modes is either negligible, or constant (independent of the excitatory pulsation).

Localization of the natural pulsation is made, in this case, using the criterion of extreme value of the imaginary component of the diagram. Thus, the $M$ point is found (the extreme point on the imaginary axis), and, corresponding to it, the $\omega_r$ frequency.

To determine the damping, the $BC$ diameter is drawn perpendicular on $O'M$; this diameter intersects the approximation circle in $\text{FIGURE 4.11}$ Polar (Nyquist) diagram.
The approximation factor is calculated with the equations:

\[ g_r = \frac{\omega_r''}{\omega_r'} \]

The modal masses are calculated with the equation:

\[ m_r = \frac{1}{\omega_r^2} g_r M \]

The experimental analysis of the physical model of the kinematic feed chain followed the stages highlighted previously. The experimental installation used (Fig. 4.12) contained the impact hammer B\&K 8202 and the real-time frequency analyzer B\&K 2034.
tion was made striking the longitudinal table in the vertical direction, and the structure response was captured from the body by a B&K 4391 accelerometer. The selected frequency domain was between 0 and 800 Hz, linear, considering the results of the theoretical analysis. Figure 4.13 presents graphics of the magnitude and phase of the response in frequency; it must be noticed that the maximum values are located at 265, 374, and 474 Hz in the magnitude/frequency graphic.
At the next stage, the signal was processed in order to obtain the real and imaginary components of the frequency response (Fig. 4.14). Nyquist diagram was then drawn using these components (Fig. 4.15). The results indicate a stable structure from the dynamical point of view, as expected from the theoretical analysis made by the finite element method. The differences between the calculated natural pulsations using the FEM and those experimentally obtained are minimal, as Table 4.1 shows.
TABLE 4.1 Differences Between Calculated Natural Pulsations Using FEA and Those Experimentally Obtained

| Calculated natural frequency, $f_c$ [Hz] | Measured natural frequency, $f_m$ [Hz] | Deviation $\epsilon = \left| \frac{f_m - f_c}{f_m} \right| \times 100$ [%] |
|----------------------------------------|---------------------------------------|----------------------------------------------------------|
| 259.6                                  | 265                                   | 2.04                                                     |
| 380                                    | 374                                   | 1.60                                                     |
| 491                                    | 474                                   | 3.59                                                     |

This leads to the conclusion that the analysis methods implied by this research have been correctly applied, and the results obtained are significant.

4.5 CONCLUSIONS AND IMPLICATIONS OF DIAGNOSTIC ANALYSIS IN FUTURE RESEARCH

Theoretical and experimental analysis of the physical model of the kinematic feed chain has yielded the possibilities of identifying the points of maximum stress in the structure of the kinematic chain, and identifying the natural frequencies of the structure. In addition, reliable stability of the physical model has been confirmed, which makes this an apt model for the study of problems related to the technical diagnosis of elements from its structure.

By analyzing the deformations of the physical model, it has been highlighted that the most important yield occurs where the zone of the mechanism is predisposed to failures, namely, the transforming mechanism screw-nut with balls and the rolling guidings of the longitudinal slide. These yields can influence the functioning of the mechanism and speed up the occurrence of the damaging processes that contribute to the mechanism's failure. The deformation values are closer to those of the preadjusted mechanical plays in these mechanisms that can lead to a fault functioning.

Knowing the natural frequencies of the structure enables us to compare them with the characteristic frequencies (of operation) of all the mechanisms in the studied kinematic chain's structure. From the technical literature and also from the theoretical and experimental research for the determination of the characteristic frequencies of some mechanisms with bearings, ball screws, and roller cam followers, it has been determined that...
been noticed that these work frequencies are in a neighboring domain with that of the investigated natural frequencies, but usually inferior. Theoretically there is a possibility of resonance occurrence with the natural frequencies because of the important increase in the power spectrum (e.g., for an element with mechanical fault) that occurs not only at the characteristic frequencies, but also superior harmonics of these frequencies. This phenomenon leads to signals of false mechanical faults and unreasonable stoppages of machines, and happens especially in online diagnosis systems having low resolution.

The results of this diagnostic analysis have oriented, from these points of view, future theoretical and applicative research concerning technical diagnostics for some elements of the general structure of kinematic feed chains.
Designing and Manufacturing a Virtual Instrument Vibroacoustic Method Diagnostic Package

5.1 VIRTUAL INSTRUMENTATION: LabVIEW GRAPHICAL PROGRAMMING ENVIRONMENT

The virtual instrumentation for vibroacoustic diagnosis, which is elaborated and presented in this chapter, uses the LabVIEW (Laboratory Virtual Instrument Engineering Workbench) program, version 2.5, made by National Instruments. The software uses a graphical programming language, G, to create programs such as block diagrams, without sacrificing any of the power or performance of a traditional programming language. LabVIEW uses terminology, symbols, and ideas that are familiar to engineers and researchers, and it is purposely based on graphical symbols, rather than a textual language, for describing programming activities. LabVIEW combines the technology of the most recent operating systems with specialized programming techniques (OOPT, object-oriented programming techniques) to obtain a simple and flexible operating environment.

The LabVIEW software objective is structured on several main levels.
1. The acquisition module provides the possibility of programming and controlling the hardware connected to the measurement/control system. This possibility is realized using a device driver software specific to each connected apparatus. At the present time over 450 of such kinds of drivers exist, made by drivers for instruments from over 45 different producers. It is important to note that all these drivers have a common programming interface (API, application programming interface) that allows the applied programs to be independent of the operating or calculus system. LabVIEW is based on the NI-DAQ (National Instruments Data Acquisition) driver, ensuring the data management, buffer memories, and other resources specific to each plate. The most used acquisition boards provided with this driver are:

- Multifunctional: AT-MIO-16D, AT-MIO-64F-5, PC-LPM-16, Lab-PC+
- With rapid analogous input: EISA-A2000
- For signal dynamical acquisition: AT-A2150
- With timing input/output (counting/time basis): PC-TIO-10

2. The processing modulus converts the primary acquisition data into significant results. LabVIEW has libraries of functions and routines for a multitude of programming requests and also a series of specific applications. LabVIEW also includes the tools necessary for building and/or developing applications developed by the user, visualization of data flow, and fixing possible programming errors. LabVIEW software offers a complete and powerful analysis ensemble for numerical data treatment, an ensemble that contains:

- Statistical process: histograms, calculus of mean and square mean, distribution calculus, error functions, rational and polynomial interpolations, and so on
- Linear and polynomial interpolations in 1D or 2D
- Linear, exponential, and polynomial regressions
- Linear algebra: vector and matrix normalization, matrix multiplication and inversions, determinant calculus, solving linear equations
- Signal generation: impulse, ramp, triangle, sinus, rectangular, aleatory, Gauss distribution, white noise
- Processing in the time domain; integration and differentials, decimation, cut off, limit detection, impulse analysis
Virtual Instrument Vibroacoustic Package 125

Processing in the frequency domain: rapid Fourier, Hartley, and Hilbert transforms, spectrogram, magnitude and power spectrum, inter- and autocorrelation, convolution and de-convolution, phase calculation

Windows: Hanning, Hamming, the triangular, Blackmann, Kaiser–Bessel, cosinus, exponential, and others

IIR filters (infinite impulse response): Butterworth, Cebisev, Bessel for pass-up, pass-down, and cross-band

FIR filters (finite impulse response): Parks–McClellan, window, pass-up, pass-down, cross-band, and user-defined filters

Nonlinear filters: environment

3. The presentation modulus is of an interactive type, the computer display having the function of a front panel, similar to traditional instruments. Using the mouse's help, all the buttons, switches, inverters, and potentiometer from the front panel can be operated. In addition a series of options exists for stocking data on the hard disk, for transferring data to a network, or obtaining hard copies on plotter or printer.

The LabVIEW programming environment can be used both by inexperienced users (because of its graphical simplicity) and by specialists (because of its flexibility and the possibility of developing sophisticated applications).

5.2 STRUCTURE OF LabVIEW VIRTUAL INSTRUMENT

The programs elaborated using the LabVIEW programming environment are called VIs—virtual instruments—because of their similarity to traditional measuring and control instruments, not only in appearance, but also in the operating mode. In reality, they are analogous to the functions from conventional programming languages.

Virtual instruments work with graphic blocks that are sequences of the program presented in a graphical shape adequate for their purpose. A graphical block accepts one or more types of input data. These data are processed and then the results are sent as output usable in other sets of graphical blocks. In this manner the continuity of signal transmission is ensured. It must be noted that the route of each type of data is presented in a certain color and line thickness. The virtual instrument can be in edit mode, when the instrument is modified with specific tools, or run mode, when the instrument is used for the purpose for which it was created.
Chapter 5

Any virtual instrument has three components: front panel, block diagram, and the graphical symbol with connectors. The front panel represents the graphical user interface. This panel simulates the front view of a traditional instrument and can contain buttons, switches, indicators, and displays for graphical representations. In addition, it must specify the inputs and outputs of the virtual instrument using adequate indicators and control elements. The panel is built using the Controls menu, where diverse options of indicators and control elements are preconfigured. Using the operating tool (the hand with the straight forefinger), which is operated by mouse, we can intervene on each element from the front panel (on-off, adjustments, rescaling). Using the positioning tool (the arrow) we can select, reposition, and resize the elements.

The block diagram represents the graphical solution of programming problems. A block diagram, that is, the equivalent of the working algorithm (of the program) for the virtual instrument, accompanies each front panel, and therefore the block diagram can be considered as a code source in the graphical programming language G. The block diagram is made by symbols framed in buckles (e.g., FOR, WHILE) and/or case structure. The components are linked in between by wires or nodes in such a way that they follow the data flow in the diagram from input to output. The block diagram is built using the Functions menu, to place the components (arithmetical and logical functions, FOR cycles, WHILE buckles, TRUE/FALSE cases), and also using the link tool to make the tracts between components. It must be noted that the LabVIEW application automatically places on the block diagram the terminals associated with the indicators and control elements from the front panel.

The Icon/Connector is the simplified graphical representation of a virtual instrument; this representation indicates only the instrument destination and the type and placement of its inputs and outputs. Concentrating a virtual instrument in such an Icon/Connector, it can be used as a subinstrument in any other block diagram connected to the other components of the operating schema. When they are defined, the icons and/or connectors are displayed in an alternative manner in the upper-right corner of the virtual instrument from the working window, in order to find the link mode between inputs and outputs. These connections are analogues to the parameters of a subroutine or of a function, and correspond to the indicators and control elements from the front panel.

LabVIEW is a modular and hierarchic programming environment. Modular because any block diagram can be concentrated in an icon and...
thus used as a subvirtual instrument (subVI), and hierarchic because any subinstrument may be used in the block diagram of an instrument of superior level. The number of virtual subinstruments from a hierarchy is practically unlimited, both on horizontal and vertical. These two characteristics of LabVIEW software facilitate creation, understanding, and maintenance of virtual instruments. A complex application may be divided into a series of simple tasks and a virtual instrument can be built to solve each of these tasks. Finally these instruments are included in a virtual instrument of superior level, which solves the complex application. Each instrument can be run individually, separated from the rest of the application, so the eventual malfunctioning can be rapidly located. More than that, subinstruments of inferior level can accomplish tasks that are common to other applications, so they can be reused.

5.3 VIRTUAL INSTRUMENTATION FOR SURFACE DIAGNOSIS

As presented above, surface diagnosis methods are useful for supervising the operating state of machine tools; they signal the overpassing of some signal levels which are considered normal, without providing other information concerning the cause or the nature of the abnormality and without evaluating the time remaining until the final stop.

Three virtual instruments have been elaborated and tested for surface diagnosis:

- FACVARF, based on evaluation of the peak factor \( F_v \)
- INDDIAG, based on evaluation of the diagnostic index \( K(t) \)
- INDKURT, based on evaluation of the captured vibrational signal

The theoretical bases of diagnosis methods utilized were presented in Chapter 3 of this work, and are not redescribed here.

Being designated for "offline" type surface diagnosis, these virtual instruments operate in a working space different from the space where captioning of signals is done. Thus grouping of the acquisition files has been in view, depending on measuring points; that is why temporary positioning of each signal acquisition has also been in view, so that the file format saves both the signal and the moment of acquisition.

The three instruments can be used separately or simultaneously for the analysis of the same signal; they do not exclude each other—rather they are complementary. Following the idea of complementarity,
vibration signal reading zone works as a function of time and as a function of finding out the characteristic values common to the three virtual instruments (Fig. 5.1). Thus, in a FOR cycle, on the basis of the path built by using the graphical block 2, the hard disk is read, and block 1 (List Directory) returns two matrices that specify the names of acquisition directories and folders met. Graphical block 3 (File/Directory Info) provides information concerning the directory or the folder (such as size and the date of creation or last modification); the date in absolute time is converted into a calendar date through block 4 (Get Date/Time String); this is used to order the function of time for different acquisitions.

The graphical block 10 (Citvib.vi) is a specially built virtual instrument, here as a sub-VI, necessary for acquisitions reading as functions of time; it also has the possibility of amplifying the signal by a

FIGURE 5.1
Vibration signal reading zone is common for FACVARF, INDDIAG, and INDKURT virtual instruments.
factor introduced by the operator. Figure 5.2a presents the block dia-
gram of this virtual instrument; the icons and connectors are shown
in Fig. 5.2b.

In the inferior zone of cycle FOR’s windows the arrangement of the
work matrices is accomplished with the help of graphical blocks 6 (Array
Max & Min) and 7 (Max & Min). The matrices are then assembled
in a single cluster, near the information referring to date in graphical
block 8 (Bundle). The continuation of processing the acquisitioned signal
is different for each of the three aforementioned virtual instruments,
depending on the diagnostic method used.

The FACVARF.VI instrument (block diagram presented in Fig. 5.3)
takes the data from the sorting block 11 (Sort 1D Arry), and displays on
the front panel (Fig. 5.4) the graphic of two recordings of the processed
signal, in the time domain, as follows: the recording considered as refer-
cence (having the machine in a perfect state of operation) and the current
recording. For each of the two recordings the maximum value (RMS) is
indicated; the value of the peak factor was calculated previously and
thus, a first evaluation of the functioning state of the supervised ele-
ment became possible. Data processing is possible by disassembling the
information in graphical block 10 (Unbundled) and then connecting it to
the blocks that make the link with the front panel (DBL). The ensemble
of statistical processing of the signal is integrated in a WHILE buckle.
FIGURE 5.4
Front panel of FACVARF.VI instrument.
A third graphic from the front panel of the instrument follows the evolution in time of the peak factor. A point is marked on the tendency graph for each new acquisition, illustrating a short history of the operating state, as this state is captured in the respective measuring point. The graphic is scalable depending on the measuring unit.

The INDIAG.VI instrument (block diagram in Fig. 5.5) performs a processing series similar to that presented previously, but this time using the algorithm specific to the diagnosis index. The front panel (Fig. 5.6) also contains the reference recording and the current recording, near the graphic of the evolution of diagnosis index. Both instruments present a short legend on the front panel next to the graphic of evolution of diagnosis index to make the reference and the current recording easier.

The INDKURT.VI instrument is based on the diagnosis algorithm specific to the Kurtosis method. It is more complex compared to the other virtual instruments. In the block diagram (Fig. 5.7) the instrument contains a sub-VI (Kurt$^{β_2}$.VI), integrated in a WHILE buckle, for the calculus of the fourth-order statistic moment ($β_2$) and the graphical representation of the probability distribution density of the captured signal.

The symbol and connectors of the graphical block Kurt$^{β_2}$.VI are defined according to Fig. 5.8a. The calculus relation of the statistical moment is shown in Section 3.2.2.3, and for its instrumentation a few virtual instruments from the LabVIEW software library have been used (Fig. 5.8b). Those virtual instruments are the following: Standard Deviation.VI, to calculate the arithmetic mean of the signal and standard deviation; Gaussian White Noise.VI to test the instrument; Numeric Integration.VI, to integrate the entire domain; and Histogram.VI, to calculate the probability density of the same signal. Figure 5.9 presents the block diagram of the Kurt$^{β_2}$.VI virtual instrument.

The INDIKURT.VI virtual instrument displays (Fig. 5.10) a table of files on the front panel; those files have the available acquisitions on the stocking directory, listed in terms of the acquisition data. When a file is selected from this table certain data processing is performed:

- Representation of the captured signal, as a time function (left-up window)
- Calculus of the maximum and effective values for the peak factor and Kurtosis index
- Graphical representation of the probability density of the signal (left-down window)
Knowing the fact that a mechanism in good functioning state is the source of some stochastic vibrations that respect a normal (Gauss) distribution of amplitude (in this case the fourth-order statistic moment is placed in the range of value 3), an evident correlation can be made between the increase of the $\beta^2$ index value and the deviation of probability from the Gaussian shape, when a defect occurs and develops itself.

Taking into consideration the previous determinations, it has been noticed that the first instrument (which notes the abnormal state produced by the occurrence and development of a damage) is INDKURT; confirmation is done gradually by INDIAG and FACVARF.

5.4 VIRTUAL INSTRUMENTATION FOR PROFOUNDNESS DIAGNOSIS

A precision vibroacoustic diagnosis cannot be accomplished using only statistical parameters associated with signal processing in the time domain. The most rapid solution to avoid this deadlock is to pass the signal...
Virtual Instrument Vibroacoustic Package 139

in a frequency range using a Fourier transform. Interpretation of the frequency spectrum produces, as seen in previous chapters, important data about the causes and the nature of the damage.

A first virtual instrument created for profoundness diagnosis, named MECOSPEC, has at its base the spectrum comparison method, and it has certain advantages:

- The diagnostic method is included within the category of those which ensure from the beginning an increased precision of defect identification.
- Identification of frequencies characteristic at defect is made automatically, excluding the subjective factor.
- It is possible to estimate the reserve time interval until the machine comes to a stop because of a defect.
- Acquisition intervals can be programmed with a fixed or variable step.
- A diagnosis specific database can be created.
- Although sophisticated, the method is simple to use.

Because of the complexity of virtual apparatus created to apply this method, the data processing has been organized on working blocks with the vibration signal.

The "acquisition and calculus of power" block, whose block diagram (partial) is presented in Figure 5.11, makes the link between the AT-MIO-16F acquisition plate and computer.

Captured signals using the Ach3p.VI virtual instrument are called and processed by another virtual instrument (Files.VI) especially created to manage the data files, whose front panel (Fig. 5.12) is made like a record of the measuring points. The virtual instrument associates a series of characteristics with each measuring point of the machine; those characteristics are useful for storing captured data such as point index, number of averages and averaging control, sensibility of acquisition transducer, and spectrum type (acceleration, speed, or displacement), as can be seen in the block diagram (Fig. 5.13). This supervising record must be completed by the user (operator). The signals are then passed through a Hanning window (Hann 2\textsuperscript{17}.VI) to avoid a cutting-up effect when the signal passes from the time domain to the frequency domain, and the power spectrum is obtained using the rapid Fourier transform (FFT).

The front panel of this first signal processing block (Fig. 5.14) contains a graphical representation in the time domain of the captured vibration signals.
Virtual Instrument Vibroacoustic Package 145

The signal, and also contains the power spectrum graphic of the same signal, on an adjusting domain between 10 Hz and 100 kHz. In order to make possible the reading of values from the two graphics, CO pointers can be used to scavenge the graphics (using the four buttons disposed as a rhombus). The abscissa and the ordinate of the point indicated by the pointer are numerically displayed in the foot of graph. The right column groups the elements for adjusting the represented parameters influencing the block diagram.

The block “Comparison of power spectra” is presented as a block diagram in Figure 5.15. Comparison of spectra has as its starting point the assignment of the reference spectrum obtained with a machine in a perfect operating state; all of the spectra obtained from the signals captured previously are compared with this power spectrum. In order to avoid the false alarms caused by possible spectrum slipping (e.g., at small variations of working rpm), the reference spectrum is boarded in a virtual subinstrument (Bord 3p.VI), whose block diagram is presented in Figure 5.16. The boarding width can be manually adjusted from the block’s front panel. Transformation of the reference spectrum, after boarding, in the warning and alarming patterns, respectively, is made by translating the reference spectrum to adjustable levels using the buttons of the front panel. The 2 levels are recommended for the warning pattern and the 10 levels for the alarm pattern.

The front panel (Fig. 5.17) “Comparison of power spectra” block contains two graphical representations as well: upwards, the currently captured spectrum superposed on the boarded reference spectrum; downwards, the difference derived as a result of comparison between the two spectra. Using the adjusting elements from the right column, the boarding width, warning level, and alarm level can be varied.

For the profoundness diagnosis, as presented in Chapter 3, a method with excellent results in identification of defects of mechanisms with rolling elements is the evolution method. A virtual apparatus that simulates the application of this method is presented in the following paragraphs.

Figure 5.18 presents a FOR buckle as a block diagram where two sinusoidal signals are composed and modulated. After the modulation an exponential damping is applied to the resulting signal. A pulse signal is obtained whose amplitude and frequency are adjustable from the front panel’s buttons (Fig. 5.19) and which simulates the excitation signal introduced by the occurrence of a defect (running of ball or roller over irregularities/pinches occurring on one of the running tracks).
impulses are identical and evenly distanced at period $T$. The spectrum of this series of impacts would be a spectral line that includes all of the harmonics of the repetition frequency $1/T$. These harmonics have the largest amplitudes in the vicinity of the resonance frequency and their diagnosing by simple evaluation of spectra is difficult.

In the next step, the critical zone, which contains the structural resonance that has been excited by the impact due to defect, is extracted from the frequency spectrum by zoom-in. Applying the Hilbert transform, evolution of the signal in the time domain is generated by the calculation of the time function amplitude. This evolution can be passed and analyzed in the frequency domain to establish the frequency or frequencies of impact. On this basis the type of defect and the place of occurrence can be identified, as well as its dimensions.

The instrument's front panel offers the representation of the simulated pulse signal (upward graphic) and the corresponding evolution from the time domain (downward graphic). The processing of this last signal in the frequency domain is similar to what was done in the "Acquisition and calculus of power spectrum" of the MECOSPEC apparatus, and it has not been included in the simulation.

Results from the work presented so far show that the evolution method has large perspectives in identification and separation of the existent modular sources in a machine tool; it allows a precise diagnosis of the type of defect and the place of occurrence, as well as its dimensions.
defects in bearings, rolling guides, and gears, even though many defects are simultaneously present.

These virtual instruments have been tested in the laboratory and then compared with traditional measurement schemes, built with traditional instrumentation. For example, the virtual instrument for the acquisition and calculus of the power spectrum has been mounted in parallel with the real-time frequency analyzer Brüel & Kjær 2034, belonging to the Eurotest laboratory, in order to process the same vibration signal. A perfect similitude has been noticed between the displayed power spectra, with a better resolution of the virtual instrument for lower frequencies. All of the virtual instruments described have been found to be adequate from the functional and operating accuracy point of view.
6.1 VIBRATION AND NOISE SOURCES DURING FEED KINEMATIC CHAIN OPERATION

Modern mechanical systems have necessitated the development of research and creation of performance mechanisms. These mechanisms are capable of reducing stresses and energy loss due to friction, and producing a substantial increase of output. Integration of these mechanisms in the kinematic chains of machine tools leads to performance increase (precision, dynamical behavior, and reliability) of these chains and furthermore to the possibility of their integration in modern flexible production systems.

The helical joint with rolling elements has an outstanding place among the above-mentioned mechanisms. Introducing the rolling bodies between screw and nut, the sliding friction is replaced by rolling friction; as a result, positioning precision and output increase. Noise and vibration accompany the functioning of feed kinematic chains with the movement-transforming element-type screw-nut with balls. The noise and vibration, together with the other sources, can negatively influence...
the manufacturing process, even though they are not very powerful. The noise and vibration can also negatively influence the dynamic and reliability of machine tools. Figure 6.1 presents the main noise and vibration sources that can appear during the functioning of modern feed kinematic chains, grouped in internal and external sources depending on the origin point. In the case of external sources it can be stated with certitude that the most important weight belongs to the cutting process. In the case of internal sources, only a careful analysis can disclose the weight of each source in the global level of noise and vibrations.

A first step of this analysis is the determination by calculus of the characteristic frequencies for each mechanism that is considered as a possible source. It follows the recording of vibroacoustic signals.
ing from the previously mentioned sources, and the treatment of these sources using an FFT algorithm. The obtained spectrograms can indicate the weight of each characteristic frequency, and, by interpolation, the importance of each source in the assembly of the feed kinematic chain.

6.2 CALCULUS OF THE CHARACTERISTIC FREQUENCIES OF BEARINGS

A few simplifying hypotheses are necessary to calculate the characteristic frequencies from bearings:

- The contact between the elements and rolling paths is done without slipping.
- The influence of inertial and weight forces is negligible.
- The effects of centrifugal force and gyroscopic couple are ignored.
- The pressure angle $\alpha_B$ is considered the same for the inner and the outer rings.

If the point $O$ from the bearing axis (Fig. 6.2) is taken as the reference point, each point of contact between the rolling body and the two rolling paths has an angular speed equal to that of the median point of the body; that is:

$$\omega_{EO} = \omega_{MO} = \omega_{IO}$$  \hspace{1cm} (6.1)
The rotational speeds of the contact points can be written as

\[ V_A = \frac{1}{2} \omega_M (D_m + D_b \cos \alpha_B) \]

\[ V_I = \frac{1}{2} \omega_M (D_m - D_b \cos \alpha_B) \] (6.2)

If we write the angular speed of median point function of \( O \) point as

\[ \omega_M = \frac{V_M}{\frac{1}{2} D_m} \] (6.3)

then the above relations become:

\[ V_E = V_M \left(1 + D_b D_m \cos \alpha_B\right) \]

\[ V_I = V_M \left(1 - D_b D_m \cos \alpha_B\right) \] (6.4)

The \( E \) point is the center of instantaneous rotation of rolling bodies and each point of these bodies rotates around \( E \) with the angular speed \( \omega_E \).

The \( M \) point results from the following formula for the rotational speed,

\[ V_M = \frac{1}{2} \omega_A D_b \] (6.5)

and for the \( I \) point

\[ V_I = \omega_A D_b \] (6.6)

This speed should be equal, according to the first hypothesis with the peripheral speed of the inner rolling path in the \( I \) point:

\[ V_I = \pi n (D_m - D_b \cos \alpha_B) \] (6.7)

From the last three relations, by substitution, the rotation speed of the median point \( M \) results. This speed has the expression:

\[ V_M = \frac{1}{2} \pi n D_m \left(1 - D_b D_m \cos \alpha_B\right) \] (6.8)

The rotational peripheral speed of the bearing cage is equal to the speed of the median point \( M \) from the rolling bodies, \( V_c = V_M \).

Coming back to the expressions of the rotational speeds of the points from the rolling paths, inner and outer (6.4), and replacing...
Theoretical and Experimental Research

157

median point speed with the previously obtained relations (6.8), the new expressions result:

\[ V_E = \frac{1}{2} \pi n D m \left[ 1 - \left( \frac{D_b D_m \cos \alpha_B}{2} \right)^2 \right] \]  

\[ V_I = \frac{1}{2} \pi n D m \left[ \left( 1 - \frac{D_b D_m \cos \alpha_B}{2} \right) \right] \] (6.9)

In this moment, the rotational frequencies characteristic to rolling bearings can be deduced:

Rotational frequency of the inner ring (rotational):

\[ f_i = f_n = \frac{n}{60} \] (6.10)

Rotational frequency of the cage:

\[ f_c = \frac{1}{2} f_n \left( 1 - \frac{D_b D_m \cos \alpha_B}{2} \right) \] (6.11)

Rotational frequency of the rolling bodies in the cage:

\[ f_m = \frac{1}{2} f_n D_m D_b \left[ 1 - \left( \frac{D_b D_m \cos \alpha_B}{2} \right) \right] \] (6.12)

Rotational frequency of the rolling bodies on the outer ring:

\[ f_E = \frac{1}{2} f_n z \left( 1 - \frac{D_b D_m \cos \alpha_B}{2} \right) \] (6.13)

Rotational frequency of the rolling bodies on the inner ring:

\[ f_I = \frac{1}{2} f_n z \left( 1 + \frac{D_b D_m \cos \alpha_B}{2} \right) \] (6.14)

where \( z \) is the number of the rolling bodies.

In the case of using balls as rolling elements, an experimental relation exists that also permits the determination of their resonance frequency:

\[ f_b = 0.848 \frac{D_b E^2 \rho}{60} \] (6.15)

where \( E \) is the elasticity modulus and \( \rho \) is the density of ball material.
FIGURE 6.3  
Vibration signal of bearing located in front of the lead screw, in perfect functioning state, recorded in time domain.
Figure 6.3a shows the vibration signal of the bearing located in front of the lead screw, in perfect functioning state, recorded in the time domain. Passing this vibration signal through a FFT of order 10, a spectrum is obtained in the frequency domain. Figure 6.3b shows this spectrum.

6.3 CALCULUS OF FREQUENCIES THAT CHARACTERIZE THE BALL SCREW-NUT MECHANISM

In the context of theoretical research regarding the vibroacoustic diagnosis of machine tools integrated in flexible manufacturing systems the following problem was posed: knowledge of characteristic frequencies of the main movement transforming mechanism in feed kinematic chains—the screw-nut with balls mechanism.

Some profoundness diagnosis methods (i.e., the evolute method) stem from the idea that a series of mechanical effects is manifesting in the frequency spectrum by large band increases near the characteristic frequencies and their harmonics from the vibrational signal. It is necessary to previously determine by theoretical procedure the characteristic frequencies, as they are not always easy to find in the standard frequency spectrum. In order to theoretically determine the characteristic frequencies an original calculus method has been set.

The study of ball movement on the rolling path is done starting from some simplifying hypothesis similar to the hypothesis presented in the previous paragraph: the contact between the balls and the rolling paths is done without sliding; and the gyroscopic couple influence, and those of inertial, weight, and centrifugal forces are ignored. To study the complex character of ball movement in the rolling channel created between screw and nut, a fixed triorthogonal axis system OXYZ (OZ direction superposes the screw axis) and a mobile system oxyz are considered. Regarding the mobile system, the oy direction is tangent to the helix described by the ball center during movement (Fig. 6.4). In the general case of ball movement on the rolling canal, it is considered that this canal is made from two trays of ogival profile, driven by axial forces of opposite directions. Two contact points will exist between the ball and the interior tray (the leading screw's canal) and one contact point between the ball and the external tray (the nut's canal). These contact points determine a plane that also passes through the center of the ball. The rolling movement of the ball will be done also around the rela...
FIGURE 6.4 Helix described by the ball center during movement in the screw-and-nut mechanism.

Consider the instantaneous rotation axis (∆) that passes through the previously mentioned contact points of the ball with the leading screw (Fig. 6.5),

\[ P(D_m^2 \cos \theta, D_m^2 \sin \theta, D_m^2 \tan \alpha) \]  

(6.16)

where \( D_m \) is the medium diameter, measured to the ball center.

The tangent to the helix in the corresponding point is expressed as:

\[ \vec{\tau} = \frac{d\vec{P}}{d\theta} \bigg|_{d\vec{P}/d\theta} \]

\[ = \left( -\sin \theta \cos \alpha, \cos \theta \cos \alpha, \sin \alpha \right) \]  

(6.17)

and the interior normal is:

\[ \vec{n} = \frac{d\vec{\tau}}{d\theta} \bigg|_{d\vec{\tau}/d\theta} \]

\[ = \left( -\cos \theta, -\sin \theta, \theta \right) \]  

(6.18)

For the mobile axis system Oxyz, the vector of which the module is 1 for the Oy axis is \( \vec{\tau} \), for the Ox axis is \( -\vec{n} \), and for the Oz axis is \( \vec{\nu} = -\vec{n} \times \vec{\tau} \).

Let us consider now \( S_1 \) and \( S_2 \) the contact points between the ball and the leading screw, \( S_3 \) the contact point with the nut (Fig. 6.6), and...
FIGURE 6.5
Rolling movement of the ball from the screw-and-nut mechanism, done also around the relative instantaneous rotation axis.

FIGURE 6.6
Contact points between the ball and leading screw, $S_1$ and $S_2$, and $S_3$, contact point with the nut.
the ball's diameter. The location of these points depending on the mobile reference point is given by the relation:

$$\vec{r}_{Si} = -D_b^2 \cos \beta_i \vec{n} + D_b^2 \sin \beta_i \vec{v} \quad (6.19)$$

Depending on the fixed reference point, the position is

$$\vec{R}_{Si} = \vec{R} + \vec{r}_{Si},$$

and the coordinates can be written as

$$X_{Si} = D_m^2 \cos \theta + D_b^2 \cos \beta_i \cos \theta + D_b^2 \sin \beta_i \sin \alpha \sin \theta \quad (6.20)$$

$$Y_{Si} = D_m^2 \sin \theta + D_b \cos \beta_i \sin \theta - D_b^2 \sin \beta_i \sin \alpha \cos \theta$$

$$Z_{Si} = \theta D_m^2 \tan \alpha + D_b^2 \sin \beta_i \cos \alpha \quad (6.21)$$

For $S_1$ and $S_2$ points from the screw, the speed is:

$$u_{Si} = \dot{X}_{Si} = \dot{\theta} \left[-D_m^2 \sin \theta - D_b^2 \cos \beta_i \sin \theta + D_b^2 \sin \beta_i \sin \alpha \cos \theta\right]$$

$$v_{Si} = \dot{Y}_{Si} \left[D_m^2 \cos \theta + D_b \cos \beta_i \cos \theta + D_b \sin \beta_i \sin \alpha \sin \theta\right]$$

$$w_{Si} = \dot{Z}_{Si} \left[D_m^2 \tan \alpha + D_b^2 \sin \beta_i \cos \alpha\right]$$

Simplifying the calculus for $\theta = 0$, and knowing that $\dot{\theta} = \omega_s$, the following speeds result.

$$u_{Si} = \omega_S D_b^2 \sin \beta_i \sin \alpha$$

$$v_{Si} = \omega_S (D_m^2 + D_b^2 \cos \beta_i)$$

$$w_{Si} = \omega_S D_m^2 \tan \alpha \quad (6.22)$$

The $S_1$ and $S_2$ points are usually symmetric related to the Ox axis, so it can be written:

$$\beta_1 = \pi - \beta, \quad \beta_2 = \pi + \beta, \quad \beta_3 = 2\pi - \beta$$

(6.23)
The theoretical and experimental research results show:

\[ u_{S_1} = \omega_D b \sin \beta \sin \alpha \]
\[ v_{S_1} = \omega S (D_m^2 - D_b^2 \cos \beta) \]
\[ w_{S_1} = \omega S D_m \tan \alpha \]
\[ u_{S_2} = -\omega D_b \sin \beta \sin \alpha \]
\[ v_{S_2} = \omega S (D_m^2 - D_b^2 \cos \beta) \]
\[ w_{S_2} = \omega S D_m \tan \alpha \]

The point belonging to the nut has no speed (the screw is considered in a rototranslation movement). If \( C \) is the center of a ball, then its vector-radius is:

\[ \vec{R}_c = \lambda_1 \vec{R}_{S_1} + \lambda_2 \vec{R}_{S_2} + \lambda_3 \vec{R}_{S_3} \]

where the coefficients have the values:

\[ \lambda_1 = \sin \beta + \beta'' \frac{2 \sin \beta \cos \beta - \beta''}{2} \]
\[ \lambda_2 = \sin \beta - \beta'' \frac{2 \sin \beta \cos \beta + \beta''}{2} \]
\[ \lambda_3 = \sin \beta \cos \beta - \cos \beta \beta'' \]

The speed of the \( C \) center can be written as a vector:

\[ \vec{v}_c = \lambda_1 \vec{v}_{S_1} + \lambda_2 \vec{v}_{S_2} \]
or detailed on components:

\[ u = \omega_s D_b^2 \cos \beta' \sin \beta \sin \alpha \cos \beta + \cos \beta' \]

\[ v = \omega_s (D_m^2 - D_b^2 \cos \beta) \cos \beta \cos \beta' \cos \beta + \cos \beta' \]

\[ w = \omega_s D_m^2 \tan \alpha \cos \beta' \cos \beta + \cos \beta' \]

(6.28)

Considering the simplifications \( \tan^2 \alpha = 1 \) and \( \sin^2 \alpha = 1 \) (\( a \ll 1 \)), the value of the ball center speed becomes:

\[ V_C = \omega_s (D_m - D_b \cos \beta) \cos \beta^2 (\cos \beta + \cos \beta') \]

(6.29)

The relative speed of the \( C \) point in a reference point with the origin in \( S_1 \), which is united with the screw, is the difference \( \Delta \vec{V} = \vec{V}_C - \vec{V}_S_1 \), and the value of this speed is

\[ |\Delta \vec{V}| = \omega_s (D_m - D_b \cos \beta) \cos \beta^2 (\cos \beta + \cos \beta') \]

(6.30)

Knowing that the balls are consecutive, the characteristic frequencies can be determined at the moment of:

The rolling frequency of the balls on the leading screw tray:

\[ f_s = \frac{\omega_s (D_m - D_b \cos \beta)}{2D_b (1 + \cos \beta')} \]

(6.31)

The rolling frequency of the balls on the nut's tray:

\[ f_p = \frac{\omega_s (D_m - D_b \cos \beta)}{2D_b (1 + \cos \beta')} \]

(6.32)

The rotation frequency of the balls themselves:

\[ f_b = \omega_s \cos \beta' \cos \beta + \cos \beta' \]

(6.33)

Figure 6.7a presents the vibration signal of the screw-nut with balls mechanism, recorded in the time domain. The signal was then passed in the frequency domain through a FFT of the tenth order. Figure 6.7b presents the signal's frequency spectrum.
FIGURE 6.7 Vibration signal of the screw-nut with balls mechanism, recorded in time domain.
Chapter 6

6.4 CALCULUS OF CHARACTERISTIC FREQUENCIES FOR THE TANKETTE WITH ROLLS

In the case of tankettes with rolls, the single simplifying hypothesis refers to the existence of the nonsliding contact between the rolls and the rolling paths.

Figure 6.8 shows that the tangential speeds of the rolls on the rolling paths are equal and of opposite direction, and in direct relation with the displacement speed of the mobile element (the saddle):

\[ \vec{v}_s = -\vec{v}_i = \vec{V} \]  

(6.34)

In this case, the angular speed of the balls is

\[ \omega = \frac{2V}{D} \]  

(6.35)

which leads to a frequency

\[ f_b = \frac{V}{\pi D} \]  

(6.36)

The number of the active rolls is approximated as

\[ z_a = \frac{L}{D} \]  

(6.37)

FIGURE 6.8  Tangential speeds of the rolls on the rolling paths are equal and of opposite direction.
In the above-mentioned conditions, it can be approximated as the rolling frequency of the rolls on the rolling paths (inferior and superior paths) 

\[
f_s = f_i = f_b = \frac{V}{\pi D^2}
\] 

or the specific rotation frequency of the rolls:

\[
f_r = \frac{V}{\pi D_r}
\]

Observations:

1. The identification on the basis of previous relations of a damage on the rolling element is burdened by the fact that the roll has a passive stroke bigger than that of the active stroke: 

\[
L_p = L + \frac{\pi}{2} (D_0 + D_b)
\]

(relative to the roll center), whose vibration signal is absent.

2. The identification of the damage from the lower rolling path (guiding) is possible only in the time interval when the guiding is covered by the tankette.

Figure 6.9a shows the vibration signal of one of the tankettes with rolls of the stand, signal recorded in the time domain. The signal was then passed in the frequency domain by a tenth-order FFT. Figure 6.9b presents the frequency spectrum of the signal.

6.5 PRELIMINARY EXPERIMENTAL RESEARCH

As shown in previous chapters, the main sources of noise and vibration in feed kinematic chains of modern construction are the bearings of the leading screw, the mechanism of movement transformation-type screw-nut with balls, and the rolling guidings of the saddle. At the same time, in the diagnostic analysis made in Chapter 4 of this book, the main sources of noise and vibration were identified as being the weak points from the feed kinematic chain structure. The diagnosis of the mechanical system of the feed kinematic chain must designate these sensible points exactly.

The common feature of these mechanisms is that they have the same principle of operation: transformation of sliding friction into rolling friction inserting intermediary elements—the rolling bodies. More than that, the damages of these mechanisms during functioning have, most
FIGURE 6.9  
(a) The vibration signal of one of the tankettes with rolls of the stand, signal recorded in the time domain; (b) frequency spectrum of the signal.
FIGURE 6.10 Causes of damage to bearings and leading screw. Often, the same causes as those generically presented in Figure 6.10. These common points allow a unitary treatment from the viewpoint of the diagnostic methods used. Thus, this chapter presents applications of the monitoring and diagnosis methods to one or another analyzed mechanism that does not exclude the use of the same methods to other mechanisms of the feed kinematic chain.

6.5.1 Experimental Research with General Use Instrumentation

The first determinations accomplished in the frame of this work were done with a general use instrumentation, of portable type, having medium performances, manufactured by RFT (Germany) and B&K (Denmark). Functioning state supervision of the 6207-P6 bearings on the test stand was done on a bearing testing machine whose kinematic schema is presented in Figure 6.11. An accelerometer B&K 4344 was connected on the cover of the tested bearing. The B&K 4344 accelerometer was connected to a general use B&K 2511 vibrometer. Peak and effective values were measured at regular intervals, each time calculating the peak factor (peak factor method). Figure 6.12 presents the results. When the bearing was dismounted, the occurrence of pitting phenomena on the rolling path of the inner ring could be noticed after the peak factor became larger than 23.
In parallel with measurements of vibrations, the noise emitted by bearings was also studied. For this purpose, a reverberant chamber was created setting panels around the testing machine for bearings. An RFT 0023 sonometer with a microphone with capacitor was also used. The preliminary calibration of the microphone was done with the pistophone RFT 0008. A good correlation was highlighted this way (between the limits $\pm 2$ dB) between the level of acceleration signal of vibration and the emitted noise, as can be observed in Figure 6.13.

The technical literature claims that the peak factor method cannot precisely locate the damage because it is strongly influenced by the elements of the mechanical transmission of movement. This statement was tested by remounting the fault bearing on the test stand, at the entering end of the leading screw. Vibration measurements were done using the same equipment as used for the previous experiments (peak value and effective value of acceleration signal had been done), to both bearing cases of the leading screw. The peak factor was calculated, with the result that the difference between calculated value for the case with the fault bearing and the case with the good bearing was only of one unit, which confirmed the imprecision of source localization using the peak factor method.
FIGURE 6.14
Method of diagnosis index has indicated the appearance of the injurious process and of the damage before the peak factor method. After the experimental determinations, it can be noticed that the peak factor method is simple, easy to handle, and a method that utilizes general equipment. This method is useful especially in the case of monitoring a large number of measuring points, when an early warning is not required, and the consequences of the damage are not considerable. In particular situations, the peak factor method can be very well completed by a profoundness diagnosis method such as, for example, Cepstrum analysis.

The diagnosis index method was applied in parallel with the peak factor method on the 6207-P6 bearing tested on a bearings' testing machine. A first determination of statistical magnitudes that characterize the vibration signal for the bearing in perfect functioning state was useful to identify the reference and effective values of the signal. It is necessary to know these values because the diagnosis method is of "with normalization" type, which means the connection to the reference values. The diagnostic index method has indicated the appearance of the injurious process and of the damage before the peak factor method (Fig. 6.14).
Theoretical and Experimental Research 173

components (Fig. 6.15) a commanded load amplifier (A), for transducers of piezoelectric type, a block of simultaneous acquisition with 16 channels (B), and an interface of 8 bits for a computer (C) having a minimum configuration of 286 XT, 1 Mb RAM, and a VGA monitor. The software that governs this system (VIB-01, then VIB-02 version) was adapted to the requests of monitoring and diagnosis together with the specialists of Emco.

Hypersignal application of the firm Hyperception was adapted later to the above-mentioned system only for signal processing. This previously mentioned software is powerful enough to allow processing the signal in the time domain, passing the signal in the frequency domain using a fast Fourier transform and multiple transformations in the frequency domain.

Several options exist in the time domain: display the captured signal (waveform display or digital oscilloscope); define and use FIR (finite impulse response) and IIR (infinite impulse response) filters; use of convolution, correlation, and autocorrelation functions; and fast Fourier transformation; and in the frequency domain: amplitude representations and phase-frequency representations, respectively; power spectrum; spectrograms in two and three dimensions, respectively; pole-zero diagram;
The Emco system of data acquisition and process, assisted by computer through VIB-02 application has been used for detection of a damage on the guidings with roll tankettes of the stand, by the Kurtosis method (Fig. 6.16). The simulated damage was the occurrence of pitting phenomena on the inferior rolling path of the tankettes. A B&K 4344 accelerometer was fixed on the longitudinal saddle in the nearest neighborhood of a tankette. The electronic block that processes the captured signal to calculate the Kurtosis index value was presented in Chapter 3 of this book (Fig. 3.4). A block of graphical process was attached to the electronic block to visualize the vibration signal and the probability density of the signal's amplitude.

Figures 6.17a and b present the vibration's acceleration and the probability density of the amplitude of this signal for guiding in a good functioning state. Figures 6.18a and b present the same thing as Figure 6.17 but for the damaged guiding. The modifications of the acceleration signal of vibration, and, more important, of the probability density
Theoretical and Experimental Research 175

FIGURE 6.17
Vibration's acceleration and amplitude probability density of this signal for guiding in a good functioning state.

function can be monitored. In relation to this function, the calculated Kurtosis factor is, in the first case, $\beta_2 = 3.48$, and in the second case $\beta_2 = 9.34$.

Determination by calculus of characteristic frequencies of some elements from the kinematic chain structure of machine tools allows the identification of certain types of faults by analysis of the frequency spec-

FIGURE 6.18
Vibration's acceleration and the amplitude probability density of this signal for the damaged guiding.
As presented before, the most useful representation in this case is the power spectrum, which is correlated directly with the vibration signal energy. The bearing testing machine presented in Figure 6.11 was used again to identify the faults that occur in the functioning of radial ball bearings, through power spectrum analysis. This time, the Emco system with the Hypersignal software was used to capture and process the vibratory signal from the case of the radial single-row ball bearings 6207 and 6209.

Table 6.1 presents the constructive parameters considered for the calculus of characteristic frequencies of 6207 and 6209 bearings, and also the values of these frequencies, depending on rotational frequency $f_n$ of the inner ring. The characteristic frequencies were calculated using the relations (6.11) to (6.13) previously presented.

Figure 6.19 presents a power spectrum that was drawn on a 6207 bearing in a state of perfect functioning. This power spectrum can be considered as the reference spectrum. After rolling a few days in the absence of any lubricant, the first signs of damage occurred and the interpretation of the power spectrum of the captured vibrational signal could be started (Fig. 6.20). It can be noticed that the peak of greatest amplitude corresponds to 78.1 Hz frequency.

Considering that the rotational speed of the inner ring is equal to the rotational speed of synchronism of the driving electrical motor ($n_{ME} = 1420$ rpm), the frequency of the inner ring is $f_n = \frac{2}{3} \cdot 66$ Hz.

In these conditions, the frequency characteristic to balls rolling on the external tray is equal to $f_e = \frac{7}{7} \cdot 77.42$ Hz, calculated with the relation to Table 6.1. The calculus of the other frequencies characteristic to bearing functioning did not offer any similitude with the significant increases of amplitude in the power spectrum. It can be stated that the frequency of

<table>
<thead>
<tr>
<th>TABLE 6.1: Constructive Parameters Considered for the Calculus of Characteristic Frequencies of 6207 and 6209 Bearings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constructive parameters</td>
</tr>
<tr>
<td>-------------------------</td>
</tr>
<tr>
<td>Test bearing</td>
</tr>
<tr>
<td>D</td>
</tr>
<tr>
<td>$D_b$</td>
</tr>
<tr>
<td>$z$</td>
</tr>
<tr>
<td>$f_n$</td>
</tr>
</tbody>
</table>

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FIGURE 6.19  Power spectrum drawn on a 6207 bearing in a state of perfect functioning.

FIGURE 6.20  First signs of damage on the power spectrum drawn for the 6207 bearing.
balls rolling on the external tray and its superior harmonics that occur in the last captured power spectrum signalize the beginning of a fault on the external rolling path—a fact confirmed by the subsequent evolution of the fault.

The same identification method of mechanical defects was applied also in the case of the movement-transforming mechanism screw-nut with balls, for a damage simulated on the rolling path from the leading screw.

Table 6.2 presents the values of the constructive parameters that enter in the calculus of characteristic frequencies of the screw-nut with balls mechanism \[\text{relations (6.31) through (6.33)}\], and also the values of these frequencies, depending on the rotation frequency of the leading screw.

Figure 6.21 shows a power spectrum resulting from a vibration signal captured on the "clean" zone of the leading screw using an Emco acquisition system and Hypersignal software. Figure 6.22 presents a power spectrum of a new signal captured rolling the nut over the area with a simulated damage (pitting) on the leading screw. The maximum values from this last spectrum correspond to a frequency of 234.4 and 254 Hz, respectively.

For the measured rotational speed of the leading screw of 960 rot/min, the rotation frequency is \(f_n = 16\) Hz, which leads to \(f_s = 237.95\) Hz and \(f_b = 253.63\) Hz, respectively, values of the characteristic frequencies. It is noticeable that even the power spectrum signals the occurrence of a damage by the significant increases in amplitude at characteristic frequencies; this time, it is not possible to locate the damage on one of the rolling paths. This behavior can be due to the play between the mechanism's elements.

In conclusion, the method of interpretation of the power spectrum is an efficient and rapid method of identification of mechanical defects—although their localization is, in some cases, more difficult. These reasons...
FIGURE 6.21
Power spectrum resulting from vibration signal captured on the “clean” zone of the leading screw using an Emco acquisition system and Hypersignal software.

FIGURE 6.22
Power spectrum of a new signal captured rolling the nut over the area with simulated damage (pitting) on the leading screw.
Chapter 6

led to the elaboration of the spectrum comparison method, which has shown excellent results in profoundness diagnosis. The theoretical presentation of this method can be found in Chapter 3 of this book.

6.6 EXPERIMENTAL RESEARCH IN VIRTUAL INSTRUMENTATION

6.6.1 Structure of Data Acquisition and Process System in Virtual Instrumentation

A data acquisition system has to be able to accomplish three fundamental functions: conversion of physical signal in a signal that can be measured; measurement of the signals generated by transducers/sensors to extract information; and construction of data analysis and data presentation in a useful form. A data acquisition and process system uses a computer (PC) as a process controller. Figure 6.23 presents the general structure of such a system, and this structure can be described as:

- Transducers for conversion of the measured signal into a signal of an electrical nature;
- Circuits to adapt the signal for isolation, conversion, and/or amplification of the signal coming from the transducer;
- A system of multiplexors and analogue–digital converters;
- And a calculus system with an adequate software.

The analogue–digital board (A/D) has the role of transforming the analogue signal (a continuous function in time), passed by the adapting circuit, in a numerical (discrete) format that can be processed by the...
The analogue–digital conversion is a comparison operation; the signal is compared to a reference value, which is then represented as a codified digital number. There are a minimum and maximum number of samples that must be captured in order to optimize the accuracy of measurements. In the data acquisition and process system architecture, the role of the analogue–digital interface is very important because this interface must have a few essential functions for the user:

- High speed data transfer to PC on the DMA (direct memory access) channel
- Electronic part for starting the hardware and software
- Amplification with programmable gain and noise filtration
- Memory buffer

The operational system through which the virtual instrumentation presented in Chapter 5 was elaborated, tested, and then applied, contains:

- an IBM PC 486 computer (100 KHz, 16 Mb RAM)
- data acquisition board AT-MIO-16L-9 National Instruments
- conditioning amplifier 2625 B&K
- piezoelectric vibrations transducer 4344 B&K
- LabVIEW 2.5 National Instruments software
- a real-time frequency analyzer 2034 B&K for testing virtual instruments

This system was provided by the S.C. Eurotest S.A. Laboratories, Seism-Vibrations department, together with their support and collaboration all throughout the experimental research.

6.6.2 Experimental Research in Surface Diagnostics

The virtual instruments for surface diagnosis FACVARF and INDDIAG, whose structure was presented in Chapter 5, have been used to monitor the evolution of mechanical damage on the radial ball bearing 6209. The experimental setup is similar to that presented in Figure 6.11, only the virtual instrumentation took the place of traditional equipment.

Figure 6.24, showing diagnosis in virtual instrumentation by the peak factor method, presents the front panel of the FACVARF virtual apparatus, which exhibits the reference acquisition graphic in the time domain, for the new bearing, and under this graphic, another graphic of a subsequent recording when the mechanical damage already started. In the graphic of peak factor evolution the spectacular decrease of the peak factor value from $F_v = 10$ to $F_v = 8.2$ is due to bearing lubrication.
Theoretical and Experimental Research 183

tion, which had been mounted without lubricant to hasten the damage occurrence.
The INDDIAG virtual apparatus for the same monitoring and diagnosis operation was used simultaneously (Fig. 6.25). Data acquisitions were also made with the bearing in perfect functioning state after the damages started, and a diagnostic index evolution graphic was automatically drawn. Both front panels display a legend to facilitate the interpretation of results.

The Kurtosis method in virtual instrumentation (virtual apparatus INDKURT) was used in many diagnostic situations both in the case of ball bearings and the screw-nut with balls mechanism, because it is possible to estimate without knowing the machine's "history," the functioning state of the analyzed element. Figure 6.26 presents this method for diagnosis of the same bearing. The value of the Kurtosis index $\beta^2 = 3.59$ and the probability density distribution of the amplitude of the captured signal confirm that the bearing is in perfect functioning state.

Other front panels of the INDKURT virtual apparatus are presented in the appendices of this book for other diagnostic situations on the basis of the vibrator signal.

6.6.3 Experimental Research in Prognostics Diagnostics

The virtual apparatus MECOSPEC was presented in Chapter 5. This apparatus is destined to establish the technical diagnostic using the spectrum comparison method. Given the precision of this apparatus, noted during the laboratory tests, this virtual instrument was used during experimental research to monitor the functioning state of some needle bearings. The purpose of this action was to see if the calculus relations presented for determination of critical frequencies for the ball bearings were verified also in case of needle bearings.

Table 6.3 presents the constructive parameters that compete with the calculus of characteristic frequencies of bearings, and also the values of these frequencies, depending on the rotation frequency $f_n$ of the inner ring. The characteristic frequencies were calculated using relations (6.12) to (6.14).

Figure 6.27 presents the captured signal in the time domain and passed in the frequency domain by a fast Fourier transform for a radial needle bearing NA 4909 in perfect functioning state. The resulting power spectrum is considered a reference spectrum and is used to obtain the warning template and alarm template, respectively.
FIGURE 6.26 Kurtosis method in virtual instrumentation (virtual apparatus INDKURT).
TABLE 6.3

<table>
<thead>
<tr>
<th>Constructive parameters</th>
<th>Characteristic frequencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bearing type</td>
<td>Characteristics</td>
</tr>
<tr>
<td>NA 4907</td>
<td>45</td>
</tr>
<tr>
<td>NA 4908</td>
<td>51</td>
</tr>
<tr>
<td>NA 4909</td>
<td>56.5</td>
</tr>
</tbody>
</table>

The current spectrum is compared to these templates in the next section of the virtual diagnosis instrument. This way the warning template obtained by raising by the power two and side plating to the octave of the reference spectrum serves as a comparison element for a wear spectrum taken after the debut of mechanical damage (Fig. 6.28). The difference between the two spectra is graphically displayed to allow a direct read.

FIGURE 6.27
Captured signal in time domain and passed in frequency domain by FFT for radial needle bearing NA 4909 in perfect functioning state.
FIGURE 6.28 Warning template obtained by raising by the power two and side plating to octave of the reference spectrum serves as comparison element for wear spectrum taken after debut of mechanical damage. During determinations only a few and the same frequencies have increased overpassing the alarm template, a phenomenon which is presented in Table 6.4. The characteristic frequencies calculated as a function of the input rotational speed $n = 960$ rpm ($f_n = 16$ Hz) applied to the inner ring are:

- Rolling frequency of needles on the outer ring, $f_E = 185.92$ Hz
- Rolling frequency of needles on the inner ring, $f_I = 214.80$ Hz
- Rolling frequency of needles in the cage, $f_m = 112.48$ Hz

It can be stated that the relations for the calculus of the characteristic frequencies for one-row ball bearings can be applied also to radial needle bearings comparing the above calculated frequencies with those experimentally obtained (Table 6.4) by the intensive wear of the bearing on the test stand.

Figure 6.29 graphically presents the evolution of overpasses to the three frequencies mentioned in Table 6.4. It is considered that the evolution of the frequencies that signal the mechanical damage is approximately linear in the regime wear domain, so the points resulting from
TABLE 6.4
Comparing the Calculated Frequencies with Those Experimentally Obtained

<table>
<thead>
<tr>
<th>Overpasses (dB)</th>
<th>At read no. 7</th>
<th>9</th>
<th>11</th>
<th>13</th>
<th>15</th>
<th>17</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency (Hz)</td>
<td>183</td>
<td>0.5</td>
<td>0.9</td>
<td>2.8</td>
<td>5.3</td>
<td>7.7</td>
</tr>
<tr>
<td></td>
<td>203</td>
<td>—</td>
<td>0.3</td>
<td>1.2</td>
<td>2.9</td>
<td>3.6</td>
</tr>
</tbody>
</table>

Measurements can be interpolated to a line. At any moment, the time left until the stop by damage can be estimated by intersecting the interpolated line with the alarm level for the researched frequency.

In the last version of the virtual apparatus diagnosis MECOSPEC (Fig. 6.30) the spectrum comparison and supplementary processing of the warning template overpass is replaced with a representation type WATERFALL, which is a tridimensional representation made for the power spectra coming from successive captured signals at the same measuring point. At the spectrum axis, frequency and amplitude, the time axis is added. The spectra are successively represented on the time axis depending on the acquisition moment (Fig. 6.31).
FIGURE 6.30  WATERFALL representation on the last virtual apparatus diagnosis MECOSPEC.

FIGURE 6.31  In the WATERFALL representation, the spectra are successively represented on the time axis depending on the acquisition moment.
with the aid of a time cursor any of the represented frequency spectra can be selected, and with the aid of a frequency cursor the evolution in time can be monitored for any frequency of the vibration signal from the power spectra.

6.6.4 Advantages of the Use of Virtual Instrumentation in Technical Diagnosis

The use of virtual instrumentation in monitoring and establishing of technical diagnosis offers special facilities to users as follows.

Visual Programming. This type of programming is primarily a rapid, sure, and easy path to the elaboration of special applications, adapted to imposed requests, easy to test and to maintain. It is the type of programming recommended to those who have not had the opportunity to familiarize themselves with a "classical" programming language. Instead of writing hundreds of rows of program, the user can build a program as a functional diagram choosing from the menu a series of visual elements that he or she logically interconnects. The rapidity and simplicity of the work stimulate conversion of traditional techniques of diagnosis and help find new virtual instrument techniques.

High Rate of Sampling. The rate of sampling (expressed in samples per second or sometimes in Hz) represents the measure of speed by which the A/D board can scan the input channel, and can identify the discrete value of the signal depending on the reference value. Theoretically, a data acquisition system must sample with a speed at least twice that of the largest frequency that can exist in the input signal; if this rule is not realized, a completely different wave shape will be obtained, having a smaller frequency, a phenomenon called aliasing. The high sample speeds that are reached at present rapidly load the computer memory but this phenomenon is no longer a problem due to the technological development of computers. The diagnostic problems need a medium level of sample rate that can be solved with 8 or 16 Mb RAM.

Good Resolution of Measurements. The resolution (expressed in percentages or bits) defines the smallest variation of the input signal that can be detected by the acquisition system. In virtual instrumentation a resolution comparable to that of dedicated traditional instruments produced by prestigious companies can be obtained.
Possibility of Choice of Sampling Mode. In applications of frequency analysis using FFT, any deviation in the period of time between sampling produces considerable errors. The acquisition system with virtual instrumentation realizes the start of the A/D converter (triggering) directly by the clock from the hardware or an external clock on the acquisition board. More than that, the possibility of choosing the pretrigger or posttrigger modes exists.

Data Transfer Speed. Using the direct memory access transfer mode the system takes over the data from the acquisition interface and puts these data directly in the computer's memory. DMA transfers are directly controlled by hardware and are extremely rapid. Ultrafast acquisition systems that use memory located directly on the acquisition plate also exist, so these systems will no longer be limited by the computer thoroughfare speed. In these conditions a "real-time" data process becomes possible, an accomplishment hard to achieve and expensive to realize with traditional instrumentation.

Possibility of Using the Multiplexor. The multiplexor is an electronic device that disposes more input channels, an output channel, and digital control inputs. Using these control inputs the needed input channel can be selected and connected to the output channel. The multiplexor is useful for supervising machines with a large number of measuring points, using the same measurement instrument.

Use of Work Programs with Annexed Apparatus (Driver-E Software). These work programs with annexed apparatus constitute a software level that directly programs the acquisition hardware, administers the functioning of the acquisition hardware, and ensures integration with computer resources. They hide the complicated details of hardware programming, ensuring an easy to understand interface for the user.

Data acquisition systems tend to be more and more mass consumption goods because of the continuous technological improvement of this peak domain. These conditions determine the transformation software, an important factor related to data acquisition and process differentiation.
A Neural Approach to Establishing Technical Diagnosis for Machine Tools

7.1 INTRODUCTION TO NEURAL NETWORK THEORY

The end of the 1980s signaled a period of research regarding the development of a new approach to data processing within computational systems. This approach earned several names: connectionism, neural network, neural processing, and parallel processing; all of these terms are synonyms for that kind of information processing that tries to simulate the thought processes of the human brain based on experience, rather than the classical method of that based on algorithms.

7.1.1 Information Neural Processing

Data neural processing means to elaborate and study networks with adaptable nodes; these networks store experiential knowledge, and are available to be utilized for the purpose for which the network was created. The word “adaptable” used for the network nodes represents that property of a node which is able to react correctly even if the stimulus received is not precisely the same as the ones already learned.
The adaptable node, the main element of a neural network, can be represented as an electronic device with a manifold input channel (Fig. 7.1). It consists of one output channel and two special connections: one for introducing data into the learning process, and the other as a switch of learning/utilizing nodes. The F node function is the way in which an output parameter is associated with each input dataset. For example, the function of an adaptive three-input node can look like a logic table in which the response is 1 only when the input dataset has a single 1 value (Table 7.1). This representation of an adaptive node makes obvious the association with the neuron, the adaptive node of the brain. The human brain has an average of $10^{11}$ neurons, organized in complex structures.

The neuron (Fig. 7.2) consists of a cellular body called the perikaryon, which contains the nucleus, and two sorts of protoplasmic prolongation: the axon (cylindrical shaped, long, usually single) and the dendrites (many and short). The dendrites represent the input channel

---

**Figure 7.1** Adaptable node, main element of a neural network.

**Table 7.1** The Function of an Adaptive Three-Input Node Can Look Like a Logic Table

<table>
<thead>
<tr>
<th>x1</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>1</th>
<th>1</th>
<th>1</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>x2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>x3</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Y</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
into the neuron, while the axon is the output channel. An electric activity characterized by short and fast impulses (about 100 impulses/second) has been noticed in the axon when the neuron “emits.” Neurons are interconnected through the ends of the dendrites, called synapses. One neuron can receive 5000 to 15,000 input signals from other neurons' axons. Synapses can be excitators, if they help the neuron to emit, or inhibitors, if they discourage the neuron from emitting.

The informational model of a neuron was first proposed in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pitts. This model is still the basis of information neural processing. According to this model, the synaptic modifications are continuous, and the neuron takes into consideration all of the synaptic signals, both excitator and inhibitor; then, it sums up their effects and determines whether to emit them through the axon. Number 1 is associated with the emission state, and 0 with the repose state.
If \( X \) denotes the neuron state and the synaptic connection effect is represented by a weight \( W \), then the effect of a synapse upon the neuron is given by the product \( X \cdot W \). The weight \( W \) can have values within the interval \(-1, \ldots, 1\); the negative values characterize the inhibitor synapses. Since there is a multitude of synapses, an index \( j \) has to be attached, which designates \( X_j \) and \( W_j \) as the input and the weight of the synapse \( j \), respectively. The neural model constantly adds those effects and compares them with a threshold value \( T \); if the sum exceeds the threshold, the neuron emits. For the McCulloch and Pitts neuron, this emission rule can be described mathematically by the relation:

\[
X_1 W_1 + X_2 W_2 + \cdots + X_j W_j + \cdots + X_n W_n > T. \tag{7.1}
\]

The electronic interpretation of this relational model is given in Figure 7.3. The basic components are: the summator amplifier, which provides an output voltage proportional to the sum of all products \( X \cdot W \), and the voltage comparator, which generates a voltage equal to 1 if the output voltage of the summator exceeds the threshold voltage \( T \). The value of the adjustable weights \( W \) is set automatically during the learning process.

On the basis of the model presented so far, two sorts of neural networks have been theorized: feedforward and feedback networks. Within these networks neurons are distributed in one or more layers that cannot be accessed directly; they are called hidden layers and have free access only at the input channel and, respectively, at the output channel of the network (Figure 7.4). The feedforward networks operate between the input channel and output terminals, learning to associate output data with the input data. In feedback networks, the information can run within a loop from the input to the output channel and vice versa, creating a so-called internal input channel. Both types of network oper-
Neural Approach to Technical Diagnosis

FIGURE 7.4 Neurons distributed in one or more layers that cannot be accessed directly.

1. Select an input dataset.
2. When an error is detected in the network’s response, calculate the deviation from the desired output parameter.
3. Adjust the active weights (i.e., those which are emitting) and the threshold value, in order to partially correct the error.
4. Return to step 1 until no input dataset causes errors.
The McCulloch and Pitts model was improved by Frank Rosenblatt by adding fixed preprocessing units; their duty is to extract specific features from the input signals. Thus the perceptron was born, which is defined as a model recognition device. Figure 7.5 shows the perceptron electronic model; $A_j$ are the preprocessing units, called associative units. In terms of these units, the perceptron order is defined; the perceptron order is equal to the number of inputs of the associative unit with the largest number of inputs.

7.1.2 The Learning Process in Neural Networks

The information neural processing paradigm principle states that neural networks can be trained merely through examples from the exterior. In other words, any learning algorithm utilized in multilayer networks is based on output error estimation. This is the so-called hard learning problem, and it is one of the most important problems in neural networks.

A major step in overcoming this problem was made in 1982 by John Hopfield, an American biologist and chemist; he presented neural networks as content addressable memories (associative memories). Through his work, he made two major contributions. He developed a type of network analysis that uses the concept of energy, concluding that a network reaches, while operating, its energetic minimum, after
which the output signal set does not change (i.e., stability occurs). In addition, he showed that learning rules, such as the delta rule, can be utilized to adjust the network parameters purposely to create the energetic minimum. The Hopfield neuron model has the characteristic parameters $V_i$, the output signal ($V = 0$ if the neuron does not emit; $V = 1$ if the neuron emits); $T_{ij}$, the weight of the connection of the neuron $i$ with the neuron $j$ ($T = 0$ if the neuron $i$ is not connected to the neuron $j$); and $U_i$, the threshold value for which the neuron emits. In short:

\[
V_i \text{ becomes } 1 \text{ if } \sum_{j \neq i} T_{ij} V_j > U_i \tag{7.2}
\]

\[
V_i \text{ becomes } 0 \text{ if } \sum_{j \neq i} T_{ij} V_j < U_i
\]

The energy of a neuron can be calculated with

\[
E_i = -V_i \left( \sum T_{ij} V_j - U_i \right) \tag{7.3}
\]

The amount between brackets is called the activation energy and is denoted by $A_i$. In order to have a stable state of a neural network, none of the nodes should be activated in such a way that the emission conditions change. So, if a neuron is emitting ($V = 1$), its activation will be positive, so that the emission is not further stopped; the same is true if the node is not emitting ($V \neq 1$); its activation will be negative, so that it does not further emit. Consequently, when the neural network changes its state, either it keeps the same energetic level, or it goes down to a lower energetic level. When lower energy levels are no longer accessible, the network remains stable at its most recent state.

From an energetic analysis perspective, it becomes clear that a learning procedure application, such as the delta rule, is simply a way to decrease the state energy to a minimum. The Hopfield model has its disadvantages: the most important is that the neural network “gets stuck” in false energetic minimums. The way that a neural system runs out of false minimums was discovered by Geoffrey Hinton; it consists of “noise” utilization (i.e., applying an uncertainty degree to the state energy). Intuitively, this method can be illustrated by representing the network state as a ball on a waved surface (Fig. 7.6). If the ball has an internal property which makes it “jump,” it is probable that it will spend the longest time in the deepest valley it can reach.
At the crux of any neural network activation remains the phenomenon of increasing the aleatory motion of gaseous molecules while temperature increases, discovered by Ludwig Boltzmann at the end of the nineteenth century. Analogously with Boltzmann’s research, the uncertainty degree, introduced to assess a neural network state, was named temperature. Thus, at zero temperature the network will behave according to the Hopfield model; at higher temperatures, an uncertainty degree proportional to the temperature has to be introduced in the neuron activation function. This procedure has the advantage of helping the network to run out of its false minima but there is another side of the coin: the network no longer remains stable. Hinton proposed a “thermal regime” be utilized to enable this trouble to be outrun: starting the network at a high temperature and then cooling it gradually until it reaches the “thermal equilibrium.” In this way, the network has the greatest chance to end in a state associated with the lowest minimum to be reached for specific input data. This manner of approach to neural networks has been called “simulated tempering.”

The introduction of temperature in the neuron activation function is done through a probabilistic function, called the emission probability Boltzmann function:

$$p(1) = \frac{1}{1 + \exp(-A/T)}$$ (7.4)

The plot of this function is represented in Figure 7.7 for “temperatures” of 0.5 and 0.25 (these are arbitrary units, not related either to Celsius or Kelvin degrees or to other measure units of temperature as a physical parameter). The result of the introduction of temperature as a moderator in the neuron activation function can be pursued in changes of the way in which the electron’s emission is interpreted. According to the Hopfield model, if the $A$ activation were negative, the neuron would not emit $[p(1) = 0]$; if the activation were positive, the neuron would
have emitted \( p(1) = 1 \); this is shown in Figure 7.8a. The new model, named the Boltzmann machine, suggests that, for negative values of the \( A \) activation, there is a probability \( p(1) = 1 \) that the neuron emits; this probability goes to zero as \( A \) becomes negatively smaller and smaller. Similarly, there is a probability \( p(0) \) that the neuron does not emit, even if the activation is positive; this probability gets lower when the activation gets higher (Fig. 7.8b).

**Figure 7.8** (a) Hopfield model; (b) new model, named the Boltzmann machine.
The Boltzmann machine showed that the probability that the network comes to an end in a certain state depends nearly exclusively on that state energy. That means that, through the learning process, the energies corresponding to the minimums of the system have to be well controlled.

Starting from the assumption that not all units of a network are defined by the learning dataset, Hinton showed the necessity of hidden units, essential for solving the hard learning problem. The learning procedure, based merely on information as to whether the visible units behave correctly, has to ensure that hidden units develop their own correct weights and thresholds, too. If we assume a neural network has \( \nu \) visible units, it can have \( 2^\nu \) possible states. If \( S_1, S_2, \ldots, S_r \) are input datasets for training the network through visible units, state probabilities can be calculated: \( P^+(S_1), P^+(S_2), \ldots, P^+(S_r) \), where the “+” sign is used to indicate that these are desired probabilities. On the other hand, the “−” sign is used for the same probabilities, but results from the free (untrained) run of the network, that is, \( P^-(S_1), P^-(S_2), \ldots, P^-(S_r) \).

The function introduced to measure “the distance” between these two probability sets is:

\[
G = \sum_a P^+(S_a) \ln \frac{P^+(S_a)}{P^-(S_a)}
\]

(7.5)

The first term of the previous relation, \( P^+(S_a) \), makes the states with the largest occurrence probability have the largest effect upon the sum; the natural logarithm becomes zero when the two probability sets are identical \( [P^+(S_a) = P^-(S_a)] \).

It can be shown that the “distance” changing rate between the two probability sets depends on the trained, respectively, untrained, visible units’ temperature and average state probabilities, after the relation:

\[
\frac{\partial G}{\partial w_{ij}} = -\frac{1}{T} (p_{ij}^+ - p_{ij}^-)
\]

(7.6)

The meaning of this relation consists of the following: in order to lower the rate \( G \) by changing the weight \( w_{ij} \), all that needs to be known is the local information \( (p_{ij}^+ - p_{ij}^-) \). If this term is positive, the weight \( w_{ij} \) has to be increased; in the opposite case, it has to be decreased. Obviously, the process is finished when \( G = 0 \), so the network learned to reproduce the state probabilities, and it is considered completely trained.
As shown before, there are two types of neural networks: feedforward and feedback. For feedback networks it is simple to introduce into the loop the signal associated with the output error, and this is done on purpose to diminish this error while training. As far as feedforward networks are concerned, they are the most utilized ones, and they cannot work freely because of the lack of reaction to inform; therefore, a training method for the hidden units is necessary, through a process of propagation of the measured error on a backward direction, from the output channel.

The hidden layers can be considered the location in the network in which input parameters are partially processed and labeled before the final result is reached in the output layer. In these layers, representations are formed, which are not provided during the training process. A generalization of the delta rule forms the basis of the hidden units’ behavior through the converse error propagation process. The goal of this method is to minimize the overall output error $\varepsilon_p$, defined as the half-sum of the squares of all neurons’ output errors:

$$
\varepsilon_p = \frac{1}{2} \sum_j (t_{pj} - o_{pj})^2
$$

(7.7)

where $t_{pj}$ is the target output of the neuron $j$ for the input dataset $p$; $o_{pj}$ is the actual output of the neuron $j$ for that input dataset.

The training process through converse error propagation has two steps. The first is the forward step, during which the input data are applied and let run to the output channel. The output parameters are calculated and compared to the target parameters (which have to be known). During the backward step, the errors (those resulting as a consequence of the comparison in step one) are propagated backwards to the input layer. The purpose is to recalculate the neural connection weights. Another forward step follows, then another backward step, until the error minimizes within a preset limit. For this manner of feedforward neural network training, it has been noted that the most suitable neuron activation function is the same type as the function presented in relation (7.4) and Figure 7.7, also called the sigmoid function. A feedforward type neural network with three layers (input, hidden, and output), having a sigmoid activation function, and being trained through the converse error propagation method, can be represented schematically as in Figure 7.9. It should be noted that a larger number of neurons in the hidden layer can guarantee a better result in network training and usage.
FIGURE 7.9 Feedforward type neural network with three layers represented schematically.

FIGURE 7.10 Structure of Windows Neural Network.
7.2 UTILIZATION OF NEURAL NETWORKS IN MACHINE TOOLS DIAGNOSTICS

7.2.1 Multicriteria Application for “Good/Defective” Classification

The problem of identifying defective elements in the kinematic structure of a machine tool can be solved by utilizing feedforward type neural networks. The following deals with elaboration and training of a neural network for bearing diagnosis. The data used for network training come from the experimental research presented in Chapter 5. Windows Neural Network is a user interface, written in Visual Basic, for building and utilizing feedforward neural networks, fully connected and trained through the converse error propagation algorithm. The structure of the neural networks with which this application works (Fig. 7.10) contains the input layer, one or more hidden layers, and the output layer. The output channel of each neuron is connected to all neural input channels of the next layer, which can introduce BIAS units (tendency or prediction units), which facilitate the network’s training. There is no activation function in the input layer; this layer can only distribute the input data to the first hidden layer. The hidden layers and the output layer have an activation function, which can be:

A linear function:

\[ f(x, T) = xT \]  \hspace{1cm} (7.8)

A hyperbolic tangent function:

\[ f(x, T) = \tanh(xT) \] \hspace{1cm} (7.9)

A sigmoid function:

\[ f(x, T) = 1[1 + \exp(-xT)] \] \hspace{1cm} (7.10)

From a mathematical point of view, the network runs the following algorithm.

For the hidden layer output:

\[ h(j) = \sum_i w(i,j)xi(i) \] \hspace{1cm} (7.11)

\[ s(i) = f(h(j)) \]
For the output layer output:

\[ h'(k) = \sum_j w(j, k)x_s(j) \]

\[ o(k) = f(h'(k)) \]

where \( i(i) \) represents the network input channels; \( o(k) \), the network output channels; \( w(i,j) \), the weight of the connection of the neuron \( i \) with the neuron \( j \) in the next layer; and \( f \), the activation function.

The objective function has to minimize the final error:

\[ \varepsilon_{RMS} = \sum_{p=1}^{P_{max}} \sum_{k=1}^{K_{max}} [t(p, k) - o(p, k)]^2 \]  

(7.13)

where \( t(p, k) \) is the output target value for the output dataset \( p \), and \( o(p, k) \) is the actual output value for the same dataset.

The DIAGNO neural network for identifying defective bearings has the structure shown in Figure 7.11. The network’s dimension is given by the number of layers and the number of neurons in each layer; consequently, the built network is a \( 3 \times 4 \times 1 \) type, with BIAS units in layers 2 and 3. The neuron activation function is the sigmoid function (Fig. 7.10).

**Figure 7.11** DIAGNO neural network for identifying defective bearings.
The selection criteria for data needed to train the network are the peak factor criterion, the diagnosis index, and the Kurtosis index. Data corresponding to the evaluation through these criteria come from the database of vibration signals stored and processed in the time field (see Chapter 5); they are provided to the network in three ways. The training datasets, containing input data and the corresponding output target parameter, are shown in Table 7.2. These data cannot be introduced in the network as they are, since they could not be processed by the activation functions. For instance, the sigmoid function can only take values between \(-2\) and \(2\) at the input channel; other values would saturate the neuron and lead to an output with value 0 or 1 all the time. To avoid this inconvenience, the input data should be logarithmically or linearly normalized, as the variation field of those data is larger or narrower. This operation is done automatically, on demand, from the main menu of the application; the normalization can be global (to all of the network’s nodes) or individual (node by node).

The next step is represented by the network’s converse propagation algorithm adjustment, through the two parameters that connect the new weights with the derivatives of the old weights, after the relations:

\[
\begin{align*}
dW(i, j, t + 1) &= \eta dW(i, j, t) + \alpha dW(i, j, t - 1) \\
W(i, j, t + 1) &= W(i, j, t) + dW(i, j, t)
\end{align*}
\]  
(7.14)

where \(\eta\) is the learning parameter and \(\alpha\) the moment parameter. The best results were obtained for \(\eta = 0.2\) and \(\alpha = 0.5\), as the front panel of this application shows (Fig. 7.12). It should be mentioned that during the network run there was no need to introduce “noise” and “temperature” to help the network avoid getting stuck in local minimums. Since temperature is a multiplicator of the activation function argument, not to take it into consideration means \(T = 1\).

The structural network training process runs in epochs. An epoch represents the number of input datasets in terms of which weights are calculated. Thus, if the length of an epoch is 1, a continuous training is done (weights are recalculated after each dataset); if the length of an epoch is equal to the number of datasets, a simultaneous training is done (weights are recalculated after each pass over all datasets). Simultaneous training is useful when there are few input datasets, as in the present case. At the same time, this sort of training is faster than continuous training. Training this neural network needed 555 iterations, that is, 555 passes over the input datasets. Training ended when the target was
<table>
<thead>
<tr>
<th>Set number</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak factor</td>
<td>10.0</td>
<td>7.5</td>
<td>20.0</td>
<td>27.0</td>
<td>6.0</td>
<td>25.5</td>
<td>26.0</td>
<td>29.0</td>
<td>14.0</td>
<td>24.5</td>
</tr>
<tr>
<td>Diagnosis index</td>
<td>.500</td>
<td>.650</td>
<td>.170</td>
<td>.013</td>
<td>.800</td>
<td>.018</td>
<td>.015</td>
<td>.010</td>
<td>.400</td>
<td>.019</td>
</tr>
<tr>
<td>Kurtosis index</td>
<td>4.1</td>
<td>3.7</td>
<td>7.2</td>
<td>9.2</td>
<td>3.4</td>
<td>9</td>
<td>9.3</td>
<td>12.0</td>
<td>5.8</td>
<td>8.8</td>
</tr>
<tr>
<td>Target output</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

**Table 7.2** Training Datasets, Containing Input Data and Corresponding Output Target Parameter

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Figure 7.12  Front panel caption.
Table 7.3 Weights $w_{ij}$ Calculated for Each Neural Connection

Total calculated weights: 21

Between input layer and second hidden layer:

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2.567564</td>
<td>-0.552004</td>
<td>-0.623598</td>
<td>0.690139</td>
<td>—</td>
</tr>
<tr>
<td>1.273501</td>
<td>0.300688</td>
<td>1.931408</td>
<td>-0.233710</td>
<td>—</td>
</tr>
<tr>
<td>-3.382554</td>
<td>1.183681</td>
<td>0.871934</td>
<td>1.333970</td>
<td>—</td>
</tr>
<tr>
<td>2.154515</td>
<td>-0.137544</td>
<td>-0.532012</td>
<td>-1.897794</td>
<td>—</td>
</tr>
</tbody>
</table>

Between second hidden layer and third output layer:

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.092981</td>
<td>-2.371565</td>
<td>4.373098</td>
<td>-1.461245</td>
<td>-0.007646</td>
</tr>
</tbody>
</table>

reached with an error smaller than the preset one, in this case. It can be noticed in the window with the training results (Fig. 7.12) that the actual root mean square error is $\varepsilon_{\text{RMS}} = 0.000379604$.

As a consequence of training the network with experimental data, weights $w_{ij}$ have been calculated for each neural connection (Table 7.3), through the converse error propagation algorithm. Weight distribution in the network is shown in Figure 7.13 in the shape of a 10-interval histogram. The number of weights in each interval is represented in terms

![Weight Distribution](image)

**Figure 7.13** Weight distribution in the network.
of the weights’ value, between $-4$ and $+4$. This representation provides information about the quality of the result obtained in the calculus of weights; normally, for a network with the same activation function in all layers, the weight distribution should be as close as possible to a Gauss distribution. Figure 7.13 shows the weight distribution for a DIAGNO neural network, correlated with data in Table 7.3. The shape of this histogram gets closer to a Gauss distribution, so the weights are correct. In these conditions, a graphical representation of the actual network outputs can be plotted at the same time as the target outputs. In Figure 7.14 the network’s target outputs, as they were set (Table 7.2), are drawn with a solid line, and the trained network’s actual outputs with a dashed line.

The error between the target output and the actual output can also be plotted, as in Figure 7.15. It can be clearly seen that the neural network observes some trouble in interpreting datasets 2 and 8 (see Table 7.2). Indeed, during the training process, the two input datasets had been introduced artificially by the author within categories “defective” and “good.”

At this time, the DIAGNO neural network training process can be considered finished and the network can be utilized in the classification. Tests of the built neural network have been carried out on a group of four datasets known from experimental research; these datasets are presented in Table 7.4. It should be noted that this time the input target value for each input dataset was not indicated; the neural network will have

![Figure 7.14](https://example.com/image.png)

**Figure 7.14** Network’s target outputs, as they were set (Table 7.2) (solid line) and trained network’s actual outputs (dashed line).
to perform the set classification, in the manner it learned during the training process. The weights of neural connections calculated during the training process were used as they were during the test. After the normalizing operation, the test data were plugged into the network. The training parameters were kept the same ($\eta = 0.2$ si $\alpha = 0.5$); it was not necessary to use noise or temperature to avoid the network getting stuck in false minimums. Data for running the classification test for the four bearing types from which input data were taken are shown in Table 7.5. The root mean square error in the test was smaller than the one that resulted in training the network, as was expected.

Figure 7.16 illustrates the result of the neural network test: indeed, the first two test datasets belonged to two radial ball bearings 6209 which were working perfectly; the last two datasets were taken from the same bearings, having pitting on the outer race track due to an intensive wear on the stand described in Chapter 5.

### Table 7.4
Test of the Built Neural Network Carried Out on a Group of Four Datasets Known from Experimental Research

<table>
<thead>
<tr>
<th>Set number</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak factor</td>
<td>6.50</td>
<td>11.00</td>
<td>26.70</td>
<td>25.40</td>
</tr>
<tr>
<td>Diagnosis index</td>
<td>0.780</td>
<td>0.480</td>
<td>0.013</td>
<td>0.017</td>
</tr>
<tr>
<td>Kurtosis factor</td>
<td>3.50</td>
<td>4.50</td>
<td>9.70</td>
<td>9.10</td>
</tr>
</tbody>
</table>

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In conclusion, the DIAGNO neural network is able, after a preliminary learning process, to distinguish perfectly working bearings and defective bearings with remarkable accuracy. Other tests carried out with the same neural network, over other experimental datasets, gave the same results every time.

7.2.2 Application for Neural Diagnosis of the Working State

The goal of a diagnostic operation is to detect “ante factum” a defect, in order to prevent a machine’s being out of operation due to damage.

**Figure 7.16** Result of neural network test.
Starting from this consideration, a neural network utilized for monitoring and diagnosing should be able to evaluate the real working state of the supervised element. Therefore, a neural network named DIAGNOZA has been built, having the structure shown in Figure 7.17; this network has been trained to classify supervised bearings into four categories:

- Bearings in a perfect working state (target $y = 1$)
- Bearings that have conditions for defects to occur (target $y = 2$)
- Bearings in a limited working state (target $y = 3$)
- Defective bearings (target $y = 4$)

The network is of the multilayer feedforward type, size $2 \times 5 \times 1$, with BIAS type prediction units, able to be trained through the conversive error propagation algorithm. The neuron activation function is a sigmoid function [relation (7.10)], the same for neurons in all layers. The network is fully connected, meaning each neural output channel from a layer is connected to all neural input channels in the next layer.

The two network input channels were given data from the experimental research and interpolations of those data (Table 7.6); the classification criteria considered this time were the peak factor criterion ($F_v$)
### Table 7.6 Data from Experimental Research and Interpolations of Those Data

<table>
<thead>
<tr>
<th>Set no.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak factor</td>
<td>25.25</td>
<td>14.50</td>
<td>7.36</td>
<td>26.64</td>
<td>24.21</td>
<td>6.64</td>
<td>26.35</td>
<td>22.89</td>
<td>17.12</td>
</tr>
<tr>
<td>Kurtosis index</td>
<td>9.79</td>
<td>5.12</td>
<td>3.61</td>
<td>11.23</td>
<td>8.73</td>
<td>3.47</td>
<td>10.68</td>
<td>8.13</td>
<td>6.25</td>
</tr>
<tr>
<td>Target</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Set no.</td>
<td>10</td>
<td>11</td>
<td>12</td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>16</td>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td>Peak factor</td>
<td>19.07</td>
<td>23.64</td>
<td>27.01</td>
<td>8.71</td>
<td>5.72</td>
<td>8.25</td>
<td>20.85</td>
<td>25.98</td>
<td>12.14</td>
</tr>
<tr>
<td>Kurtosis index</td>
<td>6.70</td>
<td>8.46</td>
<td>11.88</td>
<td>4.09</td>
<td>3.06</td>
<td>3.88</td>
<td>7.45</td>
<td>10.19</td>
<td>4.88</td>
</tr>
<tr>
<td>Target</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Set no.</td>
<td>19</td>
<td>20</td>
<td>21</td>
<td>22</td>
<td>23</td>
<td>24</td>
<td>25</td>
<td>26</td>
<td>—</td>
</tr>
<tr>
<td>Peak factor</td>
<td>15.63</td>
<td>26.83</td>
<td>6.12</td>
<td>6.00</td>
<td>14.07</td>
<td>20.03</td>
<td>25.55</td>
<td>21.79</td>
<td>—</td>
</tr>
<tr>
<td>Kurtosis index</td>
<td>5.73</td>
<td>11.57</td>
<td>3.24</td>
<td>3.14</td>
<td>4.81</td>
<td>7.22</td>
<td>9.59</td>
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<td>—</td>
</tr>
<tr>
<td>Target</td>
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<td>4</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>
and Kurtosis index criterion ($\beta_2$). Data were linearly normalized in order to be accepted by the neuron activation function. The best results were obtained for the values of the learning parameters $\eta = 0.2$ and $\alpha = 0.5$, without using noise or temperature as aiding factors in the network. On the front panel of this application (see Fig. 7.18), the results of the network training can be read, after using the converse error propagation method. Thus, after a relatively large number of iterations (6140), the working root mean square error decreased under the preset value $\varepsilon = 0.001$ for all of the input datasets.

As a consequence of the training process, 21 weights of the neural connections were evaluated: 15 connections between layers 1 and 2, and 6 connections between layers 2 and 3, also taking into consideration the connections of the BIAS prediction units in layers 2 and 3. These weights are presented synthetically in Table 7.7. The histogram of this weight distribution is shown in Figure 7.19. The envelope of these histograms is close to a Gauss distribution, which confirms the weight calculus was correct.

The neural network running on the input data was performed using the simultaneous training method (the length of an epoch is equal to the number of datasets), so the weights were recalculated after each pass over all 26 datasets, and this allowed the training time to be shortened. Table 7.8 presents the results of the run: the output actual values, the target output values, and the interpreting error for each training dataset. A graphical plot of the actual and target outputs is shown in Figure 7.20; Figure 7.21 shows the output error histogram of the trained network. It should be noted that the neural network had classification trouble with sets 5 and 25, where the concordance between the evaluation criteria was not too good.

Training of the DIAGNOZA neural network can be considered successfully finished; DIAGNOZA may now be utilized in the problems of diagnostic classification for which it was built. The test for the DIAGNOZA neural network was performed on a group of six experimental datasets (Table 7.9), coming up after monitoring the forced wear of the same radial ball bearings type 6209 (see Chapter 5).

After data were linearly normalized, they ran in a trained neural network. The output root mean square error was 0.000307, therefore under the limit of 0.001 imposed for all sets. The network identified accurately the working state of the tested bearings; furthermore, during the test a false target was indicated for one of the input datasets, but the classification performed by the network did not change. This validated
Results of network training can be read after using converse error propagation method.

**FIGURE 7.18** Results of network training can be read after using converse error propagation method.
**TABLE 7.7** Twenty-One Weights of the Neural Connections Evaluated

Total evaluated weights: 21

*Between layer 1 and layer 2*

<table>
<thead>
<tr>
<th>Weight 1</th>
<th>Weight 2</th>
<th>Total</th>
<th>Weight 3</th>
<th>Weight 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.754083</td>
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<td>-0.962436</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>4.748973</td>
<td>5.315055</td>
<td>-2.021535</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>3.361797</td>
<td>-1.410271</td>
<td>3.961644</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>1.547162</td>
<td>-6.397412</td>
<td>4.818911</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>-3.090095</td>
<td>0.540312</td>
<td>-5.167025</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

*Between layer 2 and layer 3*

<table>
<thead>
<tr>
<th>Weight 1</th>
<th>Weight 2</th>
<th>Weight 3</th>
<th>Total</th>
<th>Weight 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.278813</td>
<td>1.963403</td>
<td>5.296241</td>
<td>-4.803792</td>
<td>-3.292156</td>
</tr>
</tbody>
</table>

that a good training of the network was achieved. **Figure 7.22** represents the actual values (the white bar) and the adopted values (the black bar) of the network output, in the test case.

In conclusion, training of DIAGNO and DIAGNOZA neural networks with data obtained from experimental research led to excellent performance of recognition and classification of elements in the machine tool structure. The tests performed—the most representative ones have been presented here—confirm the capabilities of this type of information processing.

**FIGURE 7.19** Histogram of weight distribution presented in Table 7.7.
TABLE 7.8  Output Actual Values, Target Output Values, and Interpreting Error for Each Training Dataset

<table>
<thead>
<tr>
<th>Set</th>
<th>Actual Set</th>
<th>Target value</th>
<th>Error</th>
<th>Set</th>
<th>Actual value</th>
<th>Target value</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0001</td>
<td>3.966598</td>
<td>4.000000</td>
<td>0.000124+</td>
<td>0002</td>
<td>2.027430</td>
<td>2.000000</td>
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</tr>
<tr>
<td>0003</td>
<td>1.008047</td>
<td>1.000000</td>
<td>0.000007+</td>
<td>0004</td>
<td>3.988856</td>
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<td>0.000014+</td>
</tr>
<tr>
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<td>3.000000</td>
<td>0.000842+</td>
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<td>1.003739</td>
<td>1.000000</td>
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</tr>
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<td>0.000018+</td>
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<td>0.000486+</td>
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<td>2.038465</td>
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<td>0.000015+</td>
<td>0012</td>
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<td>0.000011+</td>
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<td>1.977742</td>
<td>2.000000</td>
<td>0.000055+</td>
</tr>
<tr>
<td>0019</td>
<td>2.026888</td>
<td>2.000000</td>
<td>0.000080+</td>
<td>0020</td>
<td>3.989686</td>
<td>4.000000</td>
<td>0.000012+</td>
</tr>
<tr>
<td>0021</td>
<td>1.002707</td>
<td>1.000000</td>
<td>0.000001+</td>
<td>0022</td>
<td>1.002615</td>
<td>1.000000</td>
<td>0.000001+</td>
</tr>
<tr>
<td>0023</td>
<td>2.003102</td>
<td>2.000000</td>
<td>0.000001+</td>
<td>0024</td>
<td>2.939797</td>
<td>3.000000</td>
<td>0.000043+</td>
</tr>
<tr>
<td>0025</td>
<td>3.905148</td>
<td>4.000000</td>
<td>0.001000+</td>
<td>0026</td>
<td>3.020487</td>
<td>3.000000</td>
<td>0.000047+</td>
</tr>
</tbody>
</table>

RMS error: 0.000150
Good pats: 100.0%
FIGURE 7.20 Graphical plot of actual and target outputs.

FIGURE 7.21 Output error histogram of trained network.

TABLE 7.9 Test for DIAGNOZA Neural Network Performed on 6 Experimental Datasets

<table>
<thead>
<tr>
<th>Set No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak factor</td>
<td>8.53</td>
<td>23.14</td>
<td>16.05</td>
<td>25.73</td>
<td>18.56</td>
<td>23.91</td>
</tr>
<tr>
<td>Kurtosis index</td>
<td>3.97</td>
<td>8.29</td>
<td>5.48</td>
<td>9.81</td>
<td>6.50</td>
<td>8.60</td>
</tr>
</tbody>
</table>
FIGURE 7.22 Actual values (white bar) and adopted values (black bar) of network output in the bearings test.

7.3 FINAL REMARKS AND PROSPECTS FOR UTILIZING NEURAL NETWORKS FOR MACHINE TOOL DIAGNOSIS

As noted, utilization of neural networks allowed the exploitation at a higher level of the data library coming from experimental work and running. The success rate of the neural diagnosis depends mainly on the following factors.

1. Neural network architecture: The number of the network’s hidden layers can be neither too high nor too low. A network without hidden layers becomes a simple linear separator and does not reach its goal; on the other hand, a too large number of hidden layers makes the learning process inefficient. Usually, the number of hidden layers is 1 or 2. During the DIAGNOZA neural network elaboration, the same input datasets and the same initial aleatory weights were used for two networks: type $2 \times 5 \times 1$ and type $2 \times 4 \times 4 \times 1$. It was noticed that—although both networks had a 100% success rate—the learning process took longer in the case of the network with two hidden layers (the rapidity of convergence cannot be a disadvantage, since the learning process is offline). The classification errors were nearly one size order larger for more than half of the training datasets.
2. The training dataset size: It is well known and experimentally proven that neural network performance increases when the training dataset is larger. It is recommended that, when evaluating the necessary number of datasets for training, the complexity of the problem to be learned by the neural network be taken into consideration.

Information processing by means of neural networks proved to be a viable alternative for classical monitoring and diagnostic techniques. A comparison between the success rates of these techniques and those based on neural processing (Table 7.10) proves that the latter are better.

As noted, the neural networks elaborated were trained with data that had already undergone a previous process within criterial estimations (the peak factor criterion, the diagnosis index criterion, or Kurtosis criterion). But these networks are also capable of learning from unprocessed data, provided the target is indicated correctly. Such an approach could be done by building a neural network that can be trained by means of the captured signal; this network can be represented by a power spectrum. Figure 7.23 illustrates this spectacular change from neural networks fed with structured data (Fig. 7.23a) to a neural network able to recognize defects through a global representation of vibration signals (Fig. 7.23b).

In previous chapters, an analysis of characteristic frequencies was described for some elements of a kinematic chain structure. It was shown that, within the power spectrum obtained by applying the fast Fourier transform to the signal captured in the time field, the increase of amplitude for these frequencies is the result of certain typical defects’ nucle-

<table>
<thead>
<tr>
<th>No.</th>
<th>Monitoring/diagnosing technique</th>
<th>Success rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Peak factor method</td>
<td>50–70</td>
</tr>
<tr>
<td>2.</td>
<td>Diagnosis index method</td>
<td>62–70</td>
</tr>
<tr>
<td>3.</td>
<td>Kurtosis method</td>
<td>67–75</td>
</tr>
<tr>
<td>4.</td>
<td>Spectrum comparison method</td>
<td>70–85</td>
</tr>
<tr>
<td>5.</td>
<td>Envelope method</td>
<td>75–85</td>
</tr>
<tr>
<td>6.</td>
<td>Diagnosis neural networks</td>
<td>95–100</td>
</tr>
<tr>
<td>7.</td>
<td>Classification neural networks</td>
<td>98–100</td>
</tr>
</tbody>
</table>

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FIGURE 7.23 (a) Neural networks fed with structured data; (b) neural network able to recognize defects through global representation of vibration signals.

The nature and proportion of these defects can be identified by supervising the characteristic frequencies.

It is possible to build a diagnostic and classification system for defects on the basis of power spectrum recognition, by means of a principle schema similar to the one in Figure 7.24. In the signal captured and then processed in the frequency field, characteristic frequencies and eventually other characteristic parameters should be monitored; these parameters should take the shape of a state vector. A neural network trained with this sort of dataset provides at the output the interpretation of those data from a diagnostic viewpoint. Using a simple algorithm, these output parameters are related to different types of defects for the monitored/diagnosed element; the probability of the occurrence of these defects is indicated.
Elaboration of these neural networks represents a major step in developing diagnostic expert systems. Since the algorithmic method of learning is generally accepted for expert systems over the method of learning from experience, two components are necessary to build neural networks: a memorized list of rules and a set of procedures that allows conclusion interpolation by utilizing those rules and experimental data. Under these circumstances, the information neural processing would be the most advantageous way to assimilate the experience.
Final Conclusions and Original Contributions

8.1 GENERAL ASPECTS AND CONCLUSIONS—RECOMMENDATIONS

The performance of modern machine tools and the utilization of electronics in machining processes headed the growth of the field of technical diagnosis, a very important field of research.

Machine tools are complex dynamic structures that contain various sources of noise and vibration. Consequently, it is supposed that the noise and vibration are determined by the characteristics of the component mechanisms and subsystems. Also, both the parameters of the working regime and the characteristics of material workpieces have a great influence on these phenomena.

Research for the evaluation of machine tools is now channeled in some meaningful directions:

- Diagnosis of wear and wreckage of cutting tools
- Diagnosis of bearings, especially those for main shafts
- Diagnosis of adjusting mechanisms such as the gear box or feed box
In order to use vibroacoustic evaluation for machine tools, this book describes the specific sources of noise and vibration for machine tools, the requirements undertaken for the diagnostic systems, and the steps needed to build those systems. The book emphasizes the advantages of diagnostic systems utilization related to the cost of investment for their implementation, and it also draws some conclusions regarding the efficiency of the utilization of diagnostic systems for machine tools that are integrated into manufacturing technological systems.

This research starts with a documented study of the fundamentals of establishing a technical diagnostic for machine tools. It illustrates the diagnostic methods and techniques applied to the elements of the machine tools' kinematics chain: rolling and sliding bearings, gear and belt transmissions, and other rolling parts. The researchers are interested in the identification and interpretation of these vibration sources while, from the acoustic point of view, the modern tendency is towards the supervision of acoustic emission \((f > 100\, \text{kHz})\), a method which gives information from the microphenomena field of physics. This book presents current results obtained in the field. It has studied the diagnosis of electrical drive engines, the main sources of noise and vibration, from the mechanical, magnetic, and aerodynamic phenomena points of view. The principal aspects for diagnosis of the cutting tools and the machining process are displayed in this research because the machine tool cannot be separated from the context in which it does work.

In order to determine the relationship among source–signal–working condition, one should choose adequate parameters, diagnosis criteria, proper algorithms, and admissible levels for the chosen parameters. These principles have been followed during the elaboration of different diagnostic methods. The authors grouped these in two categories: (a) surface diagnosis methods (the peak element method, diagnosis index method, kurtosis method, and the shock impulse method); and (b) profoundness diagnosis methods (the spectral comparison method, evolute method, Cepstrum analysis method, and acoustic emission method). While the first group shows the working condition and/or the existence of a defect, the methods from the second category can be used in order to appreciate the type, the place of the defect, and the time until the working condition reaches the end. The book illustrates the theoretical basis of the above-mentioned methods and refers to their utilization domain and the way they can be used for the diagnosis of machine tools, cutting tools, and the machining process.
The physical model of the feed kinematic chain has been analyzed using the diagnosis method in order to see if it is adequate for studying diagnostic problems of the elements included in its structure. The working process on the machine is stable if the structure of the machine tool has an adequate dampening capacity in order to minimize the forced and self-excitation vibrations; otherwise the working process becomes unstable and the machine chatters. The dynamic stiffness of the machine tool is very important for determining system stability.

The results and small differences between the estimates of proper structure frequencies using the analytical technique (finite element method) and experimental technique (Nyquist diagram) confirm the adequacy of the model. Moreover, analyzing the deformations of the physical model demonstrates that the most important deformation shows up in the area of the mechanisms that are inclined to defective wear: ball screw-nut transformation mechanisms and rolling slides of the longitudinal carriage. These failures can influence the working of the mechanisms, hastening the appearance of the failure processes that can drive the mechanism wreckage. However, if the structure’s proper frequencies are known, one can compare these frequencies with those of all the mechanisms from the studied kinematic chain. Based on theoretical and experimental research and studying the literature in the field, it can be shown that these working frequencies are situated in a smaller field compared to the proper frequencies.

For an element that has mechanical defects, significant increases in the power range show up not only for characteristic frequencies but also for their higher values; it is possible for resonance phenomena with proper frequencies to appear. This can lead to the discovery of mechanical defects and to stoppage of the machine tool without any reason.

The development of virtual instrumentation is necessary because of the rapid transformations in the field of measurement devices, and because of the extraordinary performances of computers; this should be taken into consideration when establishing the technical diagnosis. Introducing computerized machining techniques in the field of signal acquisition and evaluation means an important gain regarding the rapidity, reliability, complexity, and flexibility of data measurement and processing.

This book presents original virtual devices that have been developed by the authors for surface and profoundness diagnosis. The devices were built using the structures presented in Chapter 3. The front panel with instructions was shown and the detailed block diagram presented...
for every built virtual device. The authors have identified the main noise and vibration sources from feed kinematic chains. The theoretical approach allows the calculation of characteristic frequencies of the motion elements from these kinematic chains.

Preliminary experimental research, started in 1992, used traditional acquisition and machining drafts based on the physical model; they operated on a testing stand that was conceived by making small adjustments to an existing machine. Experiments have been done using a multichannel acquisition system (produced by S.C. Emco S.A. with an eight-byte board and software created by the company specialists). These tests have shown the correlation between the appearance of failure factors, then of mechanical defects, and finally the indications of diagnostic methods. The FFT transformation of acquisition signals allowed the comparison of the frequencies induced by defects and characteristic frequencies of the studied mechanisms. It was demonstrated that knowing the characteristic frequencies during the analysis of acquired vibroacoustic signals is very necessary.

The utilization of virtual instrumentation for experimental research using virtual devices has settled a comparison with the same diagnostic methods but accomplished by traditional instruments. The conclusion is that the virtual instrumentation is the best because it can be easily utilized, and it is very precise. Also, the results indicate that virtual instrumentation is satisfactory for use in vibroacoustic diagnosis. The virtual instruments achieved are operational and can be found in S.C. Eurotest S.A. laboratories; this company offered the necessary logistic support throughout the experiments. The methodology and measurements plan indicated that experimental research imposed by the diagnostic techniques should be done in normal conditions and accelerated tests. The utilized diagnostic methods proved that they were efficiently chosen, leading to a correct and precise evaluation of the working conditions of the controlled elements.

During the trials, the unmistakable correlation between the vibrating signal and the working condition for some constitutive mechanisms of feed kinematic chains was emphasized. As to the use of noise as a diagnosis basis, the main disadvantages of signal catching and processing were presented. At the same time, the correlation between noise and the vibratory signal global level was pointed out. The simultaneous utilization of different diagnostic techniques and the accumulated experience led to a firm conclusion: monitoring the working condition of the
machine tool or of the constitutive elements should be realized using
time domain techniques and establishing the technical diagnosis should
be accomplished using frequency domain techniques.

The book utilizes parallel processing theory in order to capitalize
the research database. With this type of information processing expe-
riential knowledge can be stored, which is why the neural network was
created. Two diagnostic neural networks have been elaborated: one for
choosing the good bearings from bad ones, and the other, more ad-
vanced, which is capable of classifying the bearings’ working condition
into four categories, ranging from good to bad. Information processing
using neural networks is a viable competitor to classic techniques for
monitoring and diagnosis. A comparison between the success ratio of
these techniques and those based on neural processing will definitely
favor the latter.

8.2 ORIGINAL CONTRIBUTIONS

From the theoretical point of view this book displays the following orig-
inal aspects:

The identification of noise and vibration sources from feed kine-
matic chains
The elaboration of a reckoning method for characteristic frequen-
cies of the ball screw-nut mechanism
The method and calculation of characteristic frequencies for ball
tankettes
The introduction of virtual instrumentation for machine tool diag-
nosis
The development of three virtual instruments for surface diag-
nosis, based on verified diagnostic methods, using time signal
processing
The elaboration of two virtual instruments for profoundness diag-
nosis, based on competitive methods from the signal frequency
processing domain
The introduction of information neural processing for machine tool
diagnosis
The generation of a multicriteria neural network having data from
experimental research, which creates a network capable of rec-
ognizing perfectly working bearings from deficient bearings
The elaboration of a neuronal network able to perceive the working condition of the bearings
The realization of a diagnostic analysis, using the finite element method, for the physical model of the feed kinematic chain
The systematization of theoretical and experimental diagnostic methods in order to establish the technical diagnosis of machine tools
The elaboration of some conclusions and recommendations regarding the diagnosis of vibroacoustic methods and their application for machine tools

From the point of view of experimental research, the original contributions refer to:

The investigation of the correlation between some statistical parameters of the vibration signal and the working condition of some ball bearings and needle bearings
The experimental identification of characteristic frequencies of some elements from feed kinematic chain structures and their comparison with the theoretic frequencies
Research aspects of determining the technical diagnosis using frequency analysis of the vibration signal
Diagnostic analysis of the physical model stability using a Nyquist diagram and the identification of the weak points in the system
The testing and utilization of original diagnostic virtual devices, both for surface diagnosis and profoundness diagnosis
The testing of the neural networks with experimental unsystematized data and the checking of their estimation capacity from the point of view of the working condition

8.2.1 Perspectives for Continuing Research

Based on the virtual instrumentation obtained, the concept of vibroacoustic diagnostic equipment may begin. The virtual instruments can be transformed into implemented programs that, together with an adequate hardware interface, can be easily used by everyone.

The theoretical and experimental research on working frequencies for the mechanisms of machine tool kinematic chains should continue based on the research methodology illustrated in the book. Research for correlating many different parameters in order to establish the technical
diagnosis in machine tools and the machining domain should also be continued, as should the development of a database regarding vibro-acoustic diagnosis and its use in processing information through neural network techniques for learning by practice.

Conceiving and developing diagnostic expert systems specialized for machine tools, including the diagnosis of cutting tools and the machining process is another area for future work.
Appendix 1: Surface Diagnosis

A1.1 SURFACE DIAGNOSIS

A1.1.1 INDKURT Virtual Instrument Applied to Some Elements of the Feed Kinematic Chain Structure (Tested Physical Model)
234 Appendix 1

FIGURE A1.1 Signal captured from the ways (guidings) of the saddle—ways type tankettes with rolls. Diagnosis by Kurtosis method.
FIGURE A1.2

Signals captured from the font ball bearing of the leading screw for lateral location. Diagnosis by Kurtosis method.
FIGURE A1.3 Signal captured from the longitudinal saddle of the feed kinematic chain. Diagnosis by Kurtosis method.
FIGURE A1.4 Signals captured from the front ball bearing of the leading screw for top location. Diagnosis by Kurtosis method.
FIGURE A1.5

Signal captured from the nut of the screw-nut mechanism with balls—lateral location. Diagnosis by Kurtosis method.
FIGURE A1.6 Signal captured from the nut of the screw-nut mechanism with balls—top location. Diagnosis by Kurtosis method.
Appendix 2: Profoundness Diagnosis Through Virtual Instrumentation

A2.1 PROFOUNDNESS DIAGNOSIS

A2.1.1 MECOSPEC Virtual Instrument Applied to a Radial Ball Bearing Coming from a Sheet Metal Rolling Mill
Figure A2.1  Signal acquisition and spectrum comparison.
Figure A2.2 Representations of the acquisitioned spectrums.
Appendix 3: General Notions Regarding the Diagnosis of the Functioning State of Machine Tools

A3.1 COMPELLED VIBRATIONS

Compelled vibrations appear because of kinematics and/or dynamic factors. They have a permanent occurrence and major consequences on the working of the technological equipment, and on the equipment, technological process, and workpiece quality.

The usual classification of this type of vibration incorporates (a) compelled vibrations that depend on the working process, including such factors as stock variation, the periodic variation of the chip cross-section (milling, stitching), workpiece material hardness variation, and work-speed variation; being dependent on the working process characteristics these vibrations are very difficult to avoid; and (b) compelled vibrations that are not dependent on the working process, which appear because of a deficiency mounting of the equipment, technological and assembling lack of precision of the parts, and because of some specific features. This type of vibration can be observed during idle running of the equipment.

The following are some influence areas of factors that are independent of the working process.

The floor vibrations have a complex spectrum of periodic and random components and also shocks with a frequency range of 1, ..., 40 Hz.
with amplitudes between 0.5, . . . , 15 mm. The functioning of electrical engines (especially three-phased asynchronous engines and continuous current engines) induces a wider spectrum, 16, . . . , 530 Hz, with amplitudes up to 0.4 mm.

A special influence on gearing working is made by pitch errors, profile errors, the wheels’ eccentricities, and the axle deformations on which they are mounted. Two critical zones have been observed in experiments: one corresponding to the specific frequency of the elastic system of the teeth and the other corresponding to the specific frequency of the elastic system gear-shaft.

The driving belt transmissions introduce vibrations corresponding to specific throbs. They can be computed using the formula:

$$\omega n = \frac{\pi n}{l} \sqrt{\frac{S}{m}}$$

where \(l\) is the length of the belt, \(m\) is the weight of the belt, \(S\) is the belt tension, and \(n\) is the pulsation number \((n = 1, 2, 3, \ldots)\).

The vibrations caused by the movement of the bearings depends mainly on shaft rotation frequency and on the number of rolling elements. The functioning of hydraulic systems, of cam mechanisms, Malta cross, and the like also produce compelled vibrations of frequencies and amplitudes which can be estimated.

Compelled vibrations, within or outside the process, appear and take place simultaneously, which means that vibrational phenomena have a complex nature and their consequences should be evaluated taking into account all the stages of the working process.

### A3.2 MEASUREMENT OF VIBRATIONS, SPECIFIC QUANTITIES

The vibrator signal picked up in the measurement points using translators is, usually, an aleatory sum of periodic and nonperiodic vibrations. Ways of processing and evaluating this signal are described below.

#### A3.2.1 Periodic Determinist Vibrations

The pure harmonic movement (Fig. A3.1) is characterized by the mathematical equation:

$$x(t) = X_v \cdot \sin(\omega t + \theta)$$
where $X_v$ is movement amplitude (the peak value), $\theta$ is phase difference, and $\omega$ is movement throb.

By derivation one can obtain the movement speed and acceleration, respectively:

$$v(t) = \frac{dx}{dt} = \omega X_v \cos(\omega t + \theta) = V_v \sin \left( \omega t + \theta + \frac{\pi}{2} \right)$$

$$a(t) = \frac{d^2x}{dt^2} = -\omega^2 X_v \sin(\omega t + \theta) = A_v \sin(\omega t + \theta + \pi)$$

The speed and the acceleration of the movement are also harmonic, having the same throb as the displacement, with a phase difference of $\pi/2$ and $\pi$, respectively.

The characterization of periodic determinist vibrations is possible not only by throb and amplitude but also by defining some features related to the process progress during one period:

Absolute average value (mathematical), $X_A$:

$$X_A = \frac{1}{T} \int_0^T |x(t)| dt$$

Effective value (square average), $X_{ef}$ (RMS):

$$X_{ef} = \sqrt{\frac{1}{T} \int_0^T x^2(t) dt}$$
The configuration element, $F_f$:

$$F_f = \frac{X_{ef}}{X_a}$$

The peak element, $F_v$:

$$F_v = \frac{X_v}{X_{ef}}$$

Note: in the case of pure harmonic movement between $X_V$, $X_A$, and $X_{ef}$ for $F_f$ and $F_V$, respectively, the mathematical relationships are:

$$X_{ef} = \frac{\pi}{2\sqrt{2}}X_A = \frac{1}{\sqrt{2}}X_V$$

$$F_f = \frac{\pi}{2\sqrt{2}} = 1.11 \ (\approx 1 \text{ dB})$$

$$F_V = \sqrt{2} = 1.414 \ (\approx 3 \text{ dB})$$

The deformation energy (elastic) of the elastic system, $W_p$ is

$$W_p = \frac{k}{2} \int_0^T x^2(t) dt$$

Among these parameters the most important is $X_{ef}$ because it is proportional to the vibration power; this can be seen from the previous mathematical formula.

### A3.2.2 Aleatory Vibrations

In this case movement is irregular and not repeated in time; the vibration should be monitored constantly (theoretically, infinitely); however, this is impossible. In practical terms it can work at specific intervals of time, which are called “achievements” of the periodic process. All these “achievements,” picked up in similar conditions, form the aleatory process itself. This method requires a very long time; as a result, one can introduce some probabilistic features that are capable of characterization of the aleatory vibrations.
The performances can be interpreted in terms of time or overall (Fig. A3.2). The amplitude in a specific time $t_1$ is an aleatory feature, and it is characterized by the statistical values during the considered “achievements”:

$$x_1(t_1) = [x_1(t_1), x_2(t_1), x_3(t_1) \ldots]$$

If the same probability is considered for every “achievement” $x_k(t)$ the following features can be described:

The average value of the amplitude, on time $t$:

$$m(t_1) = \lim_{n} \frac{1}{n} \sum_{k=1}^{n} x_k(t_1)$$

The autocorrelation function, which can appreciate in what measure the aleatory process remains identical with itself:

$$\psi(t_1, \tau) = \lim_{n} \frac{1}{n} \sum_{k=1}^{n} x_k(t_1) \cdot x_k(t_1 + \tau)$$

**Figure A3.2** Aleatory vibrations.
The intercorrelation function:

\[ \psi'(t_1, \tau) = \lim_{n \to \infty} \frac{1}{n} \sum_{k=1}^{n} x_k(t_1) \cdot y_k(t_1 + \tau) \]

which estimates the way two aleatory signals \( x(t) \), \( y(t) \) are similar.

### A3.2.3 Ergodic and Stationary Aleatory Vibrations

Stationary processes are those processes for which the average value and autocorrelation function do not depend on the specific time \( t_1 \):

\[
m(t_1) = m(t_2) = \cdots = m \\
\psi(t_1, \tau) = \psi(t_2, \tau) = \cdots = \psi(\tau)
\]

For every “achievement” of a stationary aleatory process one can calculate the average value and the autocorrelation function, respectively:

\[
m_x(k) = \lim_{T \to \infty} \frac{1}{T} \int_{-T/2}^{T/2} x_k(t) dt \\
\psi(k, \tau) = \lim_{T \to \infty} \frac{1}{T} \int_{-T/2}^{T/2} \frac{x_k(t) \cdot x_k(t + \tau)}{T}
\]

This means that an ergodic aleatory process can be characterized by a “single achievement” which is a great advantage in practice.

Other features for these processes include the repartition function of the amplitudes; \( F(x) \) is defined by the probability that the movement amplitude is inferior to a given value \( x \):

\[
F(x) = P(-\infty < x(t) < x) = P(x(t) < x)
\]

This function is a monotone increasing function (Fig. A3.3) and it helps determine the probability that the movement amplitude can be found in a given range \((a, b)\):

\[
P(a < x(t) < b) = F(b) - F(a)
\]

In addition, the amplitude probability density is the limit ratio between the probability that the momentary amplitude of the aleatory movement

---

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can be found stuck between a given interval and the magnitude of this interval when it tends to zero:

\[ p(x) = \lim_{\Delta x \to 0} \frac{P(x \leq x(t) \leq x + \Delta x)}{\Delta x} \]

In conformity with the previous relation it can be inferred that

\[ p(x) = \lim_{\Delta x \to 0} \frac{F(x + \Delta x) - F(x)}{\Delta x} = \frac{dF(x)}{dx} \]

The most well-known analytical form for the amplitude probability density function is the Gaussian (Fig. A3.4).

**A3.2.4 Noise and Acoustic Emission**

**A3.2.4.1 Sound and Noise**

Sound is the sensation that is perceptible by the human ear as a result of rapid fluctuations of air pressure; it represents the mechanical vibration of an elastic medium in which the energy can be propagated from the source by progressive sound waves. The noise is usually described as a sound or a sum of undesirable sounds. It is considered to be a byproduct of daily activity.

The characteristic of sound waves is that substantial particles oscillate with respect to an equilibrium position and the wave propagation speed (the sound speed) is significantly higher than the oscillation speed.
FIGURE A3.4 Gauss form for the amplitude probability density function.
of the particles. The distance traveled by the front wave during an oscillation period is called the wavelength: $\lambda = c/f = c*T$, where $c$ is the propagation of the sound speed, $f$ is the frequency, and $T$ is the period or the duration of a complete oscillation.

The dependency of the wavelength on the frequency is shown in Figure A3.5, where the medium of sound propagation is air; for this medium the speed propagation is given by:

$$c = f \sqrt{\gamma_0 \frac{p}{\rho}},$$

where $\gamma_0$ is the ratio between the specific heat on constant pressure and the specific heat on constant volume, $p$ is static pressure, and $\rho$ is the mass of the volume unit of the medium. Depending on the distance between source and receiver, the sound waves are considered to propagate in the shape of progressive plane waves or progressive spherical waves while the source can be pointlike or linear.

**Decibel.** The introduction of a decibel measurement scale (dB) for a subjective evaluation of sound power is based on Weber–Fechner physiological law. According to this law, the subjective sensation is proportional to the decimal logarithm of the excitation when the reference level of the acoustic intensity is zero. The lowest acoustic pressure that the human ear can sense is 20 mPa, which is $5 \times 10^9$ times weaker than normal atmospheric pressure.

The sonorous pressure, expressed in mPa, varies in a very large range from 20 to 108 mPa. Therefore, it is difficult to do mathematical calculus using such a scale. The decibel scale (Fig. A3.6) avoids this difficulty because it uses an audibility threshold of the value 20 mPa. This value is considered to be 0 dB. Consequently, every time the acoustic pressure (in Pa) is multiplied by 10, 20 dB will be added to the decibel

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**Figure A3.5** Dependency of wavelength by frequency.
Figure A3.6  Decibel scale.
level; hence, 200 mPa corresponds to 20 dB, 2000 mPa corresponds to 40 dB, and so on. So, the scale in decibels compresses the values from 20 to 20 million mPa in a range of 0 to 120 dB.

Another useful aspect of the decibel scale is that it offers a better approximation of the noise threshold by human perception: the human ear reacts to relative changes of threshold. On this scale, 1 dB variation is the same relative variation no matter where it is placed on the scale, 1 dB being also the lowest variation that humans can sense. An increase of 6 dB represents twice the threshold of acoustic pressure and an increase of 10 dB is necessary in order to obtain a sound twice as strong.

**Physiological Perception of the Noise.** The human auditory apparatus, the ear, allows the perception of sounds produced by different sound waves with frequencies between 16 Hz and 20 kHz (the audibility domain). The maximum sensitivity of the ear is in the range of 2000 and 6000 Hz.

If two sounds have frequencies $f_1$ and $f_2$ it is said that they are separated by the interval $f_1/f_2$. If $f_2 > f_1$ those two frequencies have the bandwidth $\Delta f = f_1 - f_2$. In the acoustic industry, bandwidths having an octave and a tierce (a third of an octave) which have the corresponding intervals of 2 and $\sqrt[3]{2} = 1.26$, respectively, are very important. The central frequency $f_c$ of an octave is the frequency that has the limited frequencies $f_1$ and $f_2$ such as $f_c = \sqrt[3]{2} f_1$. When bandwidths have an octave, the normalized central frequencies are 31, 63, 125, 250, 500, 1000, 2000, 4000, 8000, 16,000 Hz and upward.

In order for a sound to be perceptible, it is necessary that its sonorous intensity have a specific minimal level that depends on sound frequency and on the sensibility of the ear. The lower limit of the acoustic pressure, for a given frequency that can be heard by a human being is called the audibility threshold. It is considered to be a sound with the frequency of 1000 Hz and sonorous pressure of $2 \times 10^{-5}$ N/m². For lower frequency sounds (<1000 Hz) the audibility threshold increases.

On the other hand, very strong sounds create pressure on the eardrum that can induce pain. The threshold where the pain appears is $2 \times 10$ N/m² for the frequency of 1000 Hz. The power of the sounds represents a feature according to which the sounds can be arranged from weak to strong. Subjective perception of a sound or noise strength depends on the acoustic pressure level and on its spectral characteristic.

Figure A3.7 illustrates Fletcher–Munson izosonic curves. Standard sound has the frequency 1000 Hz for an acoustic pressure of 1 dB.
In order to appreciate the acoustic pressure level the term moderate acoustic level has been used. Hence, the measurement apparatus is equipped with balanced filters given by the A, B, C, or D curves in Figure A3.8. The most used moderate acoustic level is represented by the A curve, especially in industry and transportation. In the aerospace industry the moderate acoustic level is illustrated by the D curve.

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A3.2.4.2 Acoustic Emission

Acoustic emission is the sequence of elastic waves generated by the release of the internal energy stored in a structure. It becomes manifest in the higher frequency domain \((f > 100 \, \text{kHz})\) by elastic waves detected as vibrations on the structure surface. Acoustic emission represents a nondestructive method used in order to perceive when and where a flaw or a crack appears. The nature and the causes of these shortcomings are determined using complementary methods.

There are four main sources of acoustic emission:

- Movements of structural dislocation
- Phase transformations
- Friction mechanisms (microfrictions, microcollisions)
- Formation and development of cracks

In the case of dislocations (movement of a line imperfection within a crystalline structure) which develop like an avalanche, the signal is continuous while in the case of phase transformations (the formation of martensite in carbon steel) the signal is impulse type and can be detected for every transformed grain.

Flaws come into view in the material where the stress outruns strength tension. New surfaces appear and there is a release of energy that is partially transformed in acoustic emission. The signal is impulse type having high frequency. At the same time, friction mechanisms also emanate acoustic signals. The signal amplitudes in acoustic emission cover a large area; in relative units these amplitudes are 1 to 10 for structural movements, 5 to 1000 for phase transformations, and 20 to 1000 for flaws. For machining with machine tools these sources are: continuous and discontinuous chip forming; deformation of the workpiece material; cracking of the workpiece or of the tool; or friction between workpiece, tool, chip breaker, breakage, and collision of the chip. There are also sources that appear from the functioning of the mechanical sub-system (bearings, gears) and high-frequency electrical sources.

The propagation of acoustic emission is similar to radio waves. The source emits spherical wave packages that are influenced by the surfaces which are intersected; this creates reflections and surface waves (Fig. A3.9). The heterogeneities of the propagation medium distort the front waves. Consequently, the mathematical relationships that describe the real propagation phenomena become very complicated when one needs to locate and measure the sources and effects of the phenomena.
Figure A3.9 Wave packages influenced by surfaces they intersect.
Further on, the area of utilizing these methods (based on acoustic emission) on large steel structures where an uncertainty coefficient can be accepted, becomes very narrow.

In industry acoustic emission is used for controlling wear and tool breakage and also for supervising the bearings and hydrodynamic bearings.

### A3.2.4.3 Acoustic Emission Measurement

As shown in the previous section, acoustic emission is constituted from surface waves. Special piezoelectric transducers connected to the structure that is to be monitored can perceive them very well. The signal monitored by the transducer can be processed in two ways: for a continuous emission the most useful information is given by the voltameter; or for impulse type signals one can use the impulse analyzer. Another technique is based on counting the impulses using a peak indicator with an adjustable threshold level.

### A3.2.4.4 Acoustic Parameters

**Propagation Velocity of Sonic Waves.** Sound waves in solids follow the equation

\[
c_{l(t)} = \sqrt{\frac{E(G)}{\rho}}
\]

where \(E\) is the longitudinal elasticity module, \(G\) is the transversal one, and \(\rho\) is the density of the medium, which is homogeneous and isotropic.

The propagation of the sound waves in liquids follows a similar equation, where \(k_0\) is the compression modulus:

\[
c = \sqrt{\frac{k_0}{\rho}}
\]

Sound wave propagation in gases is adiabatic and follows, therefore, the formula \(pV^\gamma = \text{const.2}\), and the propagation velocity is given by the relation:

\[
c = \sqrt{\frac{\gamma p}{\rho}} = \sqrt{\frac{\gamma RT}{\mu}}
\]
where $\gamma_3 = \frac{cp}{cv}$ is the adiabatic exponent, while $R$ is the constant of perfect gases. For the case of sound wave propagation through air, the relation remains

$$c = 332\sqrt{1 + \frac{t}{273}}$$

where $t$ is the air temperature ($^\circ$C), which leads to determination of the sound wave propagation at a temperature of 20$^\circ$C to be approximately 340 m/s.

Sonic pressure, is, by definition, the average of pressure variation, meaning:

$$p_s = \sqrt{(\Delta p)^2}$$

The acoustic level (level of sonic pressure) is determined as

$$L_p = 10 \log \left( \frac{p}{p_0} \right)^2 = 20 \log \left( \frac{p}{p_0} \right)$$

where $p_0 = 20$ mPa is the threshold, considered to be the audibility limit for a sound having the frequency of 1 Hz.

The intensity of the sound can be defined as the average value of the acoustic energy that travels through the surface unit, on a direction perpendicular to the propagation, in a unit of time. The equation of the sound intensity depends on the propagation area: for the progressive wave in a free field it is

$$I = \frac{p_{s,f}^2}{\rho c}$$

and for the progressive wave in a fuzzy field it is

$$I = \frac{p_{s,f}^2}{4\rho c}$$

where $p_{s,f}^2$ is the square average value of the sonic pressure.

The sound intensity level can be described similarly to the acoustic level; that is,

$$L_i = 10 \log \left( \frac{I}{I_0} \right)$$
where $Io$ is the threshold of the acoustic intensity; that is, $Io = 10$ to $12$ W/m$^2$. It can be pointed out that in normal conditions ($po = 1$ atm. and $to = 22^\circ$C), the difference between the value of the acoustic pressure and acoustic intensity level is, for the same sound, $0.16$ dB, and, therefore, it can practically be ignored.

The level of acoustic power of a sonic source can be evaluated by using the relation

$$L_w = 10 \log \left( \frac{P}{P_0} \right)$$

where $P_0$ is the threshold of the acoustic power level, $P_0 = 10$ to $12$ W.

### A3.3 Correlation Between Sound Analysis and Machine Tool Performance: Technical Diagnosis Equipment

#### A3.3.1 Time Analysis

The acoustic signal can be considered to be created by a sum of pure harmonic pulsations having different intensities and frequencies, and therefore

$$x(t) = x_0 + \sum_{i=1}^{n} x_i \sin \frac{2\pi t}{T_i}.$$

As previously presented, it is possible to characterize a signal by using a series of parameters that define the progress of the signal in time (usually, for one period): absolute arithmetic mean, $xA$; effective value (of the squared average), $xef$; and pick value, $xv$, $xv = \max\{x(t)\}$.

Correlation analysis is the most utilized tool for time analysis, being recommended for linear systems that operate either with continuous or discrete signals, especially when the ratio between signal and noise has a small value. Acceptable input values are either stochastic signals or periodic signals, leading, as a result, to the correlation functions and, as a particular case of these, the weighted function. The correlation functions define the level of similarity between two given signals in accordance with the time delay between them (intercorrelation function):

$$R_{ab}(\tau) = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} a(t) \cdot b(t + \tau) dt$$
or, even, the level of similarity of a signal with itself, in accordance with the time delay (self-correlation function):

\[ R_{aa}(\tau) = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} a(t) \cdot a(t + \tau) dt \]

For the case of a invariant stable and linear system, by noting with \( h(k) \) the weighted function or the reaction of the considered system at an impulse, the self-correlation function and the intercorrelation function are connected by a relation having the form:

\[ R_{ab}(\tau) = \sum_{k=0}^{\infty} h(k) \cdot R_{aa}(\tau - k) \]

A correlation graph is a graphical representation of the self-correlation function in accordance with the time delay. Its form suggests the contents of the signal’s frequencies. The correlation graph gives a peak value for \( t = 0 \), which is sharper as the contents in high frequencies are richer; this value is equal to the square mean value of a random process, being, therefore:

\[ R_{aa}(0) = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} a(t) a(t) dt = \overline{x^2(t)} \]

For a linear system, the integral is proportional to the energy along the interval considered; by dividing this value by the length of the interval one can obtain the average power along that interval, and this is the physical significance of the value of the square mean.

Figure A3.10 presents some significant types of correlation graphs: (a) the correlation graph of a random and stationary ideal process (no noise); (b) the correlation graph of a nonperiodic process for large values of the time displacement \( t \) (the self-correlation functions tend to attend the square mean value); (c) idem, when the square average value is zero; and (d) the correlation graph of a random process that conceals a periodic phenomenon (the correlation graph tends to become a periodic function in time \( t \)).

By calculating the Fourier transform of the self-correlation function one can obtain the spectral density function of the square mean value (power spectral density):

\[ \Im\{R(\tau)\} = \int_{-\infty}^{\infty} R(\tau) e^{-i2\pi f \tau} d\tau = S(f) \]
**Figure A3.10** Significant types of correlation graphs: (a) correlation graph of random and stationary ideal process (no noise); (b) correlation graph of nonperiodic process for large values of time displacement $t$ (self-correlation functions tend to attend the square mean value); (c) idem, when the square average value is zero; (d) correlation graph of random process that conceals a periodic phenomenon (correlation graph tends to become a periodic function in time $t$).
This function depicts the manner in which the square mean value (and the average power, also) is distributed in the domain of frequencies. A periodic vibration can be represented in the frequency domain by a band formed by discrete lines, each line representing the square mean value of the respective harmonic component, while a random vibration determines a continuous band in the frequency domain; so, the measured value of the square mean for a given frequency depends on the utilized bandwidth; that is why the spectral power density is useful. The self-correlation function and the spectral density power form a pair of Fourier transforms in such a manner that the first one can be rapidly obtained by applying an inverse Fourier transformation on the second one.

A3.3.2 Analysis in the Frequency Domain

The acoustic signals can not be analyzed by studying only the amplitude-time characteristic because this does not furnish sufficient data for a diagnostic interpretation.

The separation of the vibrations in individual frequency components is called frequency analysis (Fig. A3.11), this being a technique that can be considered as the fundament of the diagnosis, which is based on studying vibrations and acoustic signals. The curve that indicates the amplitude of the vibrations versus frequency is called a spectrogram.

The most sophisticated and most precise techniques for establishing the diagnosis of the performance of machine tools and equipment are based on signal analysis in the frequency domain. This analysis can be accomplished using various protocols, depending on the element studied, diagnosis method, and apparatus controlled by the researcher or existing in a research laboratory.

Gauge apparatuses for measuring vibrations and noise indicate a unique band of signals evaluated along the entire bandwidth (Fig. A3.12a). To evaluate the individual frequency components a filter is utilized, which will allow passing only those signals' components within a tide bandwidth. The filter's passband is successively displaced along the entire domain and as a result a reading of the level of vibration is obtained in the bandwidth. The filter can be formed either by a series of individual filters for fixed frequencies, which are adjacent and successively scanned (Fig. A3.12b), or by a unique adjustable filter displaced within the studied frequency domain (Fig. A3.12c).
A3.3.2.1 Frequency Analysis for Tight Bandwidth

This kind of analysis is the most common vibration processing procedure and, due to its precision and the accuracy of the components of the processed signal, the most utilized method for monitoring and diagnosis.

One can utilize two basic types of filters: constant bandwidth type, having an absolute bandwidth of 3 Hz, 10 Hz, and so on, and constant proportional bandwidth type, having a bandwidth expressed as a percentage (3%, 10%, etc.) of the selected central frequency.

In Figure A3.13 the difference between these two types of filters is presented. It should be stressed that the constant proportional bandwidth filters were built in order to maintain a constant bandwidth on logarithmic scales of frequencies, which are ideal for large bandwidths.
**Figure A3.12** (a) Unique band of signals evaluated along entire bandwidth; (b) series of individual filters for fixed frequencies, adjacent and successively scanned; (c) unique adjustable filter displaced within studied frequency domain.
FIGURE A3.13  Difference between constant bandwidth and constant proportional bandwidth types of filters.
However, if the frequency scale is linear, a constant bandwidth filter will give a constant representation, while the constant proportional bandwidth filter will show an enlarged bandwidth, which is not an advantage in practical cases.

Constant proportional bandwidth filter analysis shows the natural response of the systems to mechanical vibrations and permits a compact representation of a large bandwidth; that is why this is the most commonly utilized method for measuring the vibrations.

Constant bandwidth filter analysis is utilized for high frequencies, especially for a linear scale, in order to distinguish the harmonic components.

The filter-pass bandwidth establishes the resolution of the frequency analysis to be obtained. The employment of a filter having a tight bandwidth offers numerous details and permits the isolation of individual peaks within the band, but has, at the same time, the disadvantage of an increased processing time together with a narrowed bandwidth. Sometimes a reduction of the processing time is possible through time compression, that is, fast-forward playing of the recorded signal. In that way the filter’s bandwidth increases proportionally, and this leads to an increased scanning rate along the frequency domain.

The ideal filter should let pass all the frequency components that appear in the bandwidth while eliminating all other frequency components. Practically, electronic filters have no perfectly vertical limits, and therefore do not totally eliminate the components outside the bandwidth domain.

In practice two methods are utilized for measuring the filter’s bandwidth: as the bandwidth of an ideal filter that lets pass the same quantity of power coming from a white noise source such as the described filter (Fig. A3.14a); and as the bandwidth of a filter that shows an altering of 3 dB in rapport with the normal transmission level (Fig. A3.14b).

The 3 dB bandwidth will differ considerably from the bandwidth of effective noise only for low selectivity filters, and therefore one can consider that the two definitions lead to the same practical result.

**A3.3.2.2 Frequency Analysis Using Fourier Series**

By using the Fourier theorem and for the given Dirichlet conditions, the periodic deterministic vibrations can be looked upon as a sum of harmonic pulsations, having frequencies equal to multiples of a fundamental frequency. In this case, the transform in the frequency domain can be accomplished using Fourier series by decomposing; during the
transforming process only one period of the signal is usable. The transformation relations (Fig. A3.15a) convert the continuous periodic signal from the time domain into a discrete band in the frequency domain, a band that encloses all the harmonics of the signal. The inverse situation is also possible by which a discrete signal in time is transformed in a periodic frequency (Fig. A3.15b). One can observe that due to the symmetry and the periodicity of the frequency band a component having the frequency $f_c$ in the continuous signal will appear in the discrete signal at the frequencies $f_d = n \cdot f_s \pm f_c$, where $f_s$ is the discrete frequency and $n = 0, \pm 1, \pm 2, \ldots$. In this case, in order to avoid ambiguities in the frequency contents of the continuous signal, a pass filter is utilized, which is not as broad as the half value of the discrete frequency.

The transform relations shown in Figure A3.15 prove the basic symmetry of the Fourier transform between the time domain and the frequency domain.

### A3.3.2.3 Frequency Analysis Using Discrete Fourier Transform

The discrete Fourier transform (DFT) is applied to discrete and periodic signals in the time domain and the result is, also, a discrete and periodic signal, but in the frequency domain (Fig. A3.16). Due to the periodicity in both domains, only a finite number of samples are employed, therefore...
FIGURE A3.15 Transform in frequency domain can be accomplished using Fourier series.

The transform can be calculated using digital processing, for instance, if a period of a signal is described in the time domain by $N$ samples along one period.

The determination of a discrete Fourier transform having $N$ values within a sequence implies $N \times N = N^2$ multiplication and summation operations of complex numbers, which determine a rapid increase of the calculation time for a larger number of samples $N$. Nevertheless,
Discrete Fourier transform (DFT) is applied to discrete and periodic signals in the time domain.

due to the symmetry of the frequency band, only $N/2$ of them will be independent. In addition, by utilizing an anti-over imposing filter (having a bandwidth narrower than half of the sampling frequency) the number of significant frequency components is reduced even further. Usually, for a signal in time having 1024 samples only 400 frequency lines from the band will need to be processed.

### A3.3.2.4 Frequency Analysis Utilizing Fast Fourier Transform

The algorithm of the fast Fourier transform (FFT) is based on several features of the complex exponential function in order to shorten the calculation time of a regular Fourier transform. In this case, the number of operations is diminished from $N^2$ to $N \ast \log_2 N$. The signal processing procedure for the case of FFT analysis is presented in Figure A3.17. One can observe that it is necessary to input the recorded signal into a sampling block having an analogue-to-digital conversion element because the output signal obtained at the output of the transducer has a continuous variation.

The FFT algorithm considers a record from the time domain as being a block of $N$ samples equally separated in time, and which can be transformed into another block of $N$ samples also equally separated but in the frequency domain (Fig. A3.18). The lowest frequency to be
**Figure A3.17** Signal processing procedure for the case of FFT analysis.

**Figure A3.18** Block of $N$ samples equally separated in time transformed into another block of $N$ samples also equally separated but in the frequency domain.
analyzed by FFT is determined by the length of the record in the time domain, while the maximum value of the frequency that can be separated is \( f_{\text{max}} = \frac{N}{2} \times \frac{1}{TR} \), \( TR \) being the record duration.

The necessary calculations for using the FFT algorithm require a finite time, in terms of the number of samples (usually \( N = 1024 \)), but also of the speed of the processor implied. If this calculation (TFFT) is less than the duration for the recorded signal (TR), the operation is called the analysis in real-time. In this case, the analyzer processes, along the duration of a record, a FFT analysis of the preceding record, so no information from the time domain is lost, a situation that can occur if TFFT is larger than TR.

The basic relation of the FFT algorithm is still the one known from the discrete Fourier transform; that is,

\[
G(k) = \frac{1}{N} \sum_{n=0}^{N-1} g(n)e^{-j(2\pi kn/N)}
\]

a relation that can be written using matrix form as

\[
\{G_k\} = \frac{1}{N} \times \{Akn\} \times \{g_n\}
\]

where \( \{G_k\} \) and \( \{g_n\} \) are the column vectors that include \( N \) samples from the time domain, and \( \{Akn\} \) is an \( N \)-square matrix that contains the complex unit vectors \( e^{-j2pkn/N} \).

For example, the matrix equation is shown in Figure A3.19 for \( N = 8 \). Each arrow in the square matrix depicts a complex unit vector, with respect to the attached coordinate system. One can observe that a direct calculation of this matrix implies \( N \times N \) complex multiplication operations, which are time consuming. By using the FFT algorithm the

\[
\begin{bmatrix}
G_0 \\
G_1 \\
G_2 \\
G_3 \\
G_4 \\
G_5 \\
G_6 \\
G_7 \\
\end{bmatrix}
= \frac{1}{8} \begin{bmatrix}
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & j & -1 & -j & 1 & j & -1 & -j \\
1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\
1 & j & -1 & -j & -1 & -j & 1 & j \\
1 & -1 & 1 & -1 & -1 & 1 & -1 & 1 \\
1 & -j & -1 & j & 1 & -j & -1 & j \\
1 & j & 1 & -j & -1 & j & 1 & -j \\
1 & -j & -1 & j & -1 & j & 1 & -j \\
\end{bmatrix}
\begin{bmatrix}
g_0 \\
g_1 \\
g_2 \\
g_3 \\
g_4 \\
g_5 \\
g_6 \\
g_7 \\
\end{bmatrix}
\]

Figure A3.19 Matrix equation for \( N = 8 \).
number of multiplication operations reduces to $N \cdot \log_2 N$, with the condition that $N$ is a power of 2. Typically, when $N = 1024$, the processing time is reduced approximately 100 times.

*Errors Introduced by FFT Analysis.* The aliasing effect occurs due to signal sampling in the time field; it shows up by the appearance of some high frequencies within the field of low frequencies after sampling. This effect can be removed by purposely installing a low-pass filter before sampling, to eliminate frequencies larger than one half of the sampling frequency.

The time window effect is the result of the finite length of recording in the time field; the FFT algorithm deals with this record as a periodic signal, with the period $T_R$ (Fig. A3.20). This approach is good for transitory signals with a period less than $T_R$; the effect is, however, harmful for signals with a period larger than $T_R$. Since the signal is “cut off” through a rectangular window and then is introduced in a loop in order to apply the FFT algorithm, distortions and discontinuities occur in transitory areas (Fig. A3.21a). Consequently, the frequency specter will have a few components that do not exist in the original signal. The solution is to use a “smooth” window, which has both its value and slope

![Diagram](https://via.placeholder.com/150)

**FIGURE A3.20** Result of finite recording length in time field treated by FFT algorithm as a periodic signal with period $T_R$. 

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FIGURE A3.21 (a) While applying the FFT algorithm, distortions and discontinuities occur in transitory areas; (b) Hanning window.

equal to zero at both ends. Usually, this window is a Hanning window with period \( \cos(2\pi t/TR) \), as in Figure A3.21b. The round peak of a Hanning window can lead to amplitude estimation errors up to 1.5 dB (16%). For other types of windows, errors can go down to 0.1 dB (1%).

The picket fence effect is the result of the discrete sampling of the specter in the frequency field. It appears as if the specter is seen through the slits of a fence. Consequently, some values, such as peak values, can not be observed. The possible resultant error depends on how the characteristics of the adjacent filters overlap (Fig. A3.22). This effect is much less as the overlap is bigger. For a Hanning window, the distortions introduced in this way do not exceed 1.4 dB, while for a rectangular window they reach 3.9 dB. The error can be compensated where a frequency component “fits” between two spectral lines. The
picket fence effect also occurs in a TFD analysis and it is typical when third-octave filters are used.

**A3.3.2.5 Zoom FFT Analysis**

In a FFT analysis, the resolution of the result is determined by the Nyquist frequency (equal to one half of the sampling frequency), and by the number of lines in the specter up to the Nyquist frequency. When a resolution higher than the one offered by the 400 lines of the basic specter is desired, a Zoom FFT analysis is used. The interest area, which is between \( f_1 \) and \( f_2 \), is selected by moving the origin of the frequency representation to \( f_1 \), simultaneously with the passing of the signal through a low-pass filter, in order to eliminate all components, except for the range between \( f_1 \) and \( f_2 \) (see Fig. A3.23). Zoom FFT analysis is useful for processing both low-frequency modulated signals, and signals with a large number of harmonics, as well as for separating some vibratory phenomena that have very close frequencies.

**A3.3.2.6 Frequency Response Function**

The Fourier transform allows a theoretic frequency response of a mechanical system for different types of excitations. For a linear system...
When a resolution higher than that offered by 400 lines of the basic specter is desired, a Zoom FFT analysis is used.

with one degree of freedom, the relationship between the excitation \( f(t) \) and the displacement \( x(t) \) of a mass \( m \) is given by a linear equation with constant coefficients:

\[
A_n \frac{d^nx}{dt^n} + \cdots + A_1 \frac{dx}{dt} + A_0x = B_m \frac{d^mf}{dx^m} + \cdots + B_1 \frac{df}{dx} + B_0f
\]

Applying the Fourier transform to both members of this relation, it yields:

\[
X(f) \sum_{k=1}^{n} A_k(i_f)^k = F(f) \sum_{j=1}^{m} B_j(i_f)^j
\]
where $F(t)$ and $X(t)$ are the Fourier transforms of the excitation and the response, respectively. The complex function defined through the relation

$$H(f) = \sum_{j=1}^{m} B_j(i f)^j / \sum_{k=1}^{n} A_k(i f)^k = |H(f)| e^{i\phi(f)}$$

is called the frequency response function.

The relation $X(f) = H(f) * F(f)$ shows that the response specter is easy to obtain when multiplying the excitation specter by the frequency response specter. The amplitude of the frequency response for each frequency band is the product of the excitation amplitude by the frequency response amplitude. The response phase is the sum of the excitation phase with the response phase. By squaring the relation between amplitudes, the power specter formula is derived:

$$|X(f)|^2 = |F(f)|^2 * |H(f)|^2$$

The frequency response function is most often represented through separating the real member from the imaginary member. For a proportional damping, the real member is zero, and the imaginary member reaches its maximum (Fig. A3.24a). Another way to represent the frequency response function is the Nyquist diagram, by representing the real member in terms of the imaginary member (Fig. A3.24b).

The graphical analysis of these diagrams, as proposed by Kennedy and Pancu as early as 1947 [82], proved to be the most accurate method to determine the dynamic parameters and the vibration mode shapes of a complex structure. The frequency response function is also useful for studying the effects of various excitations upon a mechanical system, for determining the mechanical impedance (if the excitation is a force and the response is a velocity), as well as for removing the effects introduced by signal propagation in order to rebuild the excitation.

### A3.3.2.7 Analysis in the Amplitude Field

In general, defects caused by harmful low-speed phenomena (e.g., wear) have a typical way of evolution: initially they show up as local singular defects, which generate impulse excitations (shocks); the frequency of these excitations increases in time and determines the appearance of a few peaks in the frequency specter. In order to monitor and diagnose the signal in such situations, an analysis in the amplitude field is indicated,
FIGURE A3.24 Frequency response function: (a) for a proportional damping, the real member is zero, and the imaginary member reaches its maximum; (b) another way to represent the frequency response function is the Nyquist diagram.
by means of two specific functions: the peak factor $F_v$ and the Kurtosis function $\beta_2$, defined by the relations:

$$F_v = \frac{X_v}{X_{ef}}$$

$$\beta_2 = \frac{1}{\sigma^2} \int_{-\infty}^{\infty} (X - \bar{X})^4 p(x) dx$$

where $X_v$ is the amplitude of the peak signal, $X_{ef}$ is the effective value (mean square) of the signal with the amplitude $X$, $\bar{X}$ is the average value of the signal’s amplitude, $p(x)$ is the probability density of the amplitude, and $\sigma$ is the amplitude dispersion.

The peak factor is utilized especially in the amplitude analysis of determinist signals; the Kurtosis function can be used for random signals, too. For different situations, the Kurtosis function is given in tables in the literature. Note that, for machines and equipment in normal operating status, this function is 3, which is considered a reference value. An increase of this value in time, determined by the appearance of impulse-type processes, shows the appearance and further evolution of a defect.

### A3.3.3 Acoustic Emission Analysis

More methods are available for acoustic emission study, depending on the type of the selected signal. Therefore, a general evaluation is first necessary.

#### A3.3.3.1 Method of Counting Impulses

This method is useful for impulse-type signals. An evaluation of impulses that pass over a previously set threshold value is done. For the evaluation, the measuring chain consists of a device that differentiates the amplitude level of impulses, followed by an impulse counter (per time unit or per total).

The simple counting of impulses (Fig. A3.25c) can be improved through an evaluation of the impulse area (Fig. A3.25a), in order to take into consideration the duration of the impulse, possibly by introducing a combination of thresholds (Fig. A3.25b).

#### A3.3.3.2 Method of Impulse Amplitude Mediation

This method is utilized when the acoustic emission shows up through continuous signals. Calculation of the effective value (RMS) is significant.
FIGURE A3.25  Evaluation of impulses: (a) Evaluation of impulse area; (b) combination of thresholds; (c) simple counting of impulses.
because, as shown in Section A3.2.2.1, this value is proportional to the signal’s power/energy. This method is sometimes called the energetic analysis of impulses.

**A3.3.3.3 Method of Source Localization**

This method provides information about characteristics and changes of the source and of the wave trajectory. Controlled elastic waves are cre-

![Figure A3.26](image)

**Figure A3.26** Locating a source using two transducers.
ated by means of ultrasound sources. The ultrasonic wavetrain is characterized by a factor of the simultaneous wave, which depends on the succession of impulse frequencies, impulse duration, and the number of peaks that exceed a certain threshold. In this way, fracture areas in composite materials can be localized in advance.

In Figure A3.26, the way in which a source is localized is presented, in two dimensions, by means of two transducers. The difference between the arrival time of the signal at two transducers determines a plane hyperbola, provided the propagation velocity of the signal is known. The intersection of the hyperbolas obtained from the transducer pairs (1,2), (1,3), and (2,3) defines the real location of the source. This method is extremely useful for diagnosing, for localizing the source of primary defects, and for reducing the time to restore the operational status.

**A3.3.4 CONCLUSIONS**

**A3.3.4.1 Requirements for Diagnostic Systems**

Usage of diagnostic systems should be related to the importance of the system monitored within a fabrication process, taking into account its complexity and performance. Usually, a monitoring process is conducted for complex or continuously working equipment.

For efficiency in monitoring and detection of defects, the analysis and diagnostic have to respect a minimum requirement set:

- Must be adequate for the monitored equipment and have the ability and enough accuracy to detect defects.
- Notification of defects must be in due time; false alarms must be avoided.
- Must allow localization of defects in order to minimize the intervention time for repairs.
- Must ensure, as much as possible, a correlation of parameters that accompany the equipment work (vibration, noise, temperature, pressure, etc.), in order to gather complete and correct information.
- Must be easy to use and must not raise maintenance problems.
- Must be resistant to shipping and handling, to dust, moisture, and industrial liquids, to low and high temperatures, and sometimes to radiation.
- Must not be supplied from the same energy sources as the monitored system, but from special, stabilized, protected sources.
The reliability of the diagnostic system must be clearly higher than the reliability of the monitored system. The cost of the diagnostic system and its installation must not exceed 10% of the cost of the monitored system.

### A3.3.4.2 Implementation Stages

Finding a technical diagnostic for complex systems is possible only after their dynamics and kinematics are well known. This will lead to determination of factors to be monitored, types of transducers to be used, as well as locations in which those transducers would be installed.

When processing signals, the normal and maximum admissible levels of the monitored parameters should be taken into consideration. The sensitive points of diagnostic systems are: the signal processor, which extracts the necessary data from the raw signal, and the diagnostic processor, which uses these data in order to identify the status of the monitored system and to localize and isolate the defect.
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