MACHINE TOOLS

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Contents

Summary

Two most common types of operations used in production engineering and manufacturing are the machine tool operations, i.e. *machining* and *welding*. Machining operations are carried out using machine tool to perform cutting, shearing, and squeezing of work pieces. Welding is carried out by introducing heat to join metallic parts by coalescence. While this chapter deals with machine tools, welding is discussed separately in *Welding*.

After a short introduction into the complex area of machine tools and machining, the problems of machine monitoring and tool wear detection using traditional and intelligent methods, essential for modeling and for its adaptive control of machining process, are considered in Section 2, and in Section 3., the aspects of machine status monitoring, quality control, and automated visual inspection are discussed.

1. Introduction

Webster's Dictionary defines the *machine tool* as "an automatic or semiautomatic power-driven tool, as an electric lathe, punch press, drill or planer, used in making machines or machine parts". According to the Encyclopaedia Britannica machine tool is "any stationary power-driven machine that is used to shape or form parts made of metal or other materials". There are three basic mechanical shaping categories: *cutting*, *shearing*, and *squeezing*.

From the automation point of view, for example, machine cutting tools are machines equipped with a mechanism capable of accurately controlling the depth of the cut and the cutting and feeding speed. In addition, because a cutting tool generates heat, it could be exposed to high temperature and thus can reduce its cutting efficiency; temperature control at the cutting interface is needed.

Automatic machine tools are able to produce repetitively parts without the loading, operating, and /or unloading support of human assistance. Otherwise, they are semi-automatic or hand-controlled tools. The automatic machine tools are usually equipped with the hardware and software for *numerical control*, abbreviated as NC. For facilitated control program generation an action-oriented language is available, such as APT (Automatically Programmed Tools). Using APT the kind and the sequences of operations can be determined, the depth of cut, feed rate, and other operations.

Remarkable progress in machine tool automation has been made by introducing the *computer numerical control* (CNC), that was triggered by the advent of microcomputers. Using CNC the implementation of advanced control of machining process was possible, including adaptive control. Besides, the door was open for implementation of intelligent control approaches based on *expert systems*, *neural networks*, *fuzzy logic*, and *evolutionary computations*.

At the same time the progress in communication technology, particularly in *local area networks* (LANs) was remarkable, that has enabled direct interconnection of individual machine tools and their connection to the central mainframe. This has opened tremendous possibilities for automated *computer-aided design and manufacturing* (CAD/CAM), *computer-integrated manufacturing* (CIM), and of *flexible manufacturing systems* (FMS).

2. Machine Tool Monitoring and Control

Since the earliest days of manufacturing the most important goal has been, besides increasing the production throughput, also improving the product quality with minimal human intervention in the production process. To achieve this goal various concepts for production monitoring, real-time process control, product quality control, and on-line process parameter tuning have been developed and used.

Being strongly related to product quality control, production monitoring also encompasses the permanent sensing of machining process parameters, identification of process status, and decision on control actions to be taken for compensation of process status deviation from its optimal value. In the case of machine tool monitoring for optimal products manufacturing, the tool wear is the major monitoring objective. Based on the tool wear status adequate control actions will be taken to compensate for the wearing progress. Some more advanced monitoring concepts include diagnostic monitoring, a kind of monitoring that also predicts the possible tool failures and provides steps to minimize their effect on product quality.

The majority of early trials in machine monitoring were focused on the use of frequency methods, such as vibration and sound analysis of manufacturing machines to detect and identify possible noise irregularities, thereby primarily to predict the possible machine imminent failures. In this way tool wear monitoring can be implemented during cutting, drilling, etc.

With the advent of neural networks technology new computational perspectives have been opened for more complex tool wear monitoring and for an improved tool break prediction, based on multiple process parameters that include, in addition to the vibration parameters, also parameters like cutting power, cutting force, tool temperature, and others.

Such multisensor-based approach, for example, has been successfully applied for robust monitoring and diagnosis of cutting tools and has been used for on-line quality control. Moreover, by compensating for tool wear by cutting force control and/or by feed rate tuning, the quality of machine operation can be kept within tolerable limits. However, for on-line tool wear identification and for its compensation, a dynamic model of the tool wear process is required, for whose implementation also neural networks can be employed.

2.1. Machine Monitoring

A broadly accepted approach to tool-condition monitoring relies on state monitoring of the machine itself, most frequently by sensing and analyzing the machine vibrations that help detect the irregularities in machine operation. For this purpose advanced monitoring algorithms have been developed mainly relying on *time-frequency analysis*, *cepstrum analysis*, *multiple-sensor analysis*, etc.

For detection of both slow and fast developing phenomena the *quadratic time-frequency representations* have been used, derived from the vibrational *spectrogram*, the best of them using the Wigner-Ville distribution. However, because this distribution fails meet the property of *positivity* for all signals, it has been further modified and made adaptive to the signal considered.

Time-frequency analysis has been successfully used for condition monitoring of drilling, milling, and some other processes.

2.2. Tool Wear Detection

Wear is the removal of the material from a solid surface. In machanical engineering it is usually removal of the material from the metal surface by another under a mechanical force in a continuous and progressive process between two sliding surfaces, one of them hard and rough sliding over the other which is softer. This is known as *abrasive wear*. For instance, to remove the chips from a workpiece a cutting tool is taken that is harder than the workpiece at the temperature determined by the friction accompanying the cutting process.

Tool wear is a process accompanying metal cutting in machining processes. It influences the dimensional changes, as well as the quality of surface and the shape of the workpiece. Besides, it also determines the total tool life that is limited by tool efficiency or terminated by tool breakage. Thus, continuous supervision of machine tool wear is crucial for establishing the tool usability in processing the workpiece within the limits of quality standard requirements and for predicting the possible tool breakage. Therefore, the approaches to the on-line tool wear estimation have attracted the attention of production engineers from the very beginning and have stimulated the research and experimental work in this area.

The earliest used and still widely popular approach to tool monitoring in mass production machines is the evaluation of sensing in *statistical quality control*.

The routine tool wear condition monitoring is found in product quality inspection where, based on the inspection results, the decision has to be made whether the actual tool wear state can guarantee the required quality standard in further machining or not. For this the relevant sensors are required and an adequate signal-processing algorithm.

For instance, using the *sensor fusion concept* to fuse the signals of vertical acceleration and drilling thrust sensors, reliable estimation of tool drill wear condition can be achieved. This is reasonable because the vibration signals generated during the drilling process indicate the drill wear condition that can be sensed through the vertical acceleration. On the other side, the thrust produced in the process of drilling increase with the increase of tool wear.

The use of two sensors is necessary because no reliable results will be achieved using one of them alone. This is because changes in acceleration and thrust during the drilling also depend on the properties of the material to be drilled, so that no sufficient information is received when only one of the signals is acquired.

The relevance of the sensor fusion based wear detection in manufacturing is demonstrated in the international SIMON (*sensor fused intelligent monitoring system for machining*) Project established by the industry as a joint action to create a sophisticated tool wear condition monitoring system. The achievements of SIMON also support the drilling, milling, and grinding tool wear monitoring process through the combined use of multisensor data and the mathematical tool wear models, based on cutting force, thermal effects, chatter vibration, etc. The monitoring results can subsequently be used for adaptive control of cutting process concerned and for similar purposes.

Some improvements in tool wear estimation have been achieved by incorporating the *dynamic state model* of tool wear into the estimation algorithm. Based on a mathematical model of flank wear and crater wear as process state variables, of feed velocity as the input variable, and of cutting force as the output variable, on-line tool wear estimation in turning was possible using an adaptive observer.

For building an adequate mathematical model, it should be taken into account that the predominant influence in flank wear exhibits the *abrasion* and the *diffusion,* represented by two simultaneous non-linear differential equations derived from first principle.

An interesting approach to the tool wear estimation relies on the fact that the tool wear dramatically affects the surface morphology of the machined work piece because it deteriorates the surface microstructure. It is thus advisable, instead of evaluating the state of the *tool area* or *tool surface*, to evaluate the machined surface of the product as the adequate indicator of the shape of the cutting tool. For surface inspection, a video sensor is required and the corresponding image processing algorithms that, apart from the traditional algorithms of image signals processing also include some special algorithms of surface texture analysis.

For texture analysis also, the use of intelligent approaches based on neuro and fuzzy technology has given very good results. The surface image data are collected by a CCD camera of high magnification capacity, required for collection of sufficient information about the machined surface. However, because the traditional texture analysis algorithms are rather computationally time-consuming they had to be simplified, so that they are at least good enough to distinguish between the sharp tool conditions from the dull one.

For application of such methods building of *gradient images* or of *binary images* is preferred, for instance using *Sobel operators* and the process of *thresholding*. In this way the modified algorithms have been successfully applied in the industry in monitoring of cutting-tool condition and even in forecasting of possible tool breakage, based on flank wear state estimated from the texture analysis of the corresponding machined surface.

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Biographical Sketch

Prof. Popovic has received his M. Sc. (Dipl.-Ing.) from University of Belgrade and his Ph. D. (Dr.-Ing.) from Technical University of Berlin. He has been with the University of Bremen since 1972 as Chair of Process Control Computer Engineering. In 1982 he has established the Institute of Automation Technology and has headed it since the very beginning. Before coming to the University of Bremen he has been for more than ten years with the AEG-Telefunken in Berlin and with Bayer AG in Leverkusen, in charge of computer application to industrial plants automation.

Prof. Popovic is author and editor of several books, including the books on *Distributed Computer Control for Industrial Automation, Methods and Tools for Applied Artificial Intelligence,* and *Mechatronic Approach to Process and Product Design,* published by Marcel Dekker, Inc., New York. Besides, he has contributed 8 chapters to various Books in the area of expert systems, neural networks in systems control, and in communication links for industrial automation. His field of research includes, besides process control, application of intelligent technology to texture analysis, video data compression, computer vision and intelligent robotics, where he has over 140 publications.