Chapter 19
Tool Condition Monitoring Using Artificial Neural Network Models

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ABSTRACT

Tool wear is a major factor that affects the productivity of any machining operation and needs to be controlled for achieving automation. It affects the surface finish, tolerances, dimensions of the workpiece, increases machine down time, and sometimes performance of machine tool and personnel are affected. This chapter deals with the application of artificial neural network (ANN) models for tool condition monitoring (TCM) in milling operations. The data required for training and testing the models studied and developed are from live experiments conducted in a machine shop on a widely used steel, medium carbon steel (En 8) using uncoated carbide inserts. Acoustic emission data and surface roughness data has been used in model development. The goal is for developing an optimal ANN model, in terms of compact architecture, least training time, and its ability to generalize well on unseen (test) data. Growing cell structures (GCS) network has been found to achieve these requirements.

INTRODUCTION

Manufacturing industries have seen lot of changes in the last few years. The focus is on reducing cost, improving productivity, by reducing downtime, losses and waste. Machining is an important process used by manufacturing industries. It can be classified as traditional and non-traditional. In traditional machining, turning, planning, shaping etc., uses a single point cutting tool and milling, drilling, grinding etc., are multi-point cutting tool operations. They can be used to machine metals or nonmetals, including

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composites. Cutting tool is an important part of the machining process. It contributes significantly to the total machining costs. Further the goal in manufacturing is towards automation. In this effort, there is a need to continuously monitor the condition of the cutting tool, so that machine tool and cutting tool are not affected. Cutting tool condition monitoring can include detection of the tool condition in terms of tool wear and fracture or breakage (Chelladurai et al., 2008). Tool breakage is a major reason for unscheduled stopping of operations in a machining centre (Rehorn et al., 2005). Traditional methods of monitoring the condition of the cutting tool has been more dependent on the operator. Hence, he or she was not able to detect the condition of the tool, when it was subjected to sudden failure or more wear. As a result, cutting tools were either underutilized or overutilized. To avoid this problem there is a need to use various types of sensing techniques, which can assist the operator in taking proper decisions. Traditionally tool condition monitoring methods are grouped as 'direct' or 'indirect'. Direct methods involve assessing material removal from cutting tool in terms of mass or volume and tend to be offline in nature, as the tool has to be removed from the machining process for measurement. Hence it takes lot of timetool failure development is not clearly visible. Indirect methods can be implemented online, as it involves measurement of 'signals' generated during machining, which have a direct relation with tool condition and includes cutting force, temperature, vibration, acoustic emission etc. (Pai, 2004).

The focus these days is on automated TCM systems, which will recognize the status of the tool, without the interruption of the machining process, under minimum human supervision. Thus, the goal is to achieve 'unattended' machining systems, which can improve the utilization of the capital equipment and substantially reduce the machining costs. For this, there is a need for an "Intelligent sensor system'', as described by Dornfeld (1986) as follows, "an integrated system consisting of sensing elements, signal conditioning devices, signal processing algorithms and signal interpretation and decision-making procedures". "Finally, the effort is towards developing an Automated / Intelligent monitoring system, which should have the capabilities of sensing, analyzing, knowledge learning and error correction".

According to Elbestawi et al. (2006), to replicate human intervention, a typical TCM system should have the following components:

(i) Sensing technique – use of different sensing signals like cutting forces, vibrations, acoustic emission. There is a need to combine data from different sensors and locations, to maximize yield of useful information.
(ii) Feature extraction – there is a need to extract information from the signals to differentiate different process and tool conditions and also to remove noise from the signals.
(iii) Decision making – strategies, which use the extracted features and map it to a tool condition.
(iv) Knowledge learning – in order to make correct decisions, learning algorithms have to be used.

"The automated TCM systems, have to learn from past information and also learn from the new information generated from the machining process" (Elbestawi, & Dumitrescu, 2006) (Elbestawi & Ng, 2006).

Monitoring systems which are based in laboratories, are multisensory based are require the need for complex Artificial Intelligence (AI) based systems, which can integrate information, extract features and make reliable decisions about the status of the tool (Balazinski et al., 2002). Multi sensor fusion has some benefits for TCM and include – since the signals get distorted by noise during measurement, using multiple signals can maximize the amount of information available for decision making process and since more signals are considered, the certainty of the estimated parameter value improves (Pai, 2004). "Artificial Neural Networks (ANN) and neuro-fuzzy techniques have been extensively studied

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