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Cutting Tool Degradation Monitoring in Turning with Artificial Neural Network

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1. Extended Abstract

During machining, the cutting tool is subjected to mechanical, thermal, and chemical stresses that lead to its degradation [1]. Consequently, both the quality of the machined surface and the compliance with manufacturing tolerances are reduced. Under nominal turning conditions, the tool is predominantly worn on its flank face. The size of this degradation is characterized by a value called Vb and defined by the ISO 3685 standard [2]. This standard defines the End Of Life (EOL) of the tool at Vb equal to 300 µm. Industrial practice is to replace the tool before its EOL, which wastes time, materials and increases production costs. Therefore, tool management is an important issue as the cost of tools can represent a significant proportion of production costs [3].

Most cutting tool replacement policies are based on knowledge of the condition of the tool. This step of monitoring and determining the condition of a tool is a growing area of research as there are many approaches to monitoring the degradation of cutting tools. These approaches can be divided into two categories: direct and indirect monitoring. Direct monitoring consists of directly measuring the degradation on the tool. This direct analysis makes it possible to accurately observe tool degradation but requires the machining operations to be stopped to carry out the measurement, which increases the downtime of the machines and consequently the production cost. To avoid having to stop the machining process to perform a tool degradation measurement, existing approaches mainly focus on indirect monitoring, which consists of estimating the tool condition from signals collected during machining. Recently, with the emergence of the industry 4.0 and the growing generation of data by machine tools, data-driven models have been implemented to this task. These machine learning approaches use different techniques such as: fuzzy logic, support vector machines, self-organizing map, neural network, … and can monitor the state of the tool with less error than conventional empirical and statistical approaches [4].

The approach presented describes the use of neural networks to monitor tool wear from data collected during instrumented turning tests.

These data consist of the cutting forces collected during the life of the tool for different cutting conditions. The database is composed of the degradation of 30 tools whose wear was measured on average every 2.8 minutes. From the temporal signals of the cutting force, several indicators are calculated. These indicators, either statistical or frequency, are not all correlated with tool wear. To identify those most correlated with the wear, a Spearman correlation analyses is performed. The most correlated data are used as input to the neural network. In our database, the root mean squared value of the feed force as well as the cutting force are used together with the machining time and the total machine length as they are most correlated with tool wear.

The choice of neural networks is based on their ability to achieve better classification results compared to other classical artificial intelligence approaches [5]. In this case, the objective of the neural network is to monitor the value of the tool's degradation (Vb). The input to the neural network is therefore the correlated indicators identified by the correlation analysis and the output is the size of the flank wear (Vb).

A neural network is defined by several parameters that control its architecture and learning method, these parameters are identified by comparing what is done in the literature and adapting these trends to the database presented above. The performance of the network is evaluated by computing the mean squared error between the value estimated by the neural network and the value measured during the tests. The best performance is achieved with neural networks with 2 hidden layers. The first layer is composed of 6 neurons and has a hyperbolic tangent activation function. The second layer is also composed of 6 neurons with a rectified linear unit activation function. This architecture optimizes the mean squared error loss with an "Adam" optimizer. Network learning is monitored to avoid overfitting. This is achieved by stopping the training when the network no longer improves its results on a validation sample. Compared to other ANN approaches that use only one activation function, this network obtains 40% better performance.

The network is evaluated on degradation trajectories with variations in cutting speed between 2 measurement points to verify that the network can generalize its results to variations in cutting conditions. After training, the proposed network can correctly track the degradation and timely detect the EOL of the tool. The results show that the network correctly estimates degradation to an average error of less than 40 µm. Consequently, the network detects the EOL with an error of about one minute. In practice, these errors have no impact on the machining process. The model also tends to give conservative results by slightly overestimating tool degradation. The approach shows that this type of simple model can obtain satisfactory results for monitoring tool degradation. This method requires the instrumentation of the machine tools, but with the rise of Industry 4.0 this is increasingly common.

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