Advances in Reliability, Safety and Security

ESREL 2024
Collection of Extended Abstracts

Industrial Tool Condition Monitoring: Integrated Direct And Indirect Approach For Automated Database Creation

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Keywords: machining, cutting tool, artificial intelligence, monitoring

The machining process inevitably induces tool wear. If this wear is not correctly monitored, the consequence on production can be disastrous. Due to the interaction of the tool with the workpiece, the state of the tool is of crucial importance as it directly dictates the quality of the production. Factors like geometry, residual stress, and surface finish are all influenced by tool wear. In some cases, the wear can also lead to catastrophic failures, which can account for up to 20% of the machining downtime (Baig et al., 2021). Furthermore, the cost of the production is directly related to the cost of the tool which can represent from 3% to 12% of the total production cost (Baig et al., 2021). In industrial practice, it is common to replace the tool after a given machining duration. This interval is often determined at the beginning of the production process and some conservative margins are taken to avoid taking any risk. This solution is suboptimal as this requires stopping the manufacturing process and changing the tool more often, leading to increased machine downtime and costs (Rizzo et al., 2020). In some cases, the tool replacement relies on the machinist experience to determine the optimal time to replace the tool. This solution leads to an evident lack of factual and homogenous criteria to replace the tool in production. Given these limitations, various decision-support methods for tool replacement have been proposed in the literature. There are two primary strategies for monitoring tool wear (Colantonio et al., 2021): direct monitoring and indirect monitoring.

Direct monitoring consists of stopping the machining process to measure the wear directly on the tool. Multiple methods exist and they generally rely on an image acquisition to measure the wear directly on the tool. This image is then processed to evaluate the state of the tool and take the decision to continue the production or not (Muthuswamy et al., 2023). This approach is technically difficult to achieve as multiple challenges due to the industrial machining environment exist. The most common limitation is the lighting condition during image acquisition, the position of the camera in the machining centre to limit the risk of interference, the presence of cutting fluid and the presence of chip on the tool. Despite these challenges, multiple solutions exist, especially since the introduction of Artificial Intelligence (AI) image processing. Indeed, direct monitoring benefits greatly from AI's ability to detect the wear on images with uneven lighting conditions, which can greatly simplify industrial applications (Muthuswamy et al., 2023).

Indirect monitoring consists of using cutting signals from the machining centre to estimate the state of the tool. This can be achieved by the instrumentation of the machine. Multiple signals are usable, such as the cutting force, the vibration, etc. (Kuntoglu et al., 2020). The advantage of indirect monitoring is that it does not require stopping the process to assess the tool's state. However, the relationship between the measured signals and the tool's condition can be complex.

Both direct and indirect monitoring approaches benefit greatly from AI techniques. Indeed, many approaches, using AI can track the degradation of the cutting tool directly or indirectly and outperform mathematical, statistical, or stochastic models (Colantonio et al., 2021). But in general, these approaches are considered independently from each other. The assumption that there exists a database that links the indirect signals directly to the wear is always taken. In industrial practice, this is not the case as the process can vary in function of time and organizing a test campaign to create this database is nor trivial nor economically viable for all application.

The presented approach, therefore, proposes the use of different AI techniques to monitor the evolution of the wear of the tool by combining both direct and indirect methods. A custom U-Net model is proposed for the direct monitoring approach to accurately detect the wear on cutting tool images. This U-Net can also detect the apparition of defects on the tool such as a build-up edge. The indirect approach uses a combination of different AI approaches: Artificial Neural Network (ANN), Support Vector Machine (SVM) and K-Nearest Neighbours (K-NN). The choice of the indirect approach depends greatly on the industrial context. To evaluate the combination of both approaches, the wear evaluation from the direct method is used to establish a database that links the cutting force to the tool's condition. This database is then used to train an indirect monitoring AI. This AI is then tested on previously unseen cutting conditions to indirectly monitor the state of the tool from the cutting forces. The indirect monitoring results are then compared with the real degradation of the tool. The results obtained with this method show that the combination of these direct and indirect methods can monitor the state of the tool and timely detects its end-of-life. On average, the end-of-life of the tool can be detected with an accuracy of around 1 minute. Furthermore, the feedback on the agreement between the indirect and direct monitoring can be used to accurately add relevant information on the database where the models tend to make more errors.

This approach thus allows to automate the creation of a database for industrial context. The particularity of the presented approach is the link between the direct approaches and the indirect approach and specifically how the direct approaches can feed the indirect approaches with relevant data to expand the database where needed thus improving the quality of the monitoring. This method is adapted to industrial scenarios. For example, the direct monitoring approach can be used on one machine equipped with a direct monitoring system to create a database. This database can then be used to train another AI model for indirect monitoring for all the other machines of the workshop equipped with only indirect monitoring equipment. Thus, allowing limited investment in direct monitoring equipment and monitoring the degradation of the tool for the whole production.

In conclusion, the combination of indirect and direct monitoring is a relevant approach for industrial applications to monitor the tool wear. It demonstrates the possibility to create and reinforce a tool condition monitoring database automatically. The results show that these developments allow us to accurately track the degradation of the tool and timely detect its optimal replacement thus improving production quality while diminishing its costs.

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