euspen's 23rd International Conference & Exhibition, Copenhagen, DK, June 2023
www.euspen.eu

Tool wear monitoring in milling processes using a sensory tool holder

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Abstract
In-process monitoring in milling, specifically tool condition monitoring (TCM), is an important technology for improving productivity and workpiece quality. However, industrial implementation of in-process TCMs remains a difficult task, since progressing tool wear is indicated by small changes of various physical parameters. Therefore, a sensitive monitoring system is needed to provide a reliable base of information while having minimal impact on the machine tool system and processes. Recent advancements in deep learning (DL) techniques are frequently applied on monitoring data for tool wear prediction as they can process and analyse raw data without prior feature engineering. This paper presents a suitable monitoring approach based on a recently developed sensory tool holder, which measures cutting forces and vibrations in direct proximity to the process zone. The system is equipped with wireless data transmission and a novel energy harvesting technology for energy supply. Two milling experiments with focus on increasing tool wear were conducted and the collected data processed. A DL based model, comprising three convolutional neural network (CNN) layers, one long short-term memory (LSTM) layer, and a multi-layer perceptron (MLP), was trained on the raw sensor signals to make predictions on the tool wear state. The model was evaluated using previously unseen test data and achieved a high prediction accuracy of at least 97,3% for all sensor signals, with the highest accuracy of 99,9% achieved when using bending moment signals.
Keywords: Milling; Monitoring; Tool; Wear

1. Introduction

Milling is a common manufacturing process, especially for machining high-quality and precise parts. With the increasing automation in the machining industry, in-process monitoring in milling becomes a key technology for improving productivity while maintaining high quality and accuracy of the parts. One area of focus for in-process monitoring in metal cutting is the monitoring of tool health, also known as TCM. Reliable detection of tool wear allows for efficient usage of tools and resources and reduces the number of tool breakages and scraped parts. However, implementing in-process tool condition monitoring in an industrial setting is challenging because small changes in several parameters indicate advancing tool wear.

Recently, Teti *et al.* [1] presented a comprehensive overview of scientific approaches for process monitoring in machining. Moreover, there are specific review articles on tool condition monitoring in milling [2, 3]. For example, tool wear monitoring is enabled through online analysis of motor current signals [4]. Such systems are already available on the market for industrial application [5, 6]. However, sensitive signals acquired closer to the cutting process, e.g. vibrations, forces, or acoustic emissions, are more suitable for reliable monitoring. Examples are given by Kuntoğlu *et al.* [7]. DL techniques are frequently applied for tool wear monitoring because they can directly process and analyse raw data without the need for prior feature engineering. CNNs and LSTM networks are popular DL models for analysis of time series data [8].

In scientific approaches, accelerometers or dynamometers are typically temporarily installed near the workpiece or spindle to capture data from the process. However, the effort for installation is comparably high and such setups are not robust enough for industrial applications. Therefore, a sensitive monitoring system is needed to provide a reliable base of information while introducing only minimal implication towards the machine tool system and processes. Sensor integration in the tool holder is a promising strategy for this problem. A review on the state-of-the-art of such systems is given in [9]. Recently, a novel multi-sensory tool holder was developed by the authors using wireless communication and wireless energy supply via electromagnetic induction, which enables the system to operate permanently without a separate power supply. The integrated sensors measure vibrations and forces in several directions [10].

This recently presented smart tool holder is utilized in this paper as basis for a new TCM method. The sensor signals of the tool holder are transmitted to an analysis unit and pre-processed there. A DL model consisting of several stacked CNNs, an LSTM layer, and an MLP is employed here for the first time to predict the wear of milling tools. It is separately trained on each raw sensor signal. Thereby, the capability of those signals to provide tool wear related information is investigated.

The paper is organized as follows. The methodology, i.e. the concept of the sensory tool holder and the DL model, is presented in section 2. The experimental setup and data preparation is described in section 3 and section 4. The results of the tool wear prediction are given in section 5, followed by conclusions in section 6.

2. Methodology

2.1. Sensory tool holder

Small changes of cutting process behaviour, for example due to tool wear, are frequently detected by external sensors. Appropriate measurement quantities with extensive information are cutting forces and vibrations [7]. For this reason, a sensory tool holder was developed and manufactured to collect sensitive data of these quantities in direct proximity to the process zone. The design is depicted in figure 1. The cutting force measurement is realised by strain gauges which are applied to the tool holder's surface. The considered mechanism is the change of the sensor resistance ΔR as a result of strain ε caused by force excitation. The corresponding equation for a single strain gauge i $(i = 1, 2, 3, \dots)$ is

$$\Delta R_i = k\varepsilon_i R_0, \quad (1)$$

where R_0 is the sensor's nominal resistance and k is the sensitivity factor. In order to compensate several disturbing influences on the strain gauge resistance and to acquire higher output signals, four strain gauges are commonly connected to Wheatstone full bridge circuits. The simplified bridge equation is

$$\frac{U_M}{U_B} = \frac{1}{4}\left(\frac{\Delta R_1}{R_0} - \frac{\Delta R_2}{R_0} + \frac{\Delta R_3}{R_0} - \frac{\Delta R_4}{R_0}\right), \quad (2)$$

where U_B is the bridge supply voltage and U_M is the electrical output voltage. Depending on the orientation of the strain gauges on the tool holder surface, the sensors' relative change of resistance either add up or eliminate each other within the bridge circuit. Thereby, measurement of different directional components of the cutting force is enabled. In terms of the proposed smart tool holder, a radial and axial measurement direction are realised. Due to typically varying tool length, the bending moment is utilized as monitoring parameter instead of the radial force. While equation (1) and (2) together define the linear conversion between strain and output signal of the sensor bridges, Hooke's law describes a linear relation between force and strain in case of linear-elastic deformation. Therefore, also a linear relation between the sensor signals and forces applies, which is determined by finite element analysis (FEA) and validated through experiments with a dynamometer as reference [10].

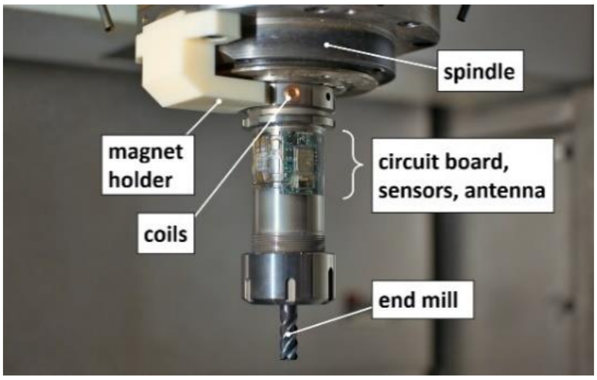

Figure 1. Sensory tool holder design with standardized HSK-A63 spindle interface (DIN 69893) and collet chuck, type ER40 (DIN ISO 15488)

Furthermore, the tool holder is equipped with the piezoelectric accelerometer 832M1 from TE Connectivity, which measures the structural vibrations and is directly mounted on the circuit board. The sensor provides a radial, axial, and tangential sensing direction. In contrast to commonly used MEMS ("micro-electro-mechanical systems") sensors, this sensor type does not measure the high static accelerations [11] in radial direction caused by the tool rotation and is therefore well suited for an off-centre application.

The mentioned five analogue sensor signals are filtered, amplified and converted into digital signals with a specified sampling rate. An overview of sensors and data acquisition properties is presented in table 1.

Table 1. Properties of tool holder sensors

Parameter	Range	Resolution	Sampling rate	Low-pass filtration frequency
Bending moment	±400 Nm	0,2 Nm	10 kHz	2,4 kHz
Axial force	±15 kN	7,5 N	10 kHz	2,4 kHz
Acceleration (triaxial)	±100 g	0,08 g	10 kHz	5 kHz

Since the tool holder is rotating, the implemented energy supply technology must be wireless and preferably permanently available. For this reason, the recently developed tool holder follows a novel approach based on energy harvesting, where the kinetic energy of the spindle rotation is used to supply the smart device with power. This results in energy self-sufficiency of the system. For this solution, four coils are mounted on the rotating tool holder. A compact stator with four magnets is mounted on the spindle face in proximity to the coils. The magnets are alternately aligned regarding their polarity. During spindle rotation, the coils with winding number N move through the static magnetic field. An electrical voltage is induced according to following equation.

$$U_{ind} = -N * d\phi/dt \quad (3)$$

The electrical voltage U_{ind} is dependent on the change in magnetic flux density ϕ over time t, which in this case is defined by the spindle speed, distance between coils and magnets as well as the remanence of the magnets. The energy supply configuration of the current tool holder prototype operates the system in a typical spindle speed range of 1800 min^{-1} to 20000 min^{-1}. If necessary, the range can be lowered or increased through adjustment of the mentioned parameters.

The data communication of the system must be wireless as well. Therefore, it is realized through radio transmission using protocol Bluetooth Low Energy (BLE). The receiver antenna is mounted at an arbitrary location inside the working space of the machine tool. All electronic components of the sensory tool holder are applied in pockets and covered with epoxy resin filling compound. Thereby, the design implies no interfering contour to the machine and process.

2.2. Tool wear prediction model

Tool wear prediction based on sensor signals is frequently realised by machine learning models [12]. Traditional methods are, for example, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests (RF) or K-Nearest Neighbours (KNN). These techniques require prior manual extraction of significant signal features to generate a better representation of raw signals regarding the targeted classification or regression. Another sub field of machine learning, that has recently shown great popularity for many fields and also does not require this pre-processing step, is deep learning. This method describes neural networks with multiple hidden layers and thus a more complex model structure, that needs to be trained on a larger volume of data, but then also promises higher prediction accuracy [12]. The prediction model of this work follows the deep learning approach. It is implemented in Python using the libraries TensorFlow and Keras. The aim of the model is the classification of different tool wear states for defined milling processes based on raw input signals. The architecture of the proposed deep learning model is shown in figure 2.

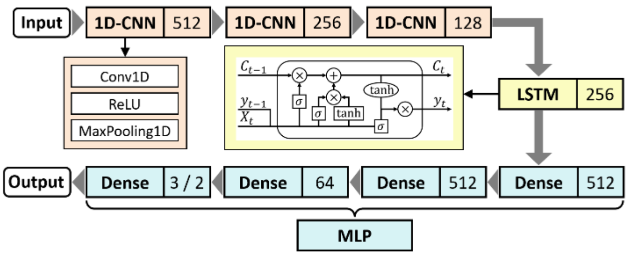

Figure 2. Tool wear prediction model architecture with number of filters (respectively units, neurons) per layer

Each 1D-CNN consists of a convolution layer, followed up by a non-linear rectified linear unit (ReLU) activation and a pooling layer. At each time step, the convolution layer applies a number of filters to the raw input signal. Each filter f represents a weighted convolutional window W_f with pre-defined size and a bias b_f. These filters move across every spatial position of the input signals X_{CNN} and thereby generate an array of convolutions as output. A single convolutional output $y_{f,CNN}$ at one spatial position can be expressed as

$$y_{f,CNN} = \left(W_f * X_{CNN}\right) + b_f, \tag{4}$$

where $*$ denotes the convolutional operation. After processing these arrays with the ReLU activation function, the pooling layer reduces the number of outputs to the most significant ones and passes them to the next unit. Thereby, the three stacked CNNs convert raw input sequences to temporally shorter representations with multiple extracted features.

The subsequent LSTM layer consists of multiple units and processes the CNN's output, considering its temporal dependencies. The algorithm of a single LSTM unit is shown in figure 2. The input signal $X_{LSTM,t}$ at a time step t is processed in combination with the unit output $y_{LSTM,t-1}$ from the previous time step and the unit memory C_{t-1} from the previous time step. In particular, weighted arrays and biases as well as $\tanh$ and sigmoid (σ) activation functions are applied for generating the unit memory C_t and unit output $y_{LSTM,t}$ for the current time step.

Finally, an MLP consisting of multiple fully connected layers (dense layers) of neurons, classifies the LSTM output regarding tool wear state. At each time step, every neuron of a dense layer receives an input signal X_{dense}. Each neuron n is characterized by an array of weights W_n and a bias b_n. The output $y_{n,dense}$ of one neuron of the dense layer is

$$y_{n,dense} = W_n^T X_{dense} + b_n, \tag{5}$$

where T denotes the vector transposition. The length of W_n equals the input signal length. The number of neurons of the last fully connected layer equals the number of potential tool wear classes. This output is passed to a softmax activation function in order to normalize it and thereby create a probabilistic distribution regarding the predicted classification.

The presented deep learning model will be trained on a data set of sensor signals with manually pre-defined classification. Achieving the highest possible compliance between classes predicted by the model and actual classes is the objective of this process. During training, the categorical cross-entropy loss is calculated as metric of the current model prediction quality and the 1.581.122 model parameters are adjusted through back propagation with a learning rate of 0,001. The Adam optimizer algorithm is used in this work to automatically adjust the parameters with the aim of minimizing the loss. The training data is provided in form of signal sequences, where 100 sequences form a batch. A total of up to 100 training epochs is performed. At the end of the training process, the model performance will be evaluated on further sensor data. Therefore, the measure of accuracy is utilized in addition to loss. Accuracy is the percentage of predicted classes that match with actual classes for each input sequence.

3. Experimental setup and observations

Millings tests with progressing tool wear were performed on a vertical turn-milling centre VMC300MT from EMAG. The presented sensory tool holder was used in combination with a coated carbide end mill with a diameter of 12 mm, 4 cutting edges and a total length of 83 mm. A workpiece made of high-alloy steel X40CrMoV5-1 is milled in form of consecutive straight cuts. The described setup as well as the kinematics of the milling operations are shown in figure 3. The straight cuts were conducted alternately as roughing and finishing process. Corresponding cutting parameters are selected from the values recommended by the end mill supplier and listed in table 2.

Table 2. Cutting parameters of the experiment

Process type	Cutting speed v_c / m·min^{-1}	Feed per tooth f_z /mm	Width of cut a_e /mm	Depth of cut a_p /mm
Roughing	100	0,045	3	6
Finishing	120	0,06	1	6

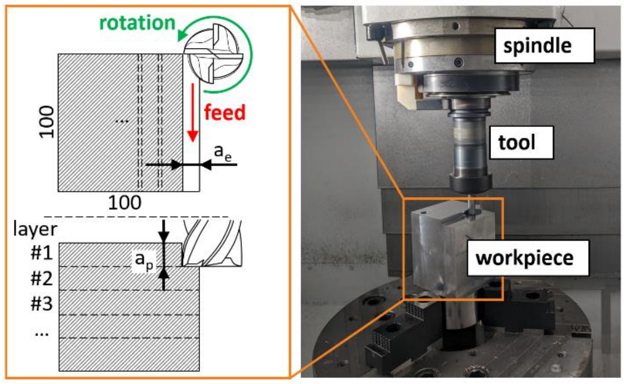

Figure 3. Experimental setup and process kinematic

In this way, the workpiece material is removed layer by layer. After each layer the flank wear VB of the end mill is measured with the video microscope PG 2000 from Gühring. During the whole experiment, the sensory tool holder monitored the process and transmitted sensor data to a PC where it is stored in a database. A total amount of 6.93 GB of data was recorded. Figure 4 shows the tool wear progress and exemplary signal sequences for the bending moment M_b over time t.

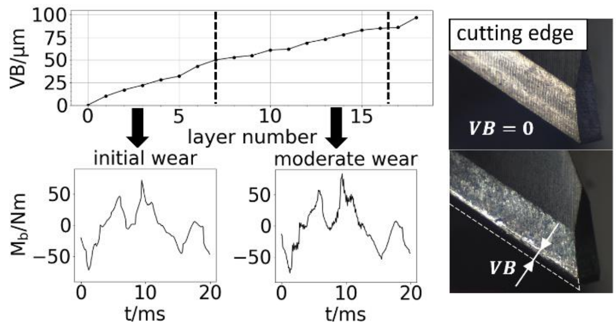

Figure 4. Progress of flank wear per layer, microscopic recordings of a cutting edge and exemplary bending moment signals for one tool revolution with initial wear and moderate wear

With progressing tool wear, it was determined that not only the amplitudes of all sensor signals increased, but also the intrinsic signal shape changed characteristically. Furthermore, signal components with higher frequency than the spindle rotation or tooth passing frequency occurred at different stages of the tool revolution. The amplitude of these high frequency components also increased with progressing tool wear.

In addition to microscopical tool wear measurements, the workpiece surface was visually checked during the cuts. It was observed that starting from the 7th layer, clear wear marks were perceptible on the machined surfaces. For this reason, the data up to this layer was classified as “initial wear” and the data of the subsequent layers as "moderate wear". Moreover, it was observed that from the 17th layer onwards, melted material occurred at the edges of the process zone during roughing cuts. In conclusion, there was assumed to be "heavy wear". The associated measurement data is classified accordingly.

4. Data preparation

One prediction model per process type is created and trained. Therefore, the experimental data were cleaned in order to improve the training quality. This included removing the signals for free rotation as well as workpiece entry and exit. Additionally, the middle cuts per layer were removed due to disturbing rapid turning movement of the workpiece table. The remaining data were divided into short signal sequences of 48 ms each. The set of signal sequences was then further subdivided into a roughing data set and a finishing data set. The signals of the roughing data are classified as “initial wear”, “moderate wear”, and “heavy wear” of the cutting edges. The signals of the finishing data are classified as “initial wear” and “critical wear” of the cutting edges, where “critical wear” involved “moderate wear” as well as “heavy wear”. To enable a balanced training of the prediction models, random sequences were removed until the data sets contained an approximately equal number of sequences per class. The data set for finishing thus comprised a total of 6111 sequences and the data set for roughing a total of 8272 sequences.

These data sets of time series sequences were then split into training, validation, and test data. The training data corresponds to 60 % of the total data and is used for training of the prediction model from section 2.2. The validation data contains 20 % of the total data and is used to trace the training progress and thus provide a suitable final criterion for optimal training duration. The test data represents 20 % of the total data and is finally used to evaluate the trained model by making predictions on the tool wear state for input sequences it has not seen before. These predictions are compared to the actual classification. The accuracy and loss values serve as indicators for model quality.

5. Results and discussion

All sensor signals that are available at the sensory tool holder have been separately tested as input to the proposed prediction models. The results are shown in table 3. High prediction quality is characterized through high accuracy values and low loss values. The loss can be interpreted as certainty of predictions. The model trained on the finishing process shows overall slightly better results than the model for the roughing process. The reason might be the additional class of “heavy wear” in the roughing data set, that is assumed to be more difficult to be distinguished from signals of “moderate wear”.

Table 3. Prediction quality of models on test sets of sensor signals

Sensor signal	**Roughing**		**Finishing**	
	loss	accuracy	loss	accuracy
Tangential acceleration	0,106	98,2 %	0,056	99,1 %
Axial acceleration	0,024	99,4 %	0,030	99,5 %
Radial acceleration	0,143	97,9 %	0,032	99,3 %
Bending moment	0,005	99,9 %	0,002	99,9 %
Axial force	0,172	97,3 %	0,075	99,0 %

Nevertheless, all sensor signals allow a reliable and highly accurate prediction of the tool wear state. The best results were accomplished for bending moment signals as input, where the prediction accuracy was nearly perfect. Only 2 out 1656 test sequences of the roughing process and 1 out of 1222 test sequences of the finishing process was classified falsely. For this approach, the testing of multivariate input data, which means training the model on a combination of multiple sensor signals, is not necessary due to the highly sufficient prediction accuracy of univariate input in form of bending moment signals.

Based on these results, a high quality of the raw sensor signals can be assumed, which enables the model to learn significant unique features that represent pertinent information about the tool wear state. Furthermore, it can be deduced from the overall high prediction accuracy that the model architecture and hyper-parameters were appropriately selected for this application.

6. Summary, conclusion, and outlook

This paper presents a tool wear prediction method based on a multi-sensory tool holder and a deep learning model. The conducted experiments include two different milling processes for a specific combination of machine tool, tool and workpiece. The smart tool holder system measured the process forces in two directions as well as vibrations in three directions. The sensor data was transmitted wirelessly to a PC, where it was analysed. For each process type and each sensor signal, a deep learning model, consisting of three CNN layers, one LSTM layer, and an MLP, was trained to predict the tool wear state. The final models were evaluated using previously unknown test data. A high prediction accuracy of minimum 97,3 % was achieved for all sensor signals. A maximum of 99,9 % accuracy was accomplished when using bending moment signals.

In conclusion, the presented methodology can be estimated as suitable for prediction of tool wear in pre-trained milling processes. Especially, the use of a sensory or intelligent tool holder to measure forces and vibrations in close proximity to the process can be recommended to generate a sensitive database for the presented deep learning model. In particular, the radially oriented cutting force provides the most expedient information.

In order to continue this work in the future, further experiments for varying combinations of tools, cutting conditions, kinematics, workpieces, and machine tool will be conducted to verify the results. The possibilities of transfer learning to extend the already trained models to new processes will also be investigated.

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