DOI 10.5162/iCCC2026/1.3

Smart Sensor for continuous condition monitoring and predictive maintenance of a milling machine

Joris Liebermann, Martin Lehmann, Dirk Mayer, André Schneider, Akshaya Bindu Gowri, Fraunhofer IIS, Dresden, Germany
joris.liebermann@iis.fraunhofer.de

Abstract

We present a wireless, retrofittable smart sensor for continuous vibration-based condition monitoring and predictive maintenance of milling machines. The work is motivated by the need to detect specific conditions of the machine, like tool wear, to protect surface quality in high-throughput machining of large, costly parts. Our goal is to evaluate a low-cost hardware solution that can be quickly applied to existing milling machines against a state-of-the-art system. Following a methodical development cycle, we build a smart sensor including hardware and software components, acquire ground-truth data of milling with a sharp and a blunt tool, develop an edge-deployable AI model, implement the AI model on the smart sensor, and validate the implementation. Final deployment demonstrates reliable classification and actionable alerts, with comparative tests indicating monitoring quality comparable to a high-cost reference at reduced cost and integration complexity. Thus, the smart sensor can operate as a milling assistant, signalling worn tools with minimal installation effort and maximal data privacy.

1 Introduction

Damage or wear of milling tools causes deteriorated surface quality of produced components. When machining expensive parts or at high speed, early detection of these effects is mandatory to minimize rejects and optimize the process. This motivates in-process assessment of milling quality using machine-integrated sensing.

The application of sensors to detect tool wear has been extensively researched in the past. However, modern sensing technologies based on microelectronics and MEMS (micro-electromechanical systems) enable compact, wireless, and smart sensor systems, that can be realized at scale and deployed to a larger range of milling machines [1]. The implementation of advanced algorithms like neural networks on these devices even allow for complete offline processing, ensuring maximal data privacy and low latency. Generating information on tool wear requires the integration of advanced signal analyses and sensors into the machine. Among the most sensitive measurands are cutting force, vibration and acoustic emission or even a fusion of these [2], [3]. With the goal of developing a scalable solution, our study puts a focus on vibration sensing, which can be integrated with a moderate effort.

Wireless sensors alleviate retrofitting of monitoring systems to machines [4]. However, since vibration signal transmission requires high bandwidth, there is a motivation to integrate the signal analysis directly with the sensor and reduce transmission to relevant information needed for controlling the process.

Artificial intelligence (AI) has proven useful for tool wear analysis in the past, however has not been implemented in commercial products widely yet. A prerequisite for the transfer of such from lab to the shop floor is the automated operation of the monitoring system and a user interface that provides useful information to the machine operator [5]. Thus, our development targets the integration of AI based signal analysis directly at the sensor to provide tool condition information to the user.

With the introduction of Industry 4.0 and the industrial internet of things (IIOT), smart sensors, that integrate acquisition, processing and communication capabilities have gathered significant attendance [6]. Low-cost MEMS sensor hardware has been successfully qualified according to industrial standards [7]. Thus, consequently signal analysis should be implemented by low-cost systems, to enable scalable smart sensor systems for industrial use cases.

In the following sections of the paper, we introduce the applied methods, including smart sensor design, experimental set ups, AI model development and validation approach. After that, we present performance results obtained and close the report with a discussion and conclusion.

2 Methods

2.1 Design Methodology

For building the smart vibration sensor we followed a previously introduced development cycle [8], that was applied before [9] allowing for efficient iterative design and rapid prototyping. The five steps of this methodical approach are as follows: 1. Ground truth data acquisition from the machine, 2. Data analysis of the obtained data, 3. Engineering of the smart sensor, 4. Validation in lab tests, 5. Integration into the target environment. This workflow allows all subsequent development, testing and optimization after a single data acquisition campaign.

2.2 System Architecture

The hardware base of the smart sensor is an Arduino Nano 33 BLE Sense Rev2 as it is a compact cost-effective microcontroller board with BLE capabilities and acceleration sensor. The board is equipped with a nRF52840 (Arm® Cortex®-M4F, 256kB RAM) possessing sufficient computational power and memory to run fully quantized neural

This work was partly funded by the Free State of Saxony within the Center for Prototyping and Test of AI systems.

networks. The on-board BMI270 is a digital MEMS-based Inertial Measurement Unit (IMU) and provides three axis acceleration measurements with up to 1600 samples/s and a selectable range of +-2g to +-16g.

For wireless operation, we integrated a Li-Ion battery with charging module. A 3D printed enclosure shields the electronic system against environmental impacts like cooling liquid and manual handling. Two magnets on the base enable for rapid mounting on the target surface of a machine. The board is screw-mounted to the bottom of the housing with a tight mechanical coupling to the bottom magnets, ensuring optimal transmission of the vibration signals from the machine into the sensor element. As the system should also work offline, an external LED was added for immediate feedback.

A custom sensor configuration for the BMI270 was uploaded to achieve the maximal sampling rate, by outputting raw data instead of processed g-values to speed up reading operation. The First-In-First-Out buffer of the IMU ensured continuous monitoring while processing or sending data. The maximal data output rate of 1600 samples/s was set at a range of +-4g.

The obtained raw data in three axes is batched into maximum sized Bluetooth Low Energy payloads and send out with the minimal connection interval to a Raspberry Pi 4 that structures and publishes it to a server.

2.3 Experimental Setup and Data Acquisition

To evaluate the smart sensor under real operation conditions, we conducted face milling of a flat steel workpiece. The objective was to capture vibration data from different tool conditions, sharp and blunt, with the smart sensor and a reference system and compare their performance.

The milling program executed two opposing roughing passes. First, the sharp tool machined from the right edge toward the center and machined the surface line after line. After an automatic tool change, the blunt tool mirrored this process from the left edge towards the center. To isolate the passes from each other, an uncut bridge in the center is left in between the milled surfaces. Cooling liquid was applied throughout the whole process. The total runtime was approximately 4 min, obtaining 1min 46s of active milling data for each tool condition. The parameters of the milling process are summarized in Table 1.

Parameter	Value
Process	Conventional face milling
Tool	10 mm end mill (6 cutting edges)
Radial depth of cut	60 %
Axial depth of cut	2 mm
Spindle speed	3500 rpm
Feed rate	600 mm/min

Table 1: Parameters of Milling Process

As reference for the sensor performance a state-of-the-art system, the SKALI.KIT data acquisition system (developed at Fraunhofer IIS and Fraunhofer IZFP) was used to acquire vibration data from piezoelectric sensors and store it in the server. The accelerometer considered for comparison was a uniaxial Kistler KS77C.100 at a sampling rate of 16kHz.

Sensors were magnetically attached to a shoulder near the machine spindle. For evaluating the smart sensor performance, the reference data was aligned during postprocessing by down-sampling with a low-pass filter, DC removal and temporal alignment through linear interpolation. The comparison of the sensors occurred in both time and frequency domain.

2.4 AI Model & Embedded Algorithms Development

The vibration time series data acquired from the smart sensor was analyzed to identify meaningful features to use as input for the neural network. The most common features for vibration data in time domain and frequency domain were inspected. Frequency-domain analysis was prioritized over time-domain features due to clearer wear signatures and embedded deployment feasibility.

To mitigate mounting misalignment, only the z-axis spectrum (normal to mounting plane) was processed, which is not affected by in-plane rotations of the sensor.

For a robust classification, we employ a compact frequency-domain feature pipeline that is also suited for smart sensor deployment. From 512 samples, we apply Hanning windows with 50% overlap and compute the magnitude of the Fourier spectrum at a size of 64 bins as computing power and memory are limited in the Arduino. Given the previously obtained time series we yield a data set with 663 training samples for each label.

A fully connected neural network (TensorFlow Keras) consisting of 64 input neurons, two hidden layers and a single output neuron was trained with 75:25 train/test split and Adam optimizer, using binary cross entropy for 40 epochs. Deployment of the neural network in the smart sensor required conversion to TensorFlow Lite for quantization to 8-bit. The resulting model was translated to a C header file and implemented into the firmware of the Arduino along with the same feature pipeline. In the final smart sensor, the classification results were signaled by the external LED that activated at detection of a worn tool.

2.5 Validation in the Laboratory

For testing the proper implementation of the signal processing pipeline in the microcontroller with respect to the Python implementation that was used during model development, a “known answer test” is conducted. After training and testing the algorithms on the PC, a prerecorded time series was processed both on the microcontroller and on the PC and the outputs of the feature generation pipeline were compared. Large differences in the feature vectors would indicate implementation errors. Also, the output of the AI model using the same features as input is compared.

To evaluate the hardware implementation, the recorded vibration time series obtained during milling were replayed on an electrodynamic shaker with 20kHz bandwidth and a closed control loop. Due to the stationary character of the

DOI 10.5162/iCCC2026/1.3

signals and the low latency of the implementation, 6 seconds for each of the signals are sufficient to test the performance of the proposed smart sensor.
For the final deployment at the machine, the smart sensor with classification firmware was placed in the same location as in the data acquisition phase and the milling program was restarted. As accuracy metric for reliable classification the LED was tracked visually during the whole process.

3 Results

3.1 Measurements

Figure 1 displays the spectrogram of the acceleration data in z axis obtained by the Arduino. During operation of both tools the signal exhibits significant excitation at the same harmonically spaced frequency bands, while there are low-energy segments in-between caused by transition of the toolpath. The sharp tool causes lower magnitudes with excitation at very defined frequency bands, while the blunt one exhibits higher excitation with less defined transitions. The active milling process is visibly divided by the reduced signal magnitude during tool change.

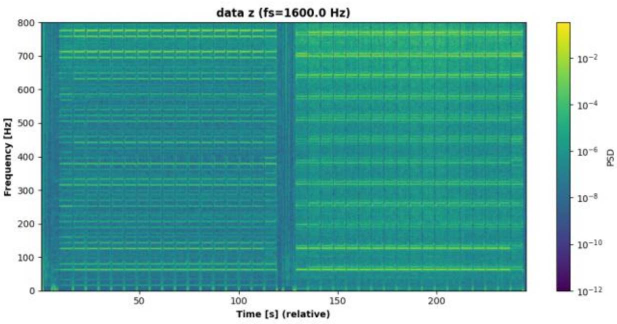

Figure 1: Spectrogram of acceleration in z direction acquired by the smart sensor displaying milling with a sharp tool (left) and blunt tool (right)

3.2 Data Comparison

Figure 2 presents the synchronized acceleration data from the smart sensor and the reference sensor (KS77C.100) over the first 5 seconds. Both signals show considerable agreement in the time domain, with similarities at transient events. After beginning of milling operation at about 3s, the amplitude of the smart sensor is slightly higher than the reference sensor.

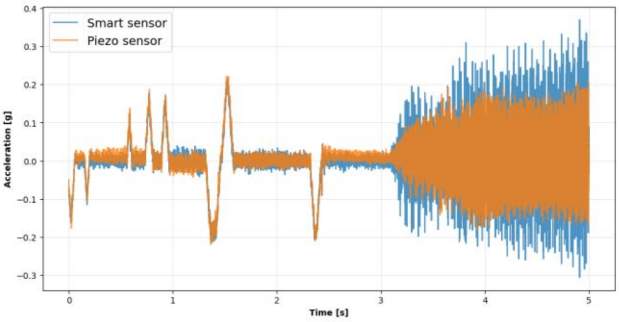

Figure 2: Acceleration data obtained from the smart sensor (blue) and the piezo sensor (orange)

The differences in power spectral density of the smart sensor to the reference sensor during the milling operation are depicted in Figure 3. Both capture the strong excitation at the specific frequency band mentioned before, while the Arduino exhibits a larger magnitude baseline and less variation across the frequency spectrum.

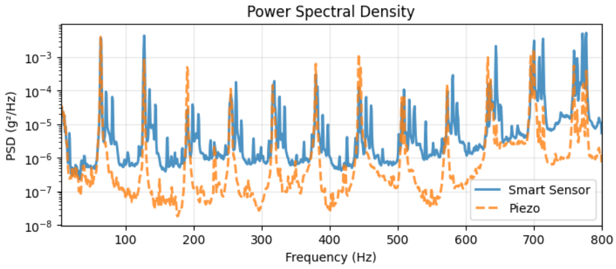

Figure 3: Power spectral density of piezo (orange) and smart sensor (blue) during milling process

3.3 AI model Performance

After training on the frequency spectrum data set, the neural network achieved a classification accuracy of 97% on the test set of 166 samples for each tool condition. Quantization of the model to 8-bit integers did not reduce the classification accuracy on the test set and produced identical results as before.

	True sharp	**True blunt**
Predicted sharp	156	0
Predicted blunt	10	166

Table 2: Confusion Matrix

Accordingly, the confusion matrix in Table 2 demonstrates that all blunt tool samples were detected correctly while a small amount of sharp tool data was classified as blunt. The only outliers are 10 false positives, where sharp tool vibrations are misclassified as blunt during low-energy segments when the toolpath changed during the active milling process.

3.4 Validation

The comparison of calculated feature vectors in Python to the microcontroller implementation only exhibited minor differences with a mean relative deviation of 0.006% between with a maximum difference of 0.022%. The resulting classification matched. During the shaker tests, the smart sensor produced correct classifications in real-time for replay of both the blunt and the sharp tool data segments. In the final deployment at the machine, the smart sensor continuously achieved reliable classification through the whole milling process. Only two incorrect classifications were observed during the sharp tool usage, whereas all blunt-tool operations were detected correctly.

4 Discussion

The results demonstrate that our five-stop development methodology is effective for rapid prototyping of a smart vibration sensor for tool condition monitoring. The system reliably distinguishes between sharp and worn tools in both lab tests and real-world applications.

The model has a small bias of occasionally predicting a sharp tool as blunt during short low-energy transition segments when there is no active cutting, as this occurs for both tool conditions. Validation shows that the feature pipeline is correctly implemented, with only minor deviations probably due to differences in numerical precision of the systems.

Through rigorous validation on our shaker test bed, performance is comparable to traditional sensor setups with data processing on a dedicated acquisition and processing unit or in the cloud.

Evidentially, low-cost hardware is generally able to capture the differences in vibration signature accurately enough to distinguish between the different tool conditions. Although the raw measurement accuracy is slightly below that of industrial grade piezo sensors, the entire system performance outweighs their advantages and allows for flexible adaptation and configurability. While traditional sensor setups often require complex cable management and bulky data acquisition hardware, our battery-driven solution exhibits quick time-to-measurement with minimal setup effort. The embedded algorithms and AI models potentially eliminate the need for any further data processing depending on the use case. However, the use of a battery also entails higher maintenance effort since the battery needs to be charged from time to time even at the most conservative energy saving modes. For a long-term monitoring setup, a wired setup with constant energy supply should be considered. Nevertheless, in contrast to traditional sensor setups, energy could be supplied to multiple sensors with a single (daisy-chain) cable reducing wiring to a minimum.

Limitations of the presented solution contain limited data variance as we only conducted a few experiments. Therefore, the results are limited to exactly this setup. No generalization over milling with other materials, cutting parameters or machines can be applied. This will be the target of ongoing research in this field.

5 Conclusion

This work successfully developed and validated a wireless, retrofittable smart sensor system for vibration-based tool condition monitoring in milling machines. The Arduino-based solution, featuring edge-deployed AI processing, achieved 97% classification accuracy in distinguishing between sharp and worn tools while operating entirely on-device. Careful and rigorous design and validation demonstrated performance comparable to high-cost commercial reference systems despite using low-cost MEMS sensors. Key advantages include minimal installation effort through magnetic mounting, complete data privacy due to on-sensor processing, and reduced integration complexity compared to traditional wired monitoring systems. The validation process confirmed reliable real-world performance with only two false classifications during extended operation. While the current implementation is specific to the tested machining parameters and would require retraining for different setups, this approach represents a practical, cost-effective solution for predictive maintenance that significantly lowers the barrier for implementing condition monitoring on existing milling equipment. Future work should address expanding the model's generalizability across different materials and machining parameters while maintaining the system's simplicity and ease of deployment.

6 Literature

[1] Teti, R. ; Mourtzis, D. ; D'Addona, D.M. ; Caggiano, A.: Process monitoring of machining. In: *CIRP Annals* Bd. 71 (2022), Nr. 2, S. 529–552

[2] Mohanraj, T. ; Shankar, S. ; Rajasekar, R. ; Sakthivel, N.R. ; Pramanik, A.: Tool condition monitoring techniques in milling process — a review. In: *Journal of Materials Research and Technology* Bd. 9 (2020), Nr. 1, S. 1032–1042

[3] Mey, Oliver ; Schneider, André ; Enge-Rosenblatt, Olaf ; Mayer, Dirk ; Schmidt, Christian ; Klein, Samuel ; Herrmann, Hans-Georg: Condition Monitoring of Drive Trains by Data Fusion of Acoustic Emission and Vibration Sensors. In: *Processes* Bd. 9 (2021), Nr. 7, S. 1108

[4] Zhang, Cunji ; Yao, Xifan ; Zhang, Jianming ; Jin, Hong: Tool Condition Monitoring and Remaining Useful Life Prognostic Based on a Wireless Sensor in Dry Milling Operations. In: *Sensors* Bd. 16 (2016), Nr. 6, S. 795

[5] Bombiński, Sebastian ; Kossakowska-Skajster, Joanna ; Jemielniak, Krzysztof: New developments and future prospects in commercial tool condition monitoring systems. In: *Measurement* Bd. 255 (2025), S. 118037

[6] Schütze, Andreas ; Helwig, Nikolai ; Schneider, Tizian: Sensors 4.0 – smart sensors and measurement technology enable Industry 4.0. In: *Journal of Sensors and Sensor Systems* Bd. 7 (2018), Nr. 1, S. 359–371

[7] Iqbal, Ali ; Mian, Naeem S. ; Longstaff, Andrew ; Fletcher, Simon: Performance Evaluation of Low-Cost Vibration Sensors in Industrial IoT Applications. In: *International Journal of Automation Technology* Bd. 16, Fuji Technology Press Ltd. (2022), Nr. 3, S. 329–339

[8] Mayer, Dirk ; Lehmann, Martin ; Beyer, Volkhard ; Schneider, Andre ; Schneider, Peter: Challenges in Design and Validation of MEMS Based Smart Sensor Systems. In: *2024 Symposium on Design, Test, Integration and Packaging of MEMS/MOEMS (DTIP)*, 2024, S. 1–6

[9] Lehmann, Martin ; Liebermann, Joris ; Mayer, Dirk ; Beyer, Volkhard: Performance And Energy Consumption Of Smart Sensors For Vibration-Based Anomaly Detection. In: *2025 Smart Systems Integration Conference and Exhibition (SSI)*, 2025, S. 1–6