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Tool Wear Prediction Upgrade Kit For Legacy CNC Milling Machines In The Shop Floor

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Abstract

The operation of CNC milling is expensive because of the cost-intensive use of cutting tools. The wear and tear of CNC tools influence the tool lifetime. Today's machines are not capable of accurately estimating the tool abrasion during the machining process. Therefore, manufacturers rely on reactive maintenance, a tool change after breakage, or a preventive maintenance approach, a tool change according to predefined tool specifications. In either case, maintenance costs are high due to a loss of machine utilization or premature tool change. To find the optimal point of tool change, it is necessary to monitor CNC process parameters during machining and use advanced data analytics to predict the tool abrasion. However, data science expertise is limited in small-medium sized manufacturing companies. The long operating life of machines often does not justify investments in new machines before the end of operating life. The publication describes a cost-efficient approach to upgrade legacy CNC machines with a Tool Wear Prediction Upgrade Kit. A practical solution is presented with a holistic hardware/software setup, including edge device, and multiple sensors. The prediction of tool wear is based on machine learning. The user interface visualizes the machine condition for the maintenance personnel in the shop floor. The approach is conceptualized and discussed based on industry requirements. Future work is outlined.

Keywords

CNC milling; predictive maintenance; condition monitoring; Tool Condition Monitoring (TCM); tool wear prediction; industry 4.0

1. Introduction

Milling is one of the most widespread manufacturing processes in the industry. A spindle motor rotates a multitooth tool to produce a variety of workpiece surfaces through Computerized Numerical Control (CNC) movements [1,2]. Forces and friction at the cutting tool are caused by high-power machining and the process-related interruption of the cut for each cutting edge [1]. To control the overall product quality and operate at high performance, it is necessary to change tools frequently [3]. Tool maintenance accounts for 20% of machine downtime and 25% of total machining costs [4]. An unexpected one-day stoppage of a milling machine caused by a tool breakage could lead to costs of about 100,000 – 200,000 EUR [5]. Due to the necessity to operate at maximum yield, finding the optimal point of time for tool change is technically challenging [5], but critical for Overall Equipment Effectiveness. On one side, premature tool change leads to efficiency losses. On the other side, tool wear leads to product quality loss, tool breakage and potential machine stoppage [6]. Tool condition monitoring promises to provide the necessary maintenance information by diagnosing the tool condition in real-time and thereby enabling the prediction and scheduling of tool changes [7,3]. In contrast to time-based maintenance strategies, the assessment is based on real-time collected sensor data in the process, instead of rigid intervals from tool suppliers or experience from maintenance technicians or operators [5]. Condition-based maintenance has been a topic in research for many years, but practical solutions are limited, as most approaches are theoretical, and implementations are conducted in laboratory environments [2]. Small and medium-sized enterprises (SME) especially struggle with the applicability because they often have deficits of experience, competence, and capital [8]. Commercially available off-the-shelve condition monitoring solutions are technically limited due to integration barriers, proprietary interfaces, software performance, flexibility issues, and high capital costs [2]. The machine park of SMEs is characterized by a variety of machines from different vendors which do not have appropriate sensing technologies for tool wear prediction and network connectivity available [9,10]. Required expertise in data science is rare [11]. Hence, practical approaches need to be developed that can be installed at various legacy machines. They shall be integrated into shop floor IT infrastructures and have an intuitive user interface. This research work conceptualizes a Tool Wear Prediction Upgrade Kit that can be applied to legacy CNC milling machines. Related work in tool wear measurement systems, tool wear prediction architectures, and Machine Learning (ML) is outlined (section 2). The system architecture and application methodology are described (section 3). The concept is discussed (section 4) and future work is concluded (section 5).

2. Related work

2.1 Tool wear measurement systems

Tool wear occurs at the flank and chip side of cutting tools. On the flank side, friction between the tool and the surface of the workpiece results in tool flank wear. On the chip side, crater wear is caused by the movement of the chip on the tool. Among the two types, flank wear is considered the predominant evaluation index because of the effects on the workpiece quality and process reliability. [12] Tool wear can be measured using direct and indirect methods. Direct methods measure the tool wear using imaging devices, such as a microscope or a machine vision system [2]. This achieves high accuracy but causes machine downtime due to the measurement [13]. Indirect methods rely on sensor data of machining processes to estimate tool wear conditions. Signals relevant to tool wear in milling processes include cutting forces, acoustic emissions, vibrations, power consumption, temperature, and sounds [2]. A dynamometer can measure the tangential and axial cutting forces applied to the workpiece, which is highly relevant to tool wear, as the decrease of tool sharpness causes the increase of cutting forces [13]. However, the dynamometer has direct contact with the workpiece. Electric current sensors can be an alternative to dynamometers, as the increase of cutting forces causes an increase of motor current [14]. Acoustic emission sensors measure the strain wave inside the workpiece. Recent studies show that it provides the most effective information for tool flank wear prediction [13]. Accelerometers can measure the vibration of the spindle and the workpiece, as the decrease of tool sharpness causes an increase of vibrational energy [15]. Temperature sensors measure the heat generated during milling. On the one side, the milling process generates high temperatures. On the other side, high temperatures cause tool wear. It is shown that temperature and tool wear have a positive correlation [16]. However, temperature measurement is affected by lubrication [17], and thus is ineffective for practical application during machining. Microphones measure the sound generated during milling. Studies show that an increase of tool wear causes an increase of sound intensity [18]. Sound signals may face interference from other machine noises; thus, they have limited applicability in noisy shop floors. Besides the relevance of sensor signals, the installation of sensors should also be considered. The sensors should be close to the milling surface without interfering with the milling process. Spindle housing and workpiece fixtures are feasible positions for sensor installation [2]. Direct measurements are time-consuming, often requiring an additional manual step and cannot run in parallel to machining processes [13]. Thus, the research work concentrates on indirect measurements instead of direct measurements. From literature, it can be derived that the indirect measurement of acoustic emissions, vibration sensors and electric motor current provide effective information for tool flank wear. The sensors can be mounted at CNC machines by a simple installation procedure and can be equipped on various machine types and vendors. Therefore, the Tool Wear Prediction Kit's sensor system consists of acoustic emission, vibration, and electric motor current. An increase in accuracy is expected due to the combination of multiple sensor types for the tool wear estimation.

2.2 IT architectures for tool wear prediction

Two approaches of system architectures for estimating the tool wear of CNC milling machines are identified. The first approach includes data pre-processing, feature engineering, modeling, and evaluation of the ML algorithms [19–22]. It considers the development of algorithms but excludes the data acquisition, storage, implementation, and productive operation. Thus, it is only applicable in corporate practice if the associated infrastructure for data acquisition, storage, and result visualization is already in place. The second approach additionally includes data acquisition, storage, and visualization of predicted results. Based on Rastegari et al. [23], vibration sensors are mounted on the CNC machine's spindle to measure its vibration when the spindle moves horizontally. The sensors are connected by cable to a measurement system unit and transformed into a digital signal. From the measurement system unit, the digitized sensor data is transferred to a database via 3G-Network. The stored data is collected and used for the training of the algorithms. Subsequently, the prediction results are visualized. Gouarir et al. [24] present an architecture based on an in-process prediction approach. A dynamometer is mounted to measure the cutting forces. The signal is amplified and sent to a data acquisition system via a cable. The data is stored in an experience database, which is used to train the prediction algorithms. The prediction results are then visualized in a human-machine interface. The architectures of the second approach are based on individual and experimental setups and do not include the productive operation and scaling of the algorithms in corporate practice. Thus, tool wear prediction is still hardly used in corporate practice, although researchers constantly improve the required ML algorithms. Therefore, this paper describes a scalable, holistic architecture that takes the productive operation for multiple machines in corporate practice into account. An edge device running relevant software is used to facilitate applicability. The software design supports the scalability by using lightweight IoT protocols, databases, and device management.

2.3 Machine learning algorithms for tool wear prediction

The ML algorithms need to consider two aspects in predicting tool wear. The first aspect is data pre-processing. Data pre-processing aims to extract representative features from the raw sensor data. Therefore, different sensor data may require different data pre-processing methods. The second aspect is modeling. Modeling aims to build a mathematical model to predict tool wear based on the input features. Thus, different input features may require differentmodeling methods. The recorded sensor data are time-series signals, and thus time-domain features can be extracted from the raw sensor data. Widely used time-domain features include the average value, the standard deviation value, the root mean square value, the kurtosis, and the skewness. For fast-fluctuating sensor data, such as vibration signals, there exists frequency information, and thus frequency-domain features can be extracted using Fourier transformation, such as the power spectrum and the spectral entropy. For non-stationary signals, the frequency spectrum may change over time. In this situation, it is suitable to extract time-frequency features from the raw sensor data, such as the wavelet transform features. [12] Besides extracting features from a single sensor, it is helpful to extract different features from multiple sensors [14]. Feature selection methods can be applied to keep the most useful features and remove useless features, such as principal component analysis, Pearson correlation analysis, and the monotonicity of the features [25,26]. After extracting representative features from the raw sensor data, a prediction model is trained to predict the tool wear. Widely used prediction models include support vector regression, fuzzy inference system, extreme learning machine, and artificial neural networks [13,27]. By extracting the frequency spectrum of the raw sensor data, convolutional neural networks can be applied, and multiple sensor data can be fused into different channels of the convolutional neural network [28]. In order to extract the sequential information from the sensor data, recurrent neural networks with the long short-term memory unit have been proven to outperform many traditional features for tool wear prediction [29]. In addition, 1D convolutional neural network can also extract sequential information [30].

The prediction models are data-driven models, and thus highly depend on the quality of the collected data. Simple models, such as linear regression and support vector regression require fewer data but have lower fitting capability. Complex models, such as neural networks, have higher fitting capability but require more data. Particularly, determining the optimized network structure, e.g., the number of hidden neurons and hidden layers in a neural network, is challenging. The interpretability of data-driven models still need improvement. Thus, it is promising to combine data-driven models with traditional physical models to improve the reliability. [11] A variety of ML models for tool wear prediction have been investigated in research. It can be observed that the selection of the most accurate model with the best performance depends on the conditions of the environment-specific milling process. There exists no one common analysis framework [12]. Therefore, a methodology to select and set the ML model for the application of the system is required.

2.4 Requirements

Related publications investigate tool wear monitoring systems only partially. Despite reasonable advancements in literature, state-of-the-art solutions mostly focus on experimental machine setups and lack an application in industry. A holistic industry-oriented system is yet missing. Therefore, a Tool Wear Prediction Upgrade Kit for legacy CNC milling machines in an industrial setting is developed within this publication. The research work has the following requirements:

a) **Independence of CNC machine vendor:**
The Upgrade Kit shall reach a high degree of sovereignty from CNC vendors; among others, it must avoid using closed protocols or non-standard interfaces to legacy machines.

b) **Adaptability to company-specific CNC machines:**
The Upgrade Kit shall be adjustable to the various CNC machine environments in the industry.

c) **Practical deployment and system scalability:**
The hardware and software framework shall be established as a platform and can be deployed to multiple machines with minor adjustments in system settings or configurations. Practical and easy deployment shall reduce setup time and underline a wide use of the Upgrade Kit.

d) **Stable and industrial-grade system design:**
The Upgrade Kit shall be capable of operating continuously 24 hours daily without supervision. The hardware follows industrial standards for deploying in a factory environment.

e) **Easy usage by maintenance team:**
The Upgrade Kit shall be used easily by the maintenance team in order to improve daily operations. Remote monitoring capabilities shall reduce visual check-ins at CNC machines or with operators on-site.

3. Tool Wear Prediction Upgrade Kit

3.1 System description

The architecture consists of the modules “User Interface”, “Software Hub” and “Machine Learning Model Tool Wear Prediction”, see Figure 1. The solution is executed on an edge device which enables low latency and fast data processing. The module “User Interface” provides components to depict live data and results from the tool wear prediction. The module “Software Hub” provides data collection, storage, processing, and device management components. The module “Machine Learning Model Tool Wear Prediction” can be divided into the productive use of the model and the training of the model. It provides components to pre-process the data, train algorithms and implement them for productive operation.

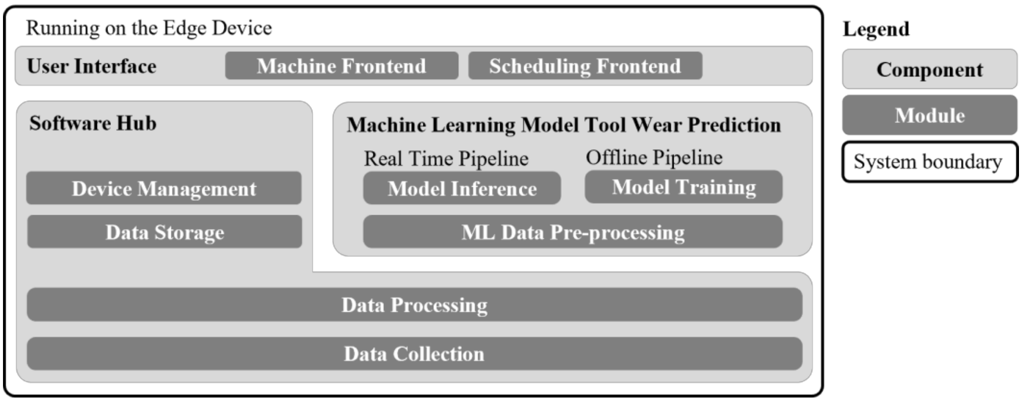

Figure 1: System architecture

As shown in Figure 2, an acoustic emission sensor, a vibration sensor, and a current sensor are used to enable data collection. Acoustic emission and vibration are measured for the spindle of a CNC machine. To process the sensor's analogue signal, a data acquisition system (DAQ) is connected to the sensors. After the transformation of the analog signal, the data is sent to the edge device for temporary storage and potential pre-processing. Raw data or pre-processed data are further transmitted to a central server via Message Queuing Telemetry Transport protocol (MQTT). The communication is organized by an MQTT broker. Utilizing MQTT ensures flexibility, modularity, and ease of implementation. [31] To realize an efficient communication, Sensor Markup Language (SenML) data format is used [32]. The edge device is used for providing computational capabilities for pre-processing as well as model training and data storage. Therefore, the edge device provides an InfluxDB time-series database as well as a PostgreSQL relational database. The time-series database is utilized to store the measurements and tool wear prediction results. The relational database is utilized to store metadata about the machine and its attached sensors and data streams. Furthermore, a device management backend interface is used to expose an application programming interface (API) for managing machine metadata and logically associating sensors and data streams. The device management manipulates the relational database mentioned above. Containerizing the software modules via Docker enables flexibility, e. g., for running the pre-processing for multiple machines on one edge device per machine while running model inference on the core infrastructure and running device management and machine frontends in the cloud. Conversely, if there is only one machine connected to the system, all modules can run in a containerized architecture.

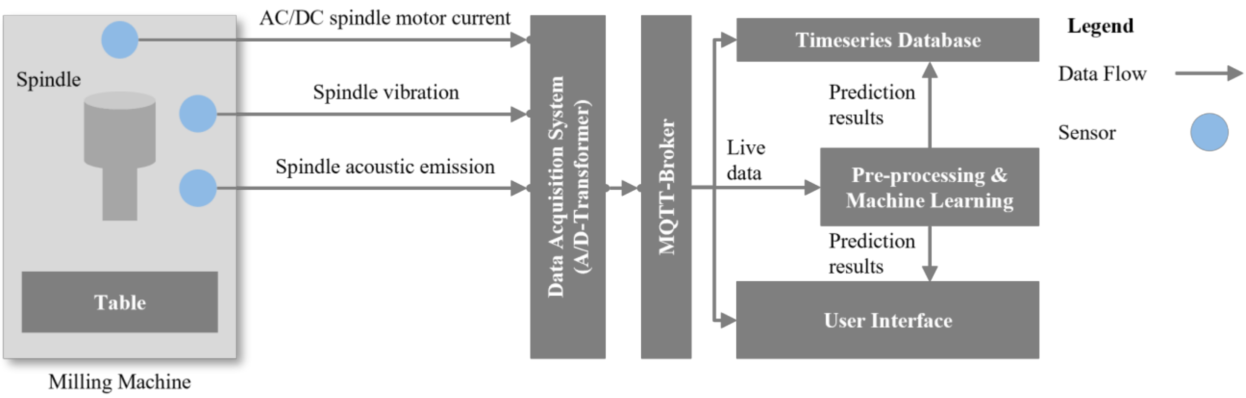

Figure 2: Data flow for the tool wear prediction

The module "Machine Learning Model Tool Wear Prediction" consists of ML data pre-processing and ML models' training and inference. Since the time-domain sensor signal (acoustic emission, vibration, electric motor current) can be well analyzed in the frequency domain and the frequency characteristic changes along time, time-frequency features can be extracted from the raw sensor signal during pre-processing. The extracted features are used as the input to the ML model for prediction purposes. Given the input sensor data, the ML model outputs the tool flank wear which is displayed on the user interface. The application of ML models to a CNC milling machine follows a parent-child methodology. The parent models are pre-trained models based on existing datasets or physical laws. The child models are obtained by further adjusting the parameters of the parent models using the sensor data collected from real-environment CNC machines. Therefore, the child models can be machine and environment-specific, which provide performance improvement over parent models.

The adoption of the parent-child methodology requires two major steps. The first step is offline pre-training, and the second step is online fine-tuning. During the offline pre-training, state-of-the-art ML models are trained using existing data, such as public datasets. Suitable features and suitable models are selected based on their prediction accuracy. These pre-trained models are parent models. Recommended features are time-frequency features, such as those based on wavelet transform and short-time Fourier transform. Recommended models include neural networks, such as multilayer perceptron, 1D convolutional neural network, and recurrent neural network. The parameters of a parent ML model are initialized randomly. Then, given the sensor data from existing datasets, the model outputs a predicted tool flank wear value. A loss function is used to measure the difference between the predicted value and the ground-truth value, to ensure the model parameters are updated towards the direction of minimizing such difference. After installing retrofitting sensors to CNC milling machines, real-time sensor data can be collected, and the online fine-tuning starts. During the online fine-tuning, the parameters of the parent models are adjusted using the sensor data, yielding the child models. The child models require fewer training data as compared to the parent models. Nevertheless, when the system continuously collects sensor data, the child models can be continuously updated to improve performance.

The prediction results are displayed on a dashboard, which enables remote monitoring of multiple machines. To handle large volumes of data and reduce network traffic, the mean data values are calculated and displayed. Figure 3 shows the design of the frontend for one machine (RN-C541). It comprises a dashboard to monitor the cutting tool of the machine connected to the edge device as well as the machine's condition. Both real-time sensor data and real-time predicted tool flank wear are displayed.

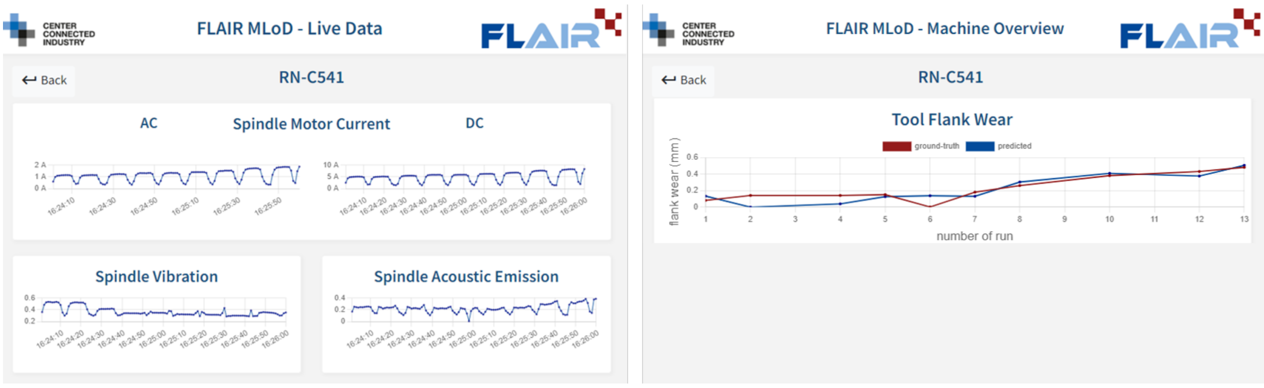

Figure 3: Design of the user interface

3.2 System hardware

Considering the effectiveness of different sensors for tool wear prediction, three types of sensors are selected: the AC current sensor, the vibration sensor, and the acoustic emission sensor. To collect the data accordingly, the current sensor should cover a range of 0 – 100 A. A frequency range of 0 – 20 kHz for the vibration sensor and 50 – 200 kHz for the acoustic emission sensor is required. The vibration sensor and acoustic emission sensor should be waterproof (Ingress Protection IP 68), as they are installed near the spindle and the workpiece, where coolant exists. Based on these requirements, for vibration sensor, the PCB Piezotronics 622B01 accelerometer has been selected, with a sensitivity of 100mV/g and a frequency range of 0.2Hz-15kHz. The vibration sensor can be connected to the edge device through a USB signal conditioner. For acoustic emission sensor, Fujicera AE204SW has been selected, with a sensitivity of 66dB and a frequency range up to 200kHz. A DAQ board is needed to do signal amplification and A/D conversion. The current sensor is a 100A AC current probe. It shares the same DAQ board with the acoustic emission sensor. For edge device, Compulab Tensor-I20 Multi-IoT is selected, with Intel Xeon E-2276ML CPU, 16GB memory, and 1TB storage. It runs Linux operating system, supports RS232/RS485, CANBUS, GPIO, and USB3.1, which should be sufficient for on-site real-time data collection, processing, storage, and transmission.

3.3 Upgrade Kit application methodology

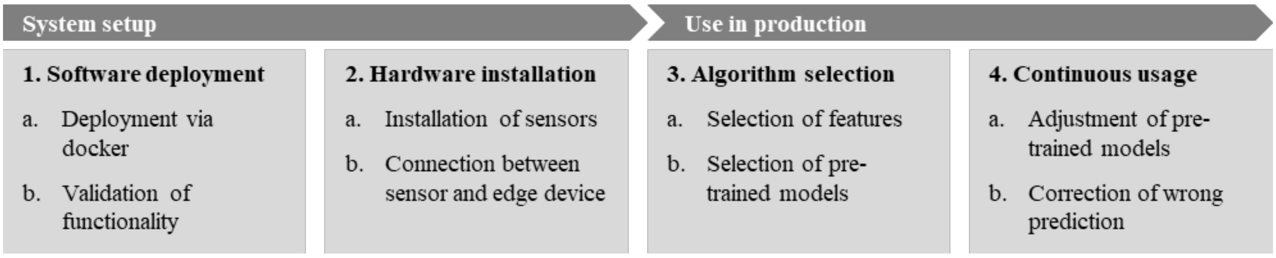

Figure 4: Upgrade Kit application methodology

The application methodology of the Upgrade Kit to real-environment CNC milling machines includes 4 steps. The first step is the deployment of the software on edge devices. The second step is the installation of retrofitting sensors on CNC machines and the communication between sensors and edge device. The third step is the selection of suitable feature extraction algorithms and suitable pre-trained ML models (i.e., parent models). The last step is the validation of the whole system and the continuous collection of data. An overview is given in Figure 4. In the first step, the designed software is deployed as Docker containers to the edge device for a specific CNC machine. Usually, one CNC machine is covered by one edge device, for on-site data collection, storage, processing, and transmission. Nonetheless, adjacent CNC machines may also share the same edge device depending on the specific situation in the shopfloor. In the second step, selected retrofitting sensors, such as current sensor, vibration sensor, and acoustic emission sensor, are installed on the CNC machine. The current probe is clamped on the spindle motor current cable; the acoustic emission sensor is installed on the spindle using a magnetic holder; the vibration sensor requires a screw mounting pad and a clamping fixture. Sensor data are transmitted to the edge device via cables. Data is stored locally and transmitted to the frontend for remote monitoring. The sensor data can be stored on a remote server for long-term recording purposes. In the third step, a default set of features and pre-trained parent ML models are selected. It is optional that the operator selects suitable features and models manually. After determining the features and parent models, real-time data collection can be started. The pre-trained parent models can be directly used to predict tool flank wear values. If newly collected sensor data are paired up with measured tool flank wear values, they can be used to adjust the parameters of the parent model, yielding a child model. In the last step, the whole system is tested for robustness and functionality in a long-term run, such as the integrity of data, the transmission efficiency of data, the proper functioning of the backend (e.g., database) and the frontend (e.g., dashboard). A feedback mechanism is adopted, through which the operator can manually correct the prediction by changing some parameters, such as the offset value.

4. Discussion of the solution

The solution is evaluated in regards to the requirements in section 2.4. The independence of CNC machine vendors (req. a) is achieved by the indirect sensor measurement of the tool wear. Thereby, no interface or API to machine-specific hardware or software is necessary. All hardware and software components are part of the system; thus, a vendor-agnostic approach is realized. The adaptability to company-specific CNC machines (req. b) is achieved by the flexibility of retrofitting sensors and the adaptability of ML models. On the one hand, suitable sensors can be chosen according to specific requirements or necessities of different CNC machines. On the other hand, the parent-child methodology enables further adjusting the parameters of pre-trained parent models to produce the machine-specific child models, using real-time collected machine-specific sensor data. The child models shall provide performance improvements.

The easy deployment (req. c) is realized by the containerized deployment strategy, which avoids cumbersome environment settings on different operating systems and enables easy transferring to multiple machines. The high scalability is achieved by using lightweight IoT protocols, such as MQTT. IoT setups at scale are mainly limited by the available data transmission rate of the utilized network as well as the computational power and storage capacity of the IoT devices. On using MQTT, a publish-subscribe architecture is established, which requires fewer resources for data transmission and makes better use of the network bandwidth.

The system is designed for industrial usage (req. d), by the adoption of industrial-grade sensors and edge device, which support 24-hour continuous operation. It is also designed to be operator-friendly (req. e), by the adoption of remote monitoring. A dashboard continuously displays real-time sensor data and the predicted tool wear. Data are stored locally in the edge device, which can be retrieved for further analysis.

5. Conclusion and future work

The research work outlines a tool wear prediction Upgrade Kit for CNC machines. The system architecture is independent of machine type and vendor. The industrial applicability of the system is reached by industrial-grade edge devices that can be deployed as an addon to legacy machines on the shop floor. The combination of multiple sensors, e.g., electric current, vibration, and acoustic emission for monitoring the machining process, increases prediction accuracy. The scalability of the approach is supported by lightweight IoT protocols and a containerized IT framework, including a backend for data storage and a frontend for data visualization. The adaptability of the approach is achieved by the flexibility in sensor selection and the adjustability of pre-trained ML models. An application methodology is outlined, which enables the application of the Upgrade Kit in diverse industry environments. In the next step, the system will be validated in an industrial environment. Preliminary experiments using an open-source data set [33] show that combining features from multiple sensors outperforms single-sensor features. Therefore, a multi-sensor setup is recommended. In addition, neural networks give better performance than traditional models, such as linear regression and support vector regression. A variety of neural architectures will be included. A feedback mechanism will also be enabled, allowing manual correction on unsatisfactory predictions and manual adjustment on ML model parameters. Data augmentation techniques shall be investigated to reduce the required amount of machine-specific training data.

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