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Procedia CIRP 118 (2023) 519–524

www.elsevier.com/locate/procedia

16th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME '22, Italy

Boundary conditions for the application of machine learning based monitoring systems for supervised anomaly detection in machining

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Abstract

Monitoring systems may contribute increasing the availability of machine tools and detecting process deviations in time. In the past, machine learning has been used to solve a variety of monitoring problems in machining. However, boundary conditions for the assessment of the principal applicability of machine learning approaches for supervised anomaly detection in machining have not been exhaustively described in the literature. In this paper, objectives as well as deficits of literature approaches are identified and influencing factors on the monitoring quality are described. As a result, we derive boundary conditions and discuss challenges for successful implementation of machine learning based monitoring systems for supervised anomaly detection in industrial practice.

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Peer-review under responsibility of the scientific committee of the 16th CIRP Conference on Intelligent Computation in Manufacturing Engineering

Keywords: Machine learning; Machining; Monitoring; Quality assurance

1. Introduction

Monitoring systems are used to prevent machine component damages during machining and to ensure compliance with quality requirements [1]. Achieving of the defined quality requirements is necessary for the subsequent functionality of the manufactured workpiece [2]. A distinction is made between process and condition monitoring. In process monitoring, the tool condition, the workpiece surface quality and the chip condition are monitored. In addition, chatter vibrations are detected [3-6]. The subject of condition monitoring is the detection of damages of machine components such as linear drives or spindles, which in turn impact the workpiece quality [1].

Monitoring approaches are divided into continuous or intermittent. Continuous monitoring takes place in parallel with the manufacturing process. In contrast, intermittent monitoring is carried out at intervals [10]. Furthermore, direct and indirect monitoring approaches are distinguished. In the case of direct monitoring, physical condition variables are monitored directly using a suitable sensor. In indirect monitoring, auxiliary variables such as machine-internal signals from the machine control system and external sensors (dynamometer, acoustic emission, acceleration) are utilized to evaluate conditions [3-5]. Sensory components such as sensory spindles, sensory tool holders and sensory workpiece holders have also been developed for process monitoring [7,8]. Indirect monitoring is used in applications where an explicit determination of machine and process conditions is time consuming or impossible due to the nature of the process [2,9].

After data acquisition and signal processing, segmentation and feature generation are performed [3-5]. Feature generation is often necessary to perform evaluations to cope with high sampling rates of sensors like acoustic emission [6].

When selecting the monitoring approach, the presence of fault data must be taken into account. In the context of semi-supervised anomaly detection, it is assumed that only data describing the normal condition of processes or machine components are available [11]. For example, fixed boundaries, tolerance bands and dynamic thresholds have been developed for process monitoring [12]. These methods are suitable for the

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10.1016/j.procir.2023.06.089

detection of anomalies with abrupt signal changes like tool breakages but less suitable for the detection of continuous process changes like tool wear [6]. Semi-supervised anomaly detection methods output a binary state variable (fault detection) and the root cause of the anomaly is unknown [13].

Given a labeled data set that contains information about anomalies, supervised anomaly detection methods are applicable [11]. In machining, labels are discrete condition classes or measured quantities that describe the quality of workpieces or the tool condition. Machine Learning (ML) methods have been used frequently to link the generated features to discrete condition classes or continuous measurands. These methods can generate rules based on the data automatically, either implicitly (black-box) or explicitly (white-box) [14,15]. The application of ML-methods requires usually a two-step procedure. In the offline phase, the data is collected and subsequently labeled. Further steps include time series segmentation, feature generation as well as choosing the most suitable ML-pipeline. In this context, a ML-pipeline comprises data preprocessing, feature extraction and selection, ML-model selection and the optimization of their hyperparameters. In the online phase, the trained model is applied to detect anomalies.

Table 1 provides an overview of typical objectives in machine condition and process monitoring. ML-methods are used in the context of supervised anomaly detection scenarios to solve regression and classification problems (see Figure 1). A typical application of regression models is the indirect determination of continuous target variables (such as measurands to classify process states based on a threshold value). Frequently predicted target variables include, for example, the tool flank wear or the surface roughness [3-5]. These quantities belong to the industry-relevant quantities [16].

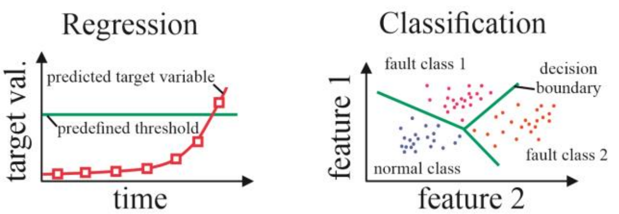

Fig. 1. Procedures for supervised anomaly detection using ML-methods.

Other approaches assign a discrete condition value to the sensor signals or the generated features (classifier). In contrast to semi-supervised anomaly detection methods, classifiers not only output a binary condition class but determine different fault classes once the fault root cause is known (fault diagnosis [13]). To ensure a broad applicability of the model in process monitoring, machining experiments with different process parameters, materials etc. are often carried out during the offline phase. To reduce the number of time-consuming experiments a design of experiments should be performed [4]. In process monitoring, sliding windows are often employed. Monitoring approaches used in condition monitoring are often intermittent and usually evaluate signals based on a predefined test cycle. For example, a test cycle may include the movement of a linear actuator in one direction and back to the origin.

However, lacking expertise in the applicability of ML-based approaches for given monitoring problems represents a barrier for domain experts in practice. To assess the applicability of ML-based monitoring systems, boundary conditions must be known which have to be satisfied. In the context of machining, there is a lack of explicit description of such boundary conditions in the literature. Therefore, we address the following question: Which boundary conditions exist to check the principal applicability of ML-based monitoring systems in the machining environment?

For this purpose, we first analyse monitoring approaches from literature and identify deficits of existing approaches. In the next step, factors influencing the monitoring quality are identified. Based on these factors, we derive boundary conditions and present challenges for practical applications.

2. Typical shortcomings of existing monitoring approaches

The presented literature approaches depicted in Table 1 show shortcomings with respect to the usage of ML-methods. Table 2 provides an overview of the type of data partitioning, hyperparameter optimization, data preprocessing, dimensionality reduction as well as the ML-model chosen. These studies arbitrarily select the algorithms at the respective stages of data preprocessing, dimensionality reduction and regression / classification. In many cases, only a single ML-model is used. However, numerous studies [29] demonstrated that no single ML-method provides the best results for all data sets. Moreover, some authors (see [17,20]) do not perform data preprocessing or dimensionality reduction. In this context, automated machine learning (AutoML) offers the possibility to systematically support the practical user in the selection of methods at the respective stages. In short, AutoML refers to methods for the optimization, automation and analysis of design decisions regarding the complete ML-Pipeline in order to obtain a model with peak performance. In addition, past studies have shown that AutoML tools like Auto-Sklearn achieve the most robust classification performances compared to various other classifiers [29].

Table 1. Overview on objectives of machine learning based indirect monitoring systems for supervised anomaly detection in machining.

Monitoring scope	Machining Process			Machine Tool Component
Approach	Output of a continuous quality or tool condition variable: • Regressor	Output of a discrete quality or tool condition class: • Classifier		Output of a discrete machine component condition class: • Classifier
Monitoring target	Tool condition: • Flank wear [17] • Flank wear and remaining useful life (RUL) [18] Workpiece quality: • Roughness [2,19,20] • Shape deviation [2]	Tool condition: • Tool chipping [21] • Tool breakage [9,21] • Tool wear [21,22] • Missing tool [9]	Workpiece quality: • Chatter [22] • Material determination [24] Chip condition: • Chip disposal [25] • Chip form [26]	Condition of: • Ball screw drive [27] • Spindle bearing [28]

Table 2. Used methods of machine learning based indirect monitoring systems in accordance with literature approaches from table 1.

Ref.	Data splitting mode	Hyperparameter optimization	Data preprocessing / Dim. Reduction	Classifier/Regressor
[17]	Hold out (train, test)	None, Change of neurons in hidden layer (grid)	None	Neural Network, Support Vector Regression, Random Forest
[19]	Hold out (train, test, validation)	Trial-and-error	Normalization	Feed-forward Neural Network
[2]	Hold out (train, test)	Three types of network architectures	Normalization, Main effect plot, Model trained with different feature subsets	Neural Network
[23]	Hold out (train, test, validation)	None	Normalization	Convolutional Neural Network
[20]	Inner cross-validation, outer hold out	Grid-search	None	Support Vector Regression
[21]	Repeated cross validation	Grid-search	Normalization, Correlation based feature selection; backward elimination	Ensemble (based on three classifiers)
[24]	Hold out (train, test, validation)	Grid-search	Normalization	Neural Network
[9]	Hold out (train, test)	None	Principal Component Analysis	Neural Network
[27]	Hold out (train, test)	None	Feature Scaling, Feature Selection (Fisher-Score, Sequential Forward Selection)	Support Vector Machine
[25]	Hold out (train, test)	None	Normalization	Neural Network
[18]	Inner hold out, outer cross-validation	Grid-search	Principal Component Analysis, ISOMAP	Support Vector Regression
[24]	Hold out (train, test, validation)	Grid-search	Normalization, Feature Selection (Statistical overlap factor)	Neural Network

In addition, the performance depends usually on the chosen hyperparameters [29]. Several literature approaches (see [9,17,25,27]) do not adjust the hyperparameters of the chosen ML-model. Often, only the hyperparameters of the classifier or regression model are optimized. Though, data preprocessing, feature selection and extraction methods often also possess adjustable hyperparameters.

To produce high prediction performances on unseen data (which is called generalization ability) overfitting needs to be avoided. Overfitting is an open problem in hyperparameter optimization. To assess the ability of the model to generalize well, data partitioning is crucial. Therefore, a separate holdout set should be used to tune the hyperparameters [30]. In contrast, some literature approaches (see [2]) use the same part of the data set for model training and hyperparameter optimization. Other literature approaches (see [17]) utilise the same part of the data set for hyperparameter optimization and model comparison.

With regard to the practical application of tool condition monitoring systems, Jemielniak [5] mentions further deficits. For example, signal features are often selected arbitrarily. In addition, required working memory and computing times are usually neglected.

The choice of the generated signal features is often connected with the adjustment of corresponding parameters of feature libraries, which influence the monitoring quality. In the literature, these parameters are often not systematically adjusted. For example, Teti et al. [3] note that when extracting signal features from the time-frequency domain using wavelets, authors select the wavelet type without providing a reason.

3. Factors influencing the monitoring quality

Based on the literature approaches analyzed in Chapter 2, we first identify influencing factors on the monitoring quality to derive boundary conditions. According to Brophy et al. [9], two factors are decisive for the successful application of monitoring systems in machining: the quality of the sensor data and the method used for condition assessment. However, for the practical use of ML-based monitoring systems these criteria are general and highly depend on the given application. In addition to the steps presented by Abellan-Nebot and Subirón [4] for developing process monitoring systems in machining, the main factors influencing monitoring quality are depicted in Figure 2.

The monitoring quality depends on the type and position of the selected sensors, the measuring chain, and the signal preprocessing. As described earlier, the selected part of the monitoring signal (segmentation) and the selected signal features possess a significant impact.

Another influencing factor is the quality of labels (accuracy of the measuring instrument, accuracy of class assignment). For classification tasks, the class balance plays an important role. Apart from samples representing the normal state, sufficient number of samples of the fault classes need to be available. In contrast, the range of values of the target variable represented in the data set regarding the desired alarm threshold plays an essential role for regression problems.

The variance of condition independent influencing factors on monitoring signals not represented in the data set influences the monitoring quality. For example, the signal course of the cutting forces in the milling process changes not only with the tool wear but with the selected process parameters and the cutting conditions as well. In addition, the tool condition is also affected by the process parameters. As a result, process parameters should be considered by the model unless the process parameters are guaranteed to be constant (for example in a mass production scenario).

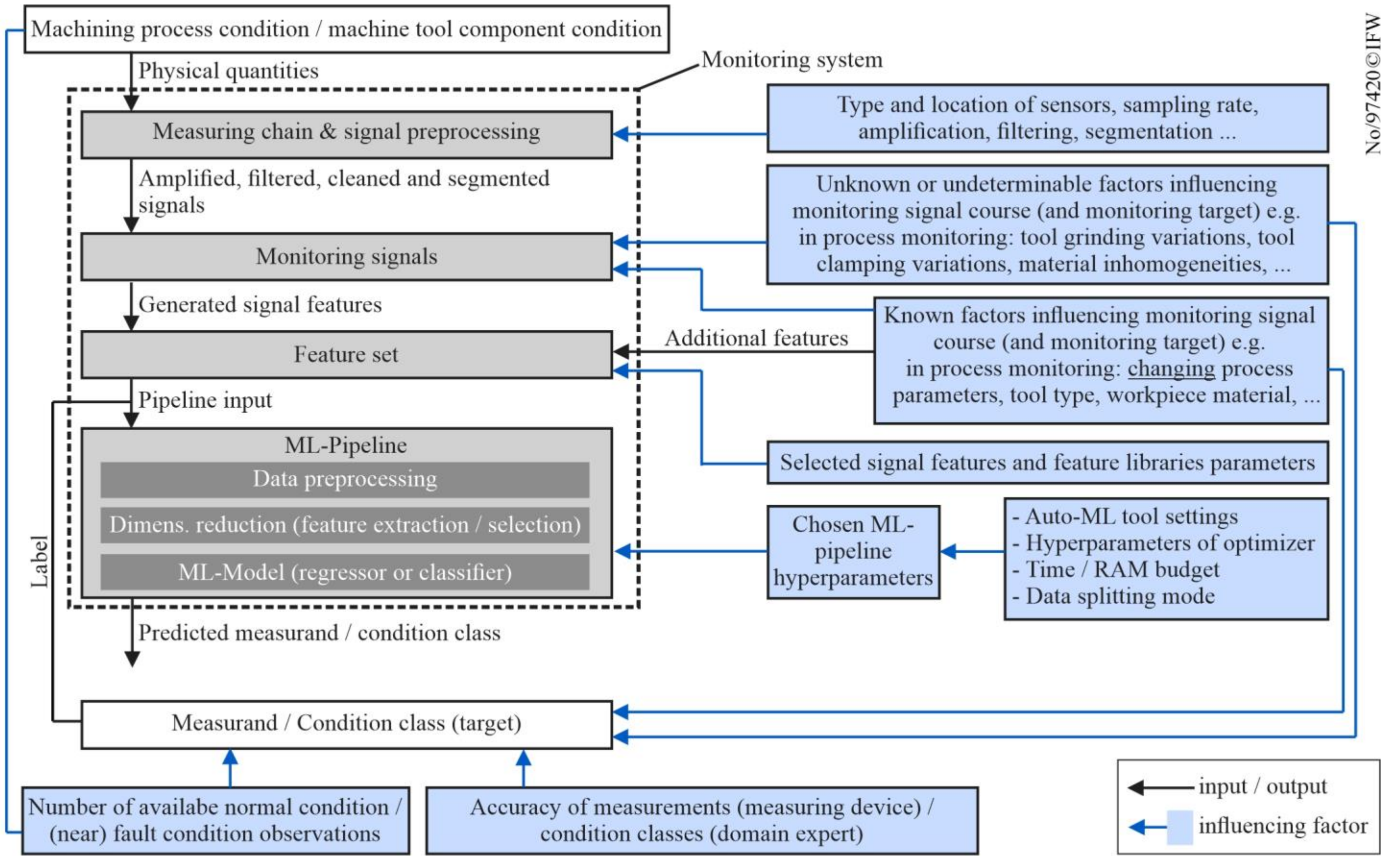

Fig. 2. Factors influencing the quality of machine learning based indirect monitoring systems for supervised anomaly detection in machining.

The selected features are the inputs for the ML-pipeline which requires the adjustment of a large number of hyperparameters. Model selection and hyperparameter optimization can be done manually or using optimizers including Auto-ML tools. Depending on the selected Auto-ML tool and the utilized optimizers, the performance of the ML-pipeline varies. In addition, the performance depends on the selected time budget for searching for an optimal pipeline and the size of the provided working memory. Auto-ML tools like Auto-Sklearn [29] introduce further hyperparameters like the number of models in an ensemble or the use of meta-learning which increases the complexity of the optimization problem. In addition, Auto-Sklearn uses Bayesian optimization for hyperparameter optimization which in turn has own hyperparameters [31]. Another important factor is data partitioning for model training, fitting the hyperparameters and determining the generalization error of the ML-pipeline.

4. Boundary conditions to assess the principal applicability of ML-based monitoring systems

In literature, it is not explained which boundary conditions need to be considered to use ML-based monitoring systems for supervised anomaly detection in machining. Boundary conditions are needed to examine the principal applicability prior starting the implementation. These boundary conditions are described as follows:

4.1 Uncertainty about the quantitative relationship between the inputs of the ML-model (represented by the features) and the monitoring target.

A common characteristic of the monitoring tasks described in Table 1 is the uncertainty about the exact quantitative relationship between the derived features and the target variables of the respective monitoring task. Machining processes are complex and the relationship of the generated signal features to specific measurands and condition classes in the machining process is non-linear. Theoretical model-based approaches attempt to link the input variables to the output variable through mathematical formulas. To derive these mathematical formulas, a precise understanding of the underlying physical relationships of the system dynamics is required. However, in practice idealizations and conventions are utilized which degrade the prediction performance [2,18,32]. In machining, industry-relevant variables like the surface roughness are influenced by a large number of influencing factors and the cause-effect relationships are not known [32]. This knowledge is not necessary in data-based approaches such as ML-methods [17,18,32]. Another feature of ML-methods is that these methods can also deal with noisy and incomplete data [32].

4.2 The monitoring target can be explicitly determined or measured with sufficient accuracy (as a discrete condition class or as a continuous measurand).

If the target variable is a measurand, the accuracy of the measuring instrument needs to be sufficiently high. The traceability of products plays an important role for predicting workpiece related quality outcomes in process monitoring. In the case of the prediction of discrete state variables using a classifier, it is necessary to be able to assign each time series to a condition class.

4.3 Data are available that a) describe fault conditions (classification) or b) include values of the monitored target variable up to the predefined alarm threshold (regression).

For classification tasks, fault classes need to be available. In contrast, machining processes are designed to run without errors in industrial practice. In addition, machine components such as ball screw drives or spindle bearings are designed to maximize the service life. As a result, class imbalance is often observed in industrial practice. Anomalous conditions are often artificially generated by scientists. Usually, assumptions are made about faults and their progressions, which are not necessarily transferable to practice.

When monitoring a continuous measurand using a regression model, the alarm threshold needs to be within the value range of the target variable in the data set. In the absence of these data, further experiments must be carried out in the offline phase.

4.4 Factors influencing the monitoring target variable are known and included in the data set (represented by the features).

For indirect monitoring, condition changes of processes and machine components must be detectable by monitoring signals [2]. When using machine-internal sensors, interfaces for data acquisition must be available. The type and position of the selected external sensors and the quality of the measuring chain is important to detect condition changes. To derive a condition assessment based on monitoring signals, signal features that correlate with the process or the machine component condition must be extracted [3,4]. The quality of the selected features cannot be estimated a priori. Therefore, the largest possible set of features should be considered [5].

In addition to sensor signals or derived features, further process-specific input variables must taken into account in process monitoring. This is because process-specific input variables (such as varying process parameters) influence the tool condition and the workpiece quality. Especially in machining, the challenge consists of a large number of influencing factors on the workpiece quality (see Figure 3). In the literature, monitoring approaches are usually limited to a few influencing variables. The applicability of ML-models depends on the input variables contained in the data set and their value range [16]. When producing small lot sizes the cutting conditions, the tool type and tool geometry used change frequently. In this case, the broad applicability of the ML-model requires a time-consuming and costly data acquisition in the offline phase. In addition, defect patterns such as cutting edge breakouts also change [6].

4.5 The variance of the monitoring signals course is explained sufficiently in normal condition by the features in the data set.

Many factors influence the course of monitoring signals during machining without changing the process state or causing anomalies [9,12,33]. In the literature, influencing factors such as material inhomogeneities, different clamping lengths of milling tools, and tolerances in the manufacture of milling tools are often not taken into account, since these factors are costly to measure [9]. Consequently, the course of monitoring signals vary even with constant process parameters [5]. The influence of unknown or undeterminable influencing variables on monitoring signals, which is not explained by features of the data set, influences the monitoring quality.

In machine condition monitoring, data from a test cycle separated from the machining process is often used. Likewise, many approaches exist where scientists evaluate the condition of machine components using an isolated test rig. In practice, monitoring signals may be influenced by other machine components. This limits the transferability of literature approaches for practical applications.

4.6 Sufficient number of training samples are available to produce low generalization errors.

The amount of required data depends on the complexity of the monitoring task. It is impossible to predict the amount of data needed to achieve the desired model quality [34]. In process monitoring, a broader validity and an increasing number of input variables considered by the model (across different process parameters, tools, materials, etc.) are also associated with a greater effort in data acquisition in the offline phase.

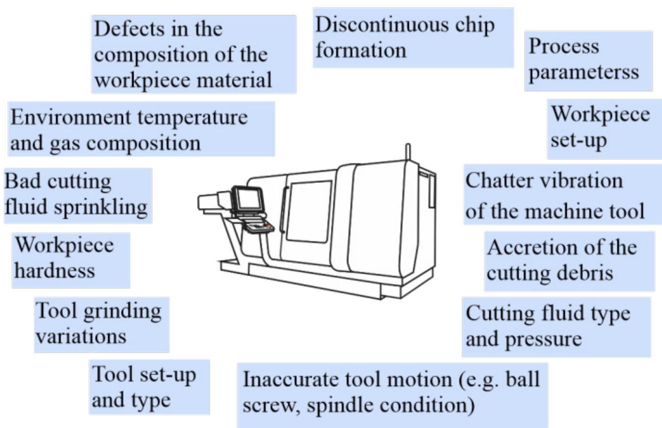

Fig. 3. Factors influencing part quality [2,12,35].

5. Conclusions

Machine learning based monitoring systems are suitable for many different monitoring scenarios. In this paper, boundary conditions are described which must be fulfilled to perform supervised anomaly detection tasks in machining. Monitoring objectives and deficits of existing approaches are identified, and influencing factors on the monitoring quality are described to derive the constraints. In addition, challenges for industrial application are discussed. The derived boundary conditions assist practitioners in industrial practice in systematically evaluating the suitability of ML-methods for monitoring tasks.

Acknowledgements

Funded by the Lower Saxony Ministry of Science and Culture under grant number ZN3489 within the Lower Saxony "Vorab" of the Volkswagen Foundation and supported by the Center for Digital Innovations (ZDIN).

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