# Intelligent configuration of condition monitoring algorithms

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**Abstract.** The aim of this paper is to present the design of a condition monitoring tool, its use for the intelligent configuration of pattern recognition algorithms, for fault detection, and for diagnosis applications. The modular design and functionality of the tool will be introduced. The tool, developed and implemented by Fraunhofer IPK, can be used, in particular, to support the development process of algorithms for condition monitoring of wear-susceptible components in production systems. An example of the industrial application of the tool will be presented. This will include the implementation of configured algorithms using the tool on an embedded system using Raspberry Pi 2 and MEMS sensor. Finally, the evaluation of these algorithms on an axis test rig at different operating parameters will be presented.

## Introduction

There are various condition monitoring applications and systems available on the market for several fields. However, these solutions are generally not flexible in use. Typically, they are designed for application specific use. Therefore, a diagnosis system for machines must be redesigned and implemented so that it can have multifarious applications. The development of a condition monitoring algorithm requires knowledge in various fields, such as mechanics, hydraulics, electrical engineering, etc. In addition, the design of a condition monitoring algorithm requires comprehensive knowledge of the methods of signal processing, feature extraction, selection and classification. To support the development of condition monitoring algorithms, a number of software tools, such as MATLAB, LabVIEW etc. can be used. Such tools, however, can only be used for general applications so that the developers are always confronted with the selection and analysis of suitable algorithms for each application.

## Research gap

Various studies have been carried out to investigate the availability of production machines. These studies have shown that the most common cause of machine failures is a mechanical breakdown of a component normally through wear [1]. The diagnosis systems for production machines available on the market are mostly designed for a concrete application and cannot offhand be used for other similar applications [2]. The reason for this would certainly be that the condition monitoring algorithms are not adaptive for a several applications [3]. An urgent need for research regarding new and robust condition monitoring methods on the component level was highlighted in [4]. The necessity for further research concerning the intelligent condition monitoring algorithms was also emphasised in [5]. Therefore a new approach for intelligent configuration of condition monitoring algorithms will be realised and used to design and link the pattern recognition algorithms for different fault detection and diagnosis applications. This approach would support the developer of condition monitoring algorithms to configure the needed algorithms for the concrete use.

## Modular structure designed tool for the configuration of condition monitoring algorithms

The condition monitoring tool (CMT) was implemented in MATLAB. This tool consists of five modules. These are the signal input module, the signal preprocessing module, the feature extraction and selection module, the classification module and the data clustering module [6]. Fig. 1 illustrates a simplified schematic representation of this tool. Signal input module: this enables the tool to read a variety of data formats for instance .mat, .csv, .wav, .txt, tdm, .tdms, .xlxs, and .xml.

Signal preprocessing module: this contains useful digital filter functions, such as low and high pass filter. For this purpose, the filter functions, already implemented in MATLAB, are used and extended for condition monitoring needs [7]. Besides this, methods for signal processing, such as envelope analysis, Fourier transformation, and scaling etc. are integrated into this module [8].

Feature extraction and selection module: this comprises a variety of features, for example statistical values and other signal features in frequency or in wavelet domain. Moreover, a combination of features calculated in time, and features calculated in frequency domain is possible [9]. This module also enables the users to analyse the extracted features for their suitability for the various applications. For this reason, an intelligent algorithm for analysing the suitability of the extracted features was implemented and will be introduced in the next chapter [10].

Classification module: this consists of a range of classification algorithms based on statistical techniques (e.g. nearest-neighbor-classifier), neural networks, and self-implemented algorithms [11]. Moreover, this module contains the methods and functions necessary for the configuration of a condition monitoring algorithm.

Clustering module: this includes two different approaches for data clustering [12]. These are the self-organizing map and k-means algorithms [13] which enables the user to cluster the data in the main categories to analyse each category in further process steps [14]. Fig. 1 shows a schematic representation of the implemented tool. The implemented XML-interface allows new methods to be added and methods which have already been implemented to be edited [2].

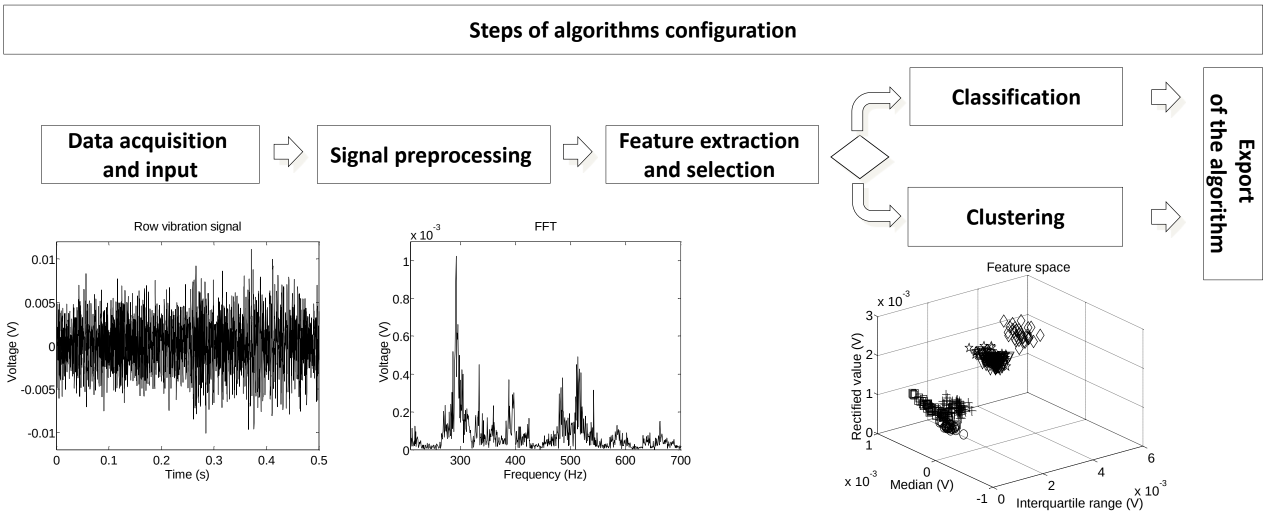


Figure 1: Schematic illustration of the implemented tool

## An intelligent approach for feature selection

Several statistical values (e.g. variance, kurtosis, minimum and maximum values) and other features (e.g. wavelet energy) are integrated into the tool. The selection of the most suitable features, which separate the damage classes in the feature space, is especially difficult. In general a damage class is a category (pattern description) of damage on a component because of a change in the material structure caused by normal wear, fatigue, etc. This can be represented by a dataset (e.g. vibration). In the paper, pattern of damage created artificially will be used to evaluate the introduced solution. For example, using the mean value as a feature is not appropriate for detecting irregularities of vibration signals, because this is approximately zero for a vibration signal in contrast to a temperature signal. For the feature selection purpose an algorithm to support the selection of the most suitable features is implemented. Fig. 2 illustrates the process of this implemented algorithm.

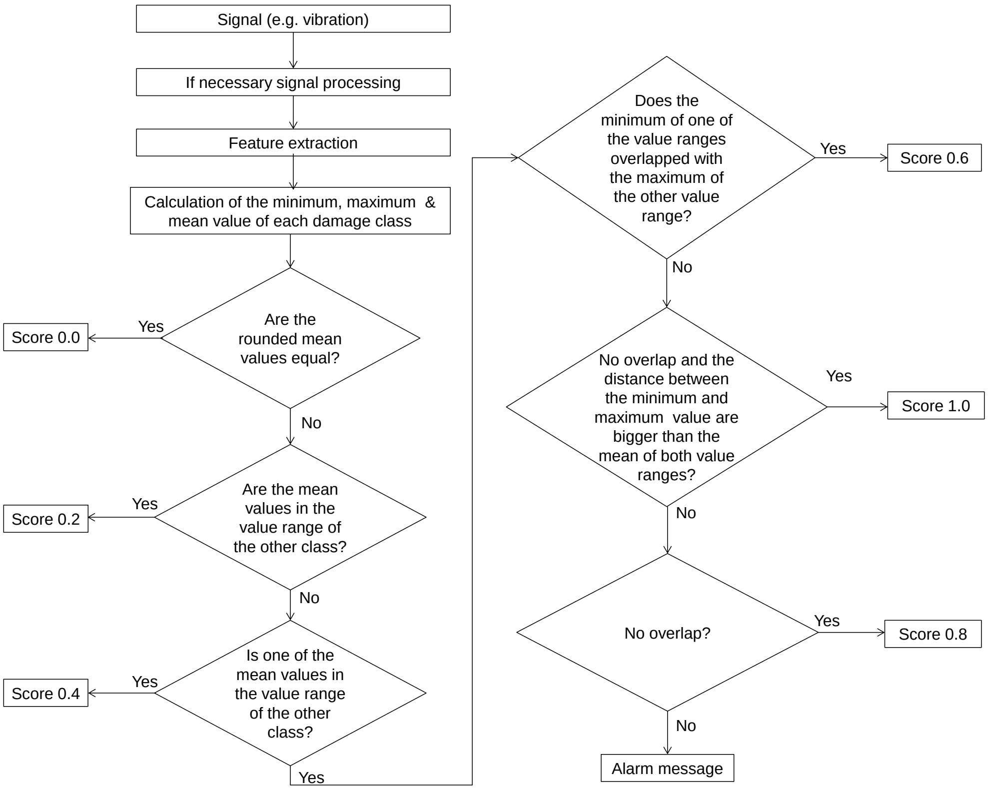


Figure 2: Procedure of the algorithm for feature selection

Firstly, all characteristic values for each measurement file are calculated. Then, the feature matrix is determined. Fig. 3 represents a comparison between suitable and non-suitable features with the example of vibration data of different damage classes. The algorithm observes and evaluates each individual feature. To do this, the minimum, mean and maximum values for each damage class of the current feature (e.g. skewness) are calculated. Then, the algorithm investigates how far the classes are separated from each other or rather how far the classes overlap. In this way, the score for the suitability of the feature under consideration is determined. There are criteria for the award of the score. Table 1 demonstrates these criteria for feature selection.

Table 1: Determination of the criteria for the feature selection algorithm

| Score S | Criterion |
|---|---|
| S = 0.0 | The rounded mean values of the classes are equal |
| S = 0.2 | The mean values are in the range between the maximum and minimum values of each other class |
| S = 0.4 | Only one of the mean values is between the minimum and maximum of other class in the range |
| S = 0.6 | Only the minimum of the both classes overlaps in the range |
| S = 0.8 | No overlap between the ranges |
| S = 1.0 | No overlap and the distances between the minimum and maximum are bigger than the mean value of the both ranges |

Fig. 4 represents the comparison of the manually selected features and the intelligent selection of the most suitable features using the realised approach. The evaluation of the algorithm is done by using real acquired ball screw vibration data at different operating parameters. Fig. 3a shows the selection of unsuitable features (form factor, crest factor and kurtosis) of the raw vibration signals. Fig. 3b illustrates the feature selection of raw signals (without any signal pre-processing) using the implemented algorithms. In the end, the best result was achieved by using this algorithm and pre-processed raw signals utilising the envelop analysis method and FFT (Fig. 3c).

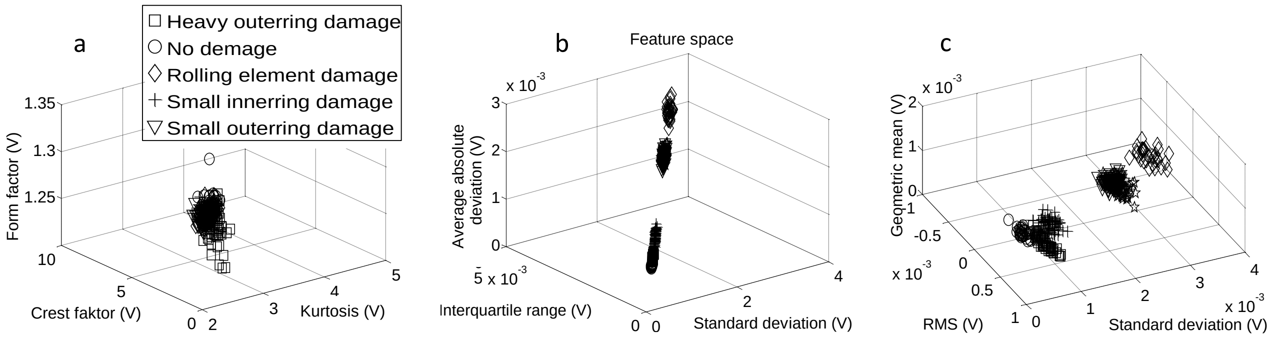


Figure 3: Example of suitable and non-suitable features

The algorithm developed for feature selection provided demonstrably better classification results. Moreover, this algorithm can be used universally, including pattern recognition applications.

## Outlier detection and elimination

The training data have a massive influence on the results of the classification algorithm. If this data includes outliers, this can have a direct negative effect on the results. For example, the evaluation of the extracted feature can be affected by measurement errors in the training data [15]. In the case of acoustic emission data, which are widely used for fault detection and diagnosis applications, measurement errors can slip in quite easily [16].

In order to deal with this problem, an algorithm for detecting and deleting outliers has been developed and integrated into CMT. This algorithm investigates the individual damage class. A measurement value rates as an outlier, if as many as two features of this value are three times further away from the mean value of the value under consideration. Fig. 4a shows the manually selected feature without elimination of the outliers an example of extracted features of training data with outliers and Fig.4b represents the result after detection and deletion of the outliers following the implemented approach.

For the evaluation of the algorithm for outlier elimination, roller bearing vibration data were used. The description of the experiments which were conducted to collect these data can be found in [17].

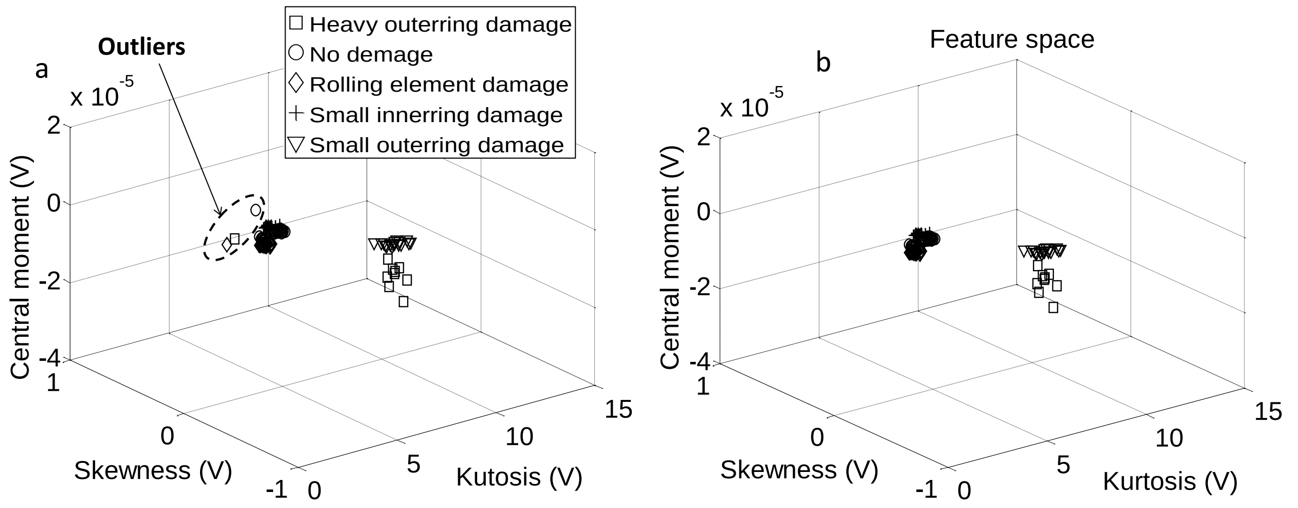


Figure 4: Outlier detection and elimination using the implemented method

## Data acquisition

For the purpose of evaluating the CMT, training data was acquired on an in-house axis test rig of a CNC-controlled centerless grinding machine in order to evaluate the CMT. This test rig incorporates a top slide, an inside slide and a machine bed. In addition, two asynchronous motors drive the ball screw, which moves the slides along the unloading axis X4, and the infeed axis and recessing axis X1 in steps of 0.2 µm. Fig. 5 shows the basic design of the axis test rig and the used ball screw for the experiments and an example for the damage, which were artificially created.

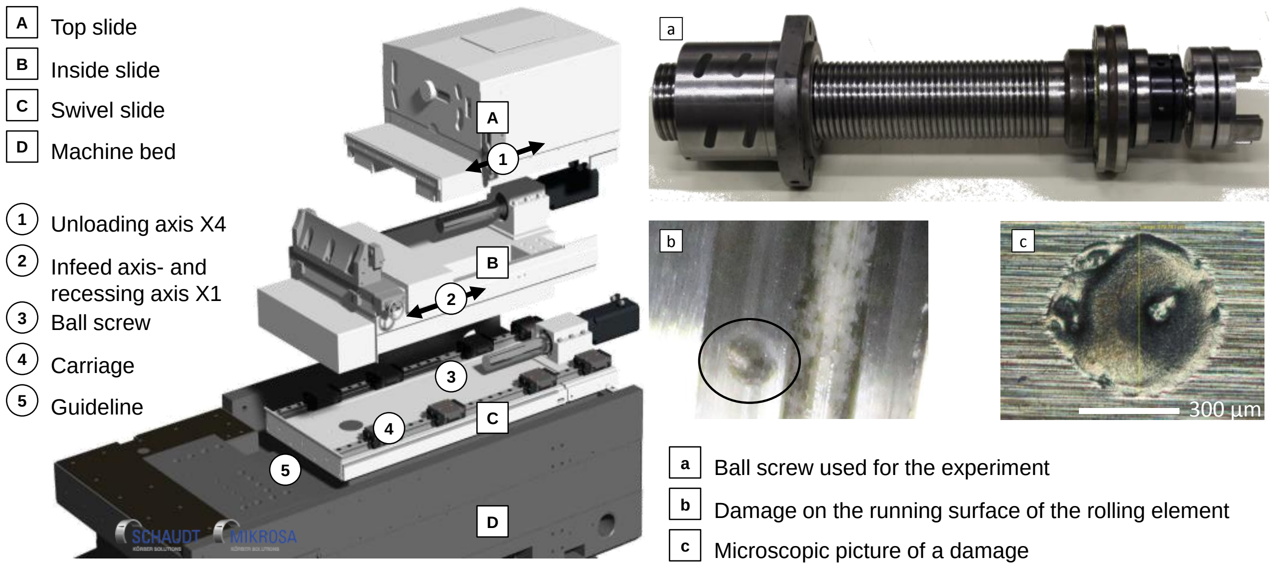


Figure 5: Schematic representation of the Axis test rig - Slide system and used ball screw for the experiment and a Microscopic picture of an example created damage

A design of experiments was developed for the acquisition of training data in order to evaluate the implemented algorithms, as well as the complete CMT. For this purpose, reproducible damages were created using the Laser powder cladding method. The five-axis Trumpf TruLaser 7020, with various laser spot diameters, was used to create the damage on the surface of the spindles. In addition, a fault was created on the needle roller/axial cylindrical roller bearing spindle. Table 2 presents the parameters of the faults generated using the laser cladding method.

Table 2: Used operation parameter to create artificial damage on the spindle surface

| Faults | Ø Laser point [mm] | Process time [ms] | Power [W] | Ø Damage [µm] |
|---|---|---|---|---|
| small damage | 0.6 | 1 | 1600 | 580 |
| heavy damage | 1.5 | 10 | 2000 | 1380 |

Because of the very short processing time and the comparatively high power of the laser, scarcely any material will be removed. In fact, only the running surface of the spindle will smelt. However, referring to the latest scientific research regarding the damage pattern of the ball screw [18], three faults, each at 120° of the rolling element running surface of the spindle, were created [19].

Table 3 represents the damage classes used to collect vibration data for the evaluation of the CMT. Deficient lubrication was created by almost completely degreasing the spindle.

Table 3: Used spindles for data acquisition

| Spindle | Damage class |
|---|---|
| Spindle 1 | No damage<br>Small damage<br>Heavy damage |
| Spindle 2 | Bearing damage<br>Deficient lubrication |
| Spindle 3 | Real damage |

The acceleration of the spindles was measured at the axis test rig using different operating parameters during the experiments. The experiments were conducted repeatedly under exactly the same conditions. Therefore, a CNC test program was developed.

## Configuration of a condition monitoring algorithm for ball screw

The vibration data collected at the axis test rig were used to train the implemented algorithms. For this reason, various configurations of the algorithms, using different classification methods with different parameters, were investigated. Thereby, condition monitoring algorithms were linked and configured. One of the configured algorithms using the CMT will be implemented on the Raspberry Pi 2 module. Moreover, this module will act as a wireless sensor node with local intelligence. Fig. 6 demonstrates a schematic sequence of the configuration steps using the CMT and the implementation of these algorithms for the application of condition monitoring in the real industrial environment.

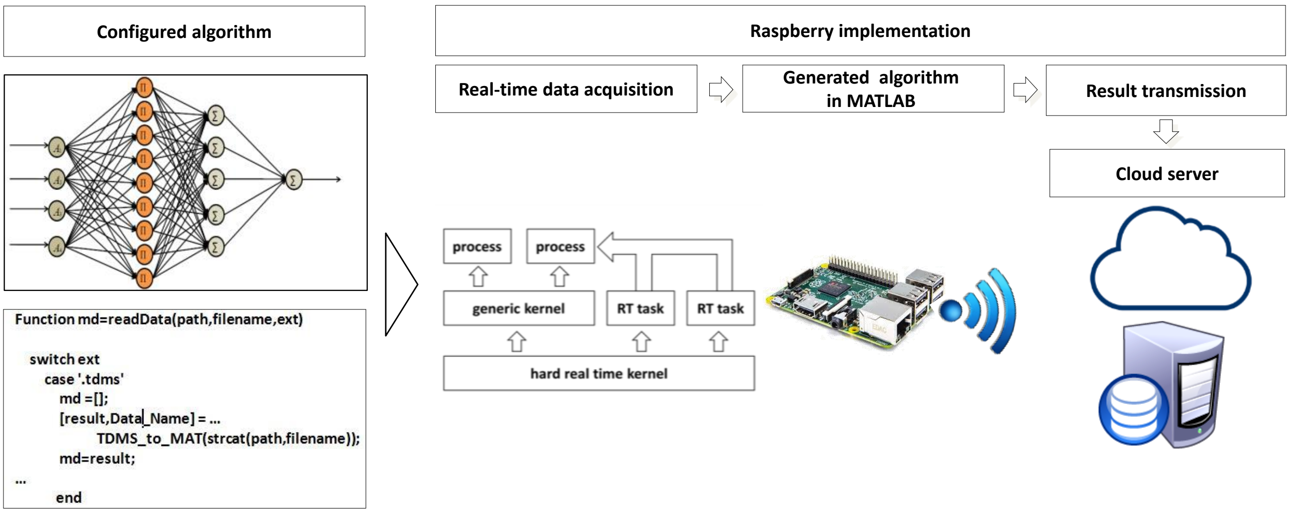


Figure 6: Steps of the individual configuration of the algorithms in CMT and their implementation on the wireless sensor

The Raspberry Pi 2 is fitted with an MEMS digital output motion sensor. This sensor is an ultra-low-power performance 3-axes “nano” accelerometer, which is capable of measuring accelerations with a sampling rate from 1 Hz to 5 kHz, and temperatures within a measuring range from -30 up to +85 °C.

One example of this application, using the wireless sensor node with integrated condition monitoring algorithms, is the monitoring of wear-susceptible components in the production field. Fig. 6 illustrates a sample application using the CMT and the embedded system in this field. This figure shows the installation of the energy self-sufficient wireless sensor which contains the configured algorithm. This sensor is installed at the wear-susceptible components (e.g. ball screw) of a machine tool. In this way the acquired data (e.g. vibration) can be preprocessed by using suitable signal processing methods, for instance digital filtering, frequency analysis, etc. Then, the extracted feature from the preprocessed signals is stored locally or transmitted to the central processing unit. Consequently, the condition of the monitored equipment can be continuously determined and documented. Obviously, wireless sensors offer huge potential for predictive maintenance. They can, moreover, be reliably combined and used for various industrial applications [20].

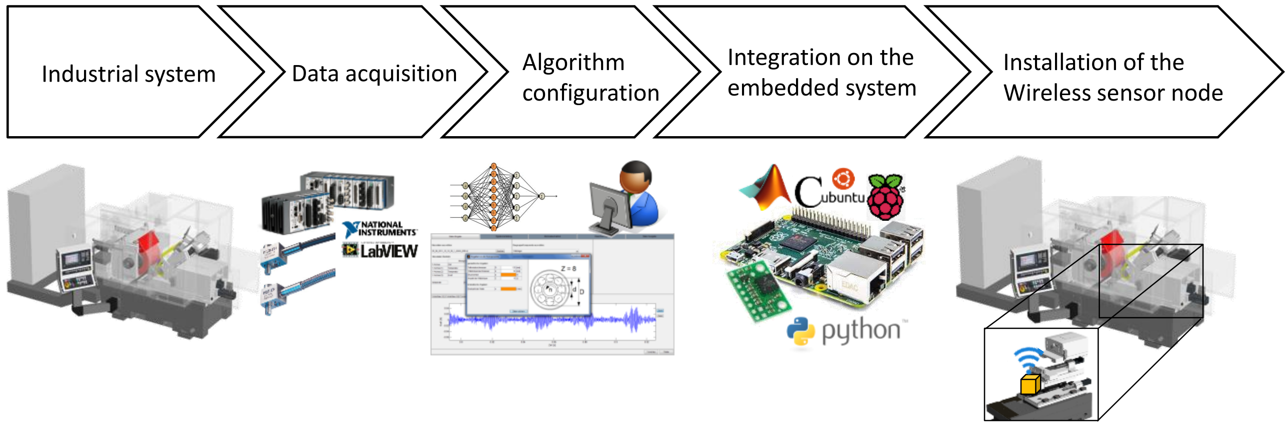


Figure 7: Using CMT to configure condition monitoring algorithms for industrial applications

A measurement chain containing the industrial sensors and data logger from National Instruments is used to generate real data for the evaluation of the tool Fig 7. During the experiments, vibration and acoustic emission signals were collected. In addition, the drive current signal was determined and will be used for further condition monitoring of the ball screw, because it has great potential for the detection of creeping changes, for example, caused by wear on wear-susceptible parts.

## Summary and Outlook

The CMT developed by Fraunhofer IPK enables the developers of condition monitoring application to configure individually and rapidly both, the algorithm necessary for concrete fault detection and the algorithm for diagnosis. Furthermore, the tool introduced in this paper can be used for data clustering applications. In particular, the implemented data clustering methods can be used to extract information from massive amounts of data. Finally, new findings regarding the pattern recognition algorithms and other useful methods can easily be integrated into this tool. This means that this tool can be extended continually.

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