Received: xxxxxxxx / Accepted: xxxxxxxx / Published online: xxxxxxxx

Condition monitoring, data analysis, sensor network, algorithm, MEMS sensor, cloud

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# SMART WIRELESS SENSOR NETWORK AND CONFIGURATION OF ALGORITHMS FOR CONDITION MONITORING APPLICATIONS

Due to high demand on availability of production systems, condition monitoring is increasingly important. In recent years, the technical development have improved for realization of condition monitoring applications as a result of technological progress in fields such as sensor technology, computer performance and communication technology. Especially, the approaches of Industrie 4.0 and the use of the Internet of Things (IoT) technologies offer high potential to implement condition monitoring solutions. The connection of several sensor data of components to the cloud allows the identification of anomalies or defect pattern, this information can be used for predictive maintenance and new data-driven business models in production industry. This paper illustrates a concept of a smart wireless sensor network for condition monitoring application based on simple electronic components such as the single-board computer Raspberry Pi 2 modules and MEMS (Micro-Electro-Mechanical Systems) vibration sensors and communication standards MQTT (Message Queue Telemetry Transport). The communication architecture used for decentralized data analysis using machine learning algorithms and connection to the cloud is explained. Furthermore, a procedure for rapid configuration of condition monitoring algorithms to classify the current condition of the component is demonstrated.

## 1. INTRODUCTION

Industrial companies are forced to use high automated and networked production processes in order to meet customers' requirements. Therefore, industrial companies are under pressure to increase their innovation and efficiency situation. Maintenance is a key factor to ensure the competitiveness of companies especially in the industry sector. It plays an essential role to guarantee high availability of technical systems and plants in the corporate environment. This is important for the purpose of manufacturing high-quality and innovative products. The increased use of complex production systems requires a rethink

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regarding maintenance strategy. The breakdown of these systems during the operation causes in addition to the costs for repair in particular high costs resulting from the system downtimes. Normally the repair works of modern production systems takes several working days, which increases the downtime of the production system. The main reason is that the reaction time of the system manufacturer from the receipt of the fault report till the on-site operation and non-availability of components, and difficulties of diagnosis.

Condition-based maintenance as a maintenance strategy provides an opportunity for manufacturing companies to decrease the machine downtimes. As a result of the implementation of this maintenance strategy the maintenance costs will be significantly reduced. In this context the maintenance measures can be deducted from the current wearing condition of the production system. The implementation of condition-based maintenance can be realized with condition monitoring systems. These systems acquire data (e.g. vibration) and analyze it continuously in order to detect the current condition of the production system and its critical components.

Although the benefits available by using condition monitoring systems e.g. in the production environment are clear, the high investment costs and inflexibility of these systems in use for different monitoring applications are an obstacle for its wide implementation. On one hand, the condition monitoring systems available on the market use industrial sensors for external data acquisition that are application-specific, wired and cost-intensive. On the other hand, the condition monitoring applications in the practice are very heterogeneous. Moreover, the access to the system-internal data of several machine control systems is rarely possible. Because of this, the retrofitting of existing plants with monitoring systems based on system-internal data is not simple to realize.

The maintenance expenses in the production environment represent a significant part of the operating costs of a production system. According to Abele et al. [1], the costs for maintenance and inspection and unplanned repair make a total of 46 % of the operating costs of a machine tool in Germany, Fig. 1.

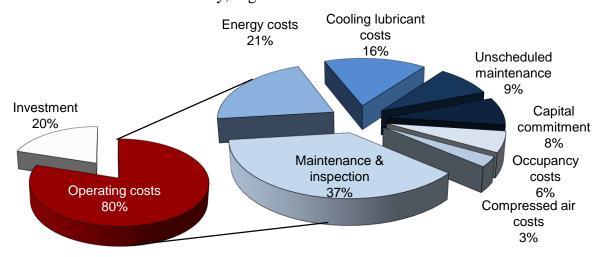


Fig. 1. Operating costs of a machine tool in Germany according to Abele et al. [1]

According to a study of McKinsy [8], predictive maintenance is one of the major application areas of the Internet of Things (IoT). It estimates a savings potential of 630 billion USD by 2025 through using of IoT technologies in many fields such as aviation, production and

medical sector. In addition, a reduction of 50 % of machine downtimes and 3 % of investment needs can be achieved through use of IoT in maintenance environment. In this context, MEMS sensor (micro-electro-mechanical systems) offers a high potential for condition monitoring application. These sensors are in comparison to industrial sensors cost-effective, wireless, and highly integrable and configurable. In the last years, the amount of powerful MEMS sensors such as vibration sensors has increased. In particular, the MEMS sensors from the consumer and automotive sector provide a good opportunity for cost-effective integration of smart sensor systems for different condition monitoring applications and, therefore, for extensive usage in cyber-physical systems and for the implementation of diagnose system for networked production in Industrie 4.0 context [5]. In several research works is the ability of MEMS sensors for condition monitoring addressed, especially in the field of vibration diagnoses [2,4,11]. In the industrial environment, MEMS sensors are still not used because of high requirements regarding robustness and sensitivity to environmental conditions such as humidity and performance.

## 2. CONDITION MONITORING IN THE CLOUD

#### 2.1. APPLICATION SCENARIO

The aim is to develop and realize a smart sensor network concept for intelligent condition monitoring of various technical plants. On one hand, this concept contains the needed steps for condition monitoring use such as data acquisition using MEMS vibration sensor, signal pre-processing, and feature extraction and classification on the sensor node level [12]. On the other hand this concept includes data transmission to the cloud and mobile data distribution and provision for different stakeholders involved in the production environment. The basic idea of this application scenario is to provide cost-effective monitoring solutions based on simple electronic components. Therefore, the developed sensor network leads to realization of low-cost solutions for integrating of intelligent sensor systems to be used in cyber-physical plants in various industrial sectors. The sensor network is composed of a number of sensor nodes. Each node acts independently from other ones and equipped with a MEMS sensor for vibration and temperature collection. The recorded data is analyzed on the node level of the sensor network. The data analysis process includes various steps. Firstly, the raw data are pre-processed with appropriate methods such as band-pass filter. Then, features are extracted from the pre-processed data such as statistical descriptors. Lastly, these features are used to classify the current condition to one of the known fault conditions. Each sensor node is able to transmit data in the cloud server, where a data base system is implemented for data management. The transmission takes place using a wireless connection.

Depending on the application, pre-processed raw data, extracted feature or classification results of each node can be transmitted to the data management system in the cloud server. There are several services available for different users such as data visualization or report generation concerning the current system condition. These services are available on mobile

devices and can be used from various stakeholders involved in the production environment such as service technician or maintenance planer. Therefore, the condition of the production system is available at any time and can be continuously monitored. This introduced sensor network is implemented and evaluated for monitoring application of wear-susceptible component of machine tools. The monitoring application which will be introduced in this article is implemented for condition monitoring of a ball screw and is realized at an axis test rig of Fraunhofer IPK. The schematic representation of the sensor network for monitoring application is showed in Fig. 2.



Fig. 2. Implementation of the Sensor network in the production environment

#### 2.2. COMPONENTS SPECIFICATION

The realized sensor network for monitoring applications using single-board computer Raspberry Pi and MEMS vibration sensor is highly scalable. Table 1 shows the specifications of the components that were used to realize the sensor network.

Raspberry Pi 2 M. B	Specification	MEMS Sensors	Specification
Processor	ARM710	Measuring range	1 Hz to 5 kHz
Processor speed	900 MHz	Input voltage	1.71 V to 3.6 V
RAM	1 GB	Dynamically selectable full	$\begin{array}{c} \pm 2g/\pm 4g/\pm 8g/\pm 1 \\ 6g \end{array}$
Storage technology	LPDDR2- SDRAM	Scale	16 bit
Input voltage	5 Volt	Operating temperature range	-40 °C to +85 °C
Operating system	Linux	Digital interface	I2C/SPI

Table 1. Specification of sensor network components

# 3. COMMUNICATION ARCHITECTURE

A schematic illustration of the communication architecture of the sensor network in the production environment is illustrated in Fig 3.

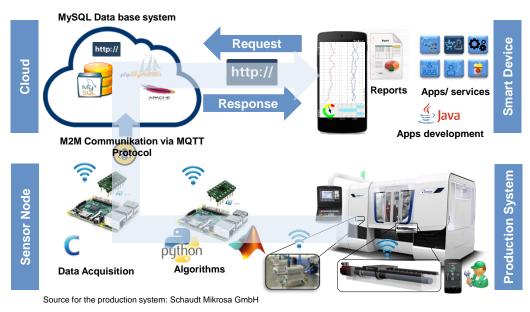


Fig. 3. Communication architecture of the sensor network

The communication between each sensor node and cloud server is realized using MQTT (Message Queue telemetry Transport). MQTT is a message protocol used to transfer telemetry data especially in the areas with limited network capacity. This protocol is a M2M protocol (Machine-to-Machine) and, therefore, an essential component of IIoT (Industrial Internet of Things).

The communication between the mobile devices and cloud server is implemented using HTTP (Hypertext Transfer Protocol) with the request/response procedure. MQTT offers a secure authentication mechanism to ensure the communication and messages transmitted. The messages are protected by access name and password. Furthermore, the communication can be encoded via external protocols such as SSL or VPN.

#### 4. ALGORITHMS CONFIGURATION

For rapid and intelligent linking and configuration of algorithms for various condition monitoring applications, a tool was designed and implemented [7,13]. Fig. 4 illustrates a simplified schematic representation of this tool.

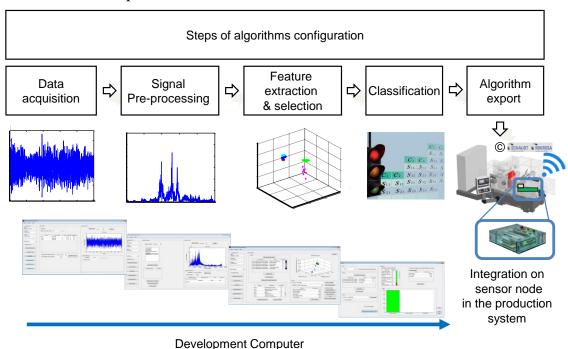


Fig. 4. Steps of algorithms configuration using implemented tool according to [7]

The objective of the tool realized, is to provide a procedure for configuration process of algorithms for monitoring uses. The tool implemented has a modular construction. It comprises a data input module for target data, which has to be analyzed, a data preprocessing module for data preparation, a feature extraction and selection module, and a module for data classification and clustering [7,13]. The data input module provides methods for conversion of different data formats. Moreover, this module offers

functionalities to structure the input data for further processing. The data preprocessing module have several methods and function for data filtering, transformation, norming and scaling. Feature extraction and selection module provides features calculation methods and algorithms for selection of the suitable features for current application. The classification and clustering modules offer pattern recognition algorithms. The configuration process is interactively supported in each step by the implemented tool. The configured algorithm can be exported as independent software, which can be used on the sensor node level for data analysis procedure. The reliable analysis of the collected data is the basic for condition monitoring with introduced sensor network. Data analysis is performed on each node of the sensor network using configured algorithm.

#### 5. EVALUATION

#### 5.1. EXPERIMENTAL SETUP

To evaluate the developed sensor network for monitoring applications, an axis test rig was used (Fig. 5). The objective was to monitor the condition of a ball screw under different operating conditions. This test rig is a machine bed with a three sledge system of a centerless grinding machine. The three sledge system consists of two ball screws for infeed and recessing axis of the grinding wheel and for the unloading axis [10]. The sensor position were determined using an previous experimental modal analysis on the axis test rig and following the the VDI guideline VDI 3832 [14].

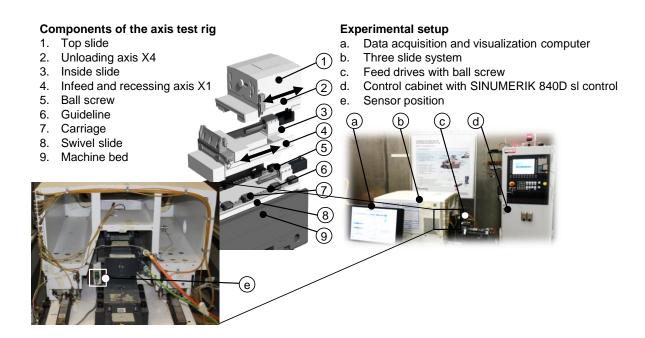
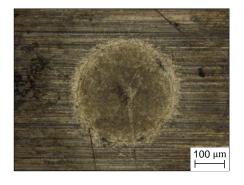


Fig. 5. Axis test rig for experimental tests

#### 5.2. DAMAGE GENERATION

To generate condition data of the ball screw, different damage type onto spindle surface was artificially created. The damage creation was done using laser welding process. The aim is to produce damage types similar to wear damages pitting in the practice. In total, five different damage classes were generated. To create various damage classes, the diameter of the damaged surface area of the spindle was varied between 350 and 950  $\mu m$ . Following damage classes are created using a Laser powder cladding machine: the damage classes were produced with different damage diameter (dd). For damage class 1 (no damage class) is dd = 0  $\mu m$ , for damage class 2 is dd  $\sim$  350  $\mu m$ , for damage class 3 is dd  $\sim$  550  $\mu$ , for damage class 4 dd  $\sim$  650  $\mu m$  and dd  $\sim$  950  $\mu m$  for damage class 5. The damage classes were created according to the DIN 631 [15] (Norm of testing conditions of roller bearing consisting of carriage and profiled rails) that describes the failure criteria of roller bearings that have identical mechanical characteristics as ball screws. For the ball screw used in this work is the damage diameter that fulfil the failure criteria according to [10] is dd = 1050  $\mu m$ . Fig. 6 represents microscopic images of created damages.



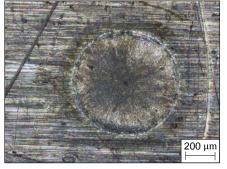


Fig. 6. Damages onto spindle surface

#### 5.3. DATA ACQUISITION

A MEMS vibration sensor was used to acquire data at different wear-susceptible components of machine tools. This MEMS sensor LIS3DH [9] is able to collect acceleration values in three dimensions, x, y and z direction. The sensor was positioned near the screw nut. This sensor position is represented in Fig. 5. The measurement set up is shown in Fig. 7. This set up (sensor node) is composed of a Raspberry Pi module and a MEMS vibration sensor. The acceleration data was acquired using different operating condition. To reproduce the measurements, a CNC Program which allows an automated sequence of the tests at varied feed rate. The sample rate of the used sensor is limited at 5000 kHz. For the experiments in this article, a sampling rate of 2.5 kHz was used. The reason for selection of this

sampling rate is the limitation of the used single-board computer Raspberry Pi 2 relating processing of maximum 3700 samples per second per measurement direction. The idea behind choosing simple electronic components is to determine the ability of using cost-effective parts to realize condition monitoring application at machine tools.

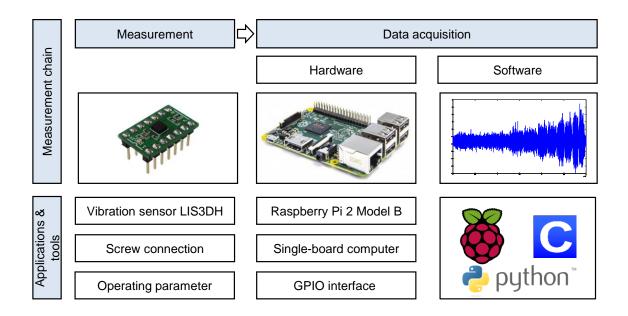


Fig. 7. Experimental set up for data acquisition

#### 5.4. RESULTS

The data analysis on the sensor node level is performed with configured algorithm with the tool presented in Fig 4. The algorithms are implemented in Python. Fig. 8 shows a raw data representation in time, frequency and time-frequency domain, fault-free condition (left) and damage condition (right). This figure represents the comparison of the time-frequency analysis between no damage class 1 and the damage class 5 at the speed rate  $v_f = 5000$  mm/min. The spectral analysis can be used to estimate power of the frequency components of the signal (e.g. vibration signal). This analysis is essential for understanding the frequency dependence of the acceleration signal of the ball screw used for the evaluation in this work.

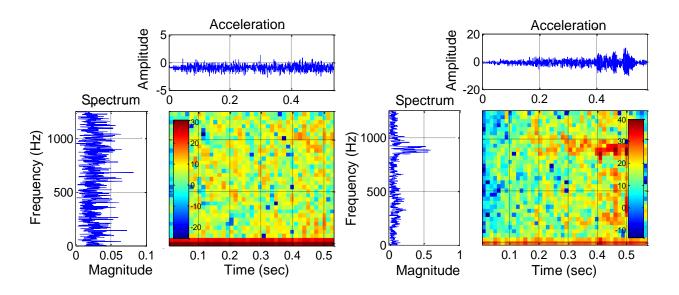


Fig. 8. Raw data representation in various domains

For linking and configuration of the suitable algorithms for monitoring of the ball screw condition at axis test rig, different algorithms were analyzed. The linking and configuration process include the identification of appropriate parameters for the preprocessing step (e.g. filter parameter) and the suitable features in the feature extraction and selection step. In addition, the classifier with the highest accuracy regarding the classification of the selected features to the related damage class has to be identified. Thereby the suitable algorithm for condition monitoring of the ball screw is configured and can be used on the sensor node level. For the evaluation purposes of the algorithms, several datasets was recorded under various feed rate. These datasets are split in several classes. Each class represents a category of one of the damage types described by different feed rate 1000 mm/min, 2000 mm/min, 3000 mm/min, 4000 mm/min and 5000 mm/min. The datasets are used to configure and train the algorithms for this monitoring application of the ball screw. These algorithms include all needed steps for condition monitoring, from data preprocessing, feature extraction and selection till classification with several classifier [3,6]. The training of the configured algorithm using the procedure introduced in Fig. 4 is done on the computer. In the next step, the trained algorithm is integrated on the sensor node for ball screw monitoring application.

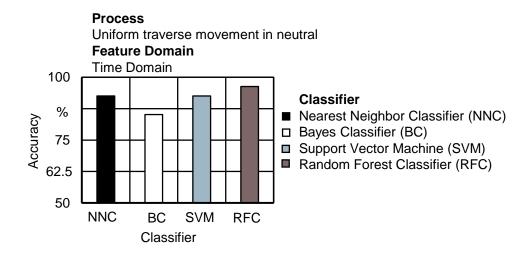


Fig. 9. Raw data representation in various domains

# 6. CONCLUSION

This article illustrates an approach for condition monitoring applications based on simple electronic components, which were used to build high integrable and scalable, and cost-effective sensor network. This presented solution can be used to monitor production systems and their wear-susceptible and critical components such as ball screw and bearings. This solution is to realize due to decentral data processing on the sensor nodes, concentration of data and services in the cloud; mobile provision of data and merging varied distributed sensors into a sensor network. It is simple to adapt to specific monitoring applications, such production systems, and auxiliary units such as pumps or mobile systems. Furthermore, new and existing systems can be equipped and upgraded within meaning of cyber-physical system to enable technical systems for predictive maintenance in context of Industrie 4.0.

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