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Condition Monitoring Concept for Industrial Robots

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Abstract **– Industrial robots are used in production technology for a wide variety of tasks. The most frequently used type worldwide is the so-called vertical articulated arm robot, often designed with 5 or 6 axes. Due to their relative movement, the axes are tribological systems, they are subject to wear and tear and must be maintained regularly. An important aspect of maintenance is the inspection, which aims to assess the current state of wear and tear. This paper presents a concept for condition monitoring by means of self-tests for industrial robots. The basis is formed by MEMS-based vibration sensors, which are mounted on the axis joints. The vibration signals acquired during the self-test are analyzed in an Edge Gateway and the condition is classified using methods from the field of machine learning. The result of the classification and the features used for it are then sent to a cloud platform where they can be further analyzed. With this approach, service calls can be planned in advance and unplanned downtimes avoided. The article concludes with a critical discussion of the advantages and disadvantages of the presented concept and gives an outlook on still open research questions.**

Keywords – Condition Monitoring, Self-test, Predictive Maintenance, Retrofit, Machine Learning, Industry 4.0

I. INTRODUCTION

A. Industrial Robots

The history of industrial robots began more than 60 years ago [1]. In 2018, worldwide more than 2.4 million industrial robot installations existed. The annual growth rate has been 19 % since 2013 [2]. Industrial robots are used in production technology for a wide variety of tasks, e.g. painting, welding, riveting, assembly or even machining [1, 3-5]. Their advantage in comparison to other automation solutions from the field of special machine construction is their great flexibility with regard to the area of application and the relatively simple programming by means of teaching. Numerous types of industrial robots exist, which differ in size, power and the number of degrees of freedom with respect to the kinematic chain. The most frequently used type worldwide is the so-called vertical articulated arm robot, often designed with 5 or 6 axes. Due to their relative movement, the axes are tribological systems, they are subject to wear and tear and must be maintained regularly.

B. Maintenance

Due to the increase in the capital value of machinery and the extensive expansion of production capacities, the importance of maintenance increased after the Second World War and new requirements arose. The new strategies focused on minimizing the risk of malfunctions by means of visual inspection and preventive replacement of damaged machine parts in order to reduce the cost of repair after a breakdown. With the beginning of the 1970s, the requirements for high reliability of production systems increased as automation grew and the failure of individual elements had a greater impact on the entire system than before. This led to a restructuring of maintenance operations with the aim of increasing the effectiveness and efficiency of the equipment in operation and reducing costs. Among other things, the concept of condition-based maintenance was developed with the aim of making optimum use of the remaining useful life without the risk of unplanned downtimes [6].

An important aspect of maintenance is the inspection, which aims to assess the current state of wear and tear. The automation of parts of the inspection process with a condition monitoring system enables the remaining useful life to be optimally exploited in an efficient way with the strategy of condition-based maintenance. Condition monitoring of feed axes using specially developed self-tests is an established method for avoiding unplanned downtimes in machine tools since the early 2000s [7-8].

Unfortunately, this has not been introduced in industrial robots in this way, although robots are also subject to wear and tear and high demands are placed on their technical availability [10].

II. STATE OF THE ART

Industrial robots represent highly stressed production systems and their wear-related breakdown can lead to long production downtimes and thus to high costs. Commonly, industrial robots are maintained at fixed time intervals, ranging from a daily inspection to 800 operating hours [9].

In practice, Condition Monitoring solutions to support Predictive Maintenance approaches are found only to a limited extent. They are rather subject to scientific considerations. The most commonly used raw data for condition monitoring is the motor current or vibrations. Statistical moments such as mean, variance, skewness and kurtosis are typically used for the extracted health indicators respectively features [10-14]. The approaches have in common that they focus on the development and evaluation of analytical algorithms. Among the applied methods, statistical methods and methods based on artificial intelligence respectively machine learning techniques predominate. Accurate physical models are hardly considered due to their complexity and lack of robustness in practice [11]. Only peripheral statements are made about the traverse movements of the robot axes during which data acquisition takes place. Jaber & Bicker state that each robot axis should move independently in a cyclic movement during data acquisition [12]. Holistic concepts for condition monitoring of industrial robots are still missing. Therefore, this paper presents such a holistic concept for condition monitoring for industrial robots by means of self-tests.

III. DESCRIPTION OF THE CONCEPT

C. Self-test Design

Self-tests are commonly used to perform defined procedures under constant boundary conditions. This involves the acquisition of sensor data and their analysis with regard to the functionality to be tested. In the case of testing feed axes of machine tools, a self-test has become established, at which the axes are moved sequentially along the maximum possible traverse range at constant feed rate in both directions [7]. Fig. 1 shows a screenshot of the application developed at Fraunhofer IPK for the analysis of data from the use phase of machine tools. It shows the history of a feature extracted from the drive current data recorded during the performed self-tests. The period covered is approximately two years. It can be seen that the feature shows a clear upward trend about three months before the service visit to replace the feed axis became necessary.

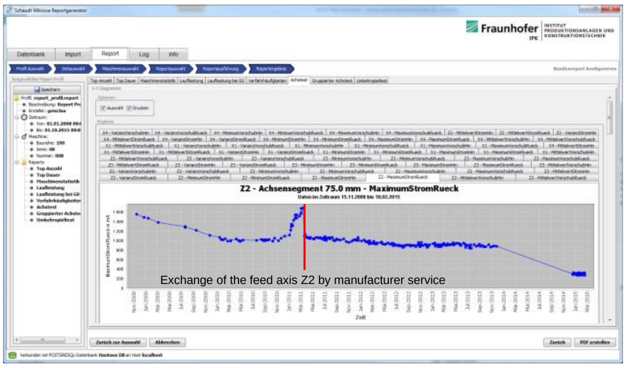

Fig. 1. Development of a feature for monitoring feed drives over a period of approx. 2 years

This procedure was adopted at Fraunhofer IPK for the development of a self-test for robot axes. For this purpose, it must be determined which maximum travel ranges the working area of the industrial robot allows. Then an appropriate robot program must be implemented, which moves the robot axes sequentially at constant speed. The sequential procedure is to ensure that the movements of the individual axes do not negatively influence the quality of the acquired data. When determining the travel speed, care should be taken to ensure that it is as high as possible in order not to unnecessarily prolong the non-productive time resulting from the self-test. On the other hand, it should be ensured that the wear phenomena to be recorded are reflected in the measured signal. Since there is often little knowledge of the specific design of the gears and bearings to be tested, it has proved suitable in practice to determine the optimum travel speed in the course of experiments. The intervals at which self-tests should be performed depend mainly on the velocity at which the wear to be determined progresses. Since wear and tear usually develops very slowly, the intervals can be selected correspondingly long.

D. System Architecture

The basis is formed by MEMS-based vibration sensors, which are mounted on the axes joints. The vibration signals acquired during the self-test are analyzed in an Edge Device and the condition is classified using methods from the field of machine learning. The result of the classification and the features used for it are then sent to an IoT platform in the cloud where they can be further analyzed. For example, trends can be determined and future progress can be predicted based on the historical development of the features. The system architecture intends that an arbitrary number of sensor nodes can be connected to an IoT platform in the cloud via a central communication interface, the so-called edge device. The communication between the sensor nodes and the edge device is done via an event bus, following the publish-subscribe pattern. The communication protocol used is MQTT (Message Queuing Telemetry Transport), which is widely used for IoT communication. To keep the energy consumption of the sensor nodes as low as possible, it should be ensured that data acquisition and transmission to the edge device only take place in the context of the self-test. Therefore the sensor nodes have subscribed to a start/stop event at the MQTT Broker. If the industrial robot under consideration is IoT-capable, it should also be actively integrated into the system architecture so that data acquisition can be automatically synchronized with the actual self-test. Fig. 2 gives a general overview of the proposed system architecture. For the sake of clarity, the integration of the robot controller has been omitted.

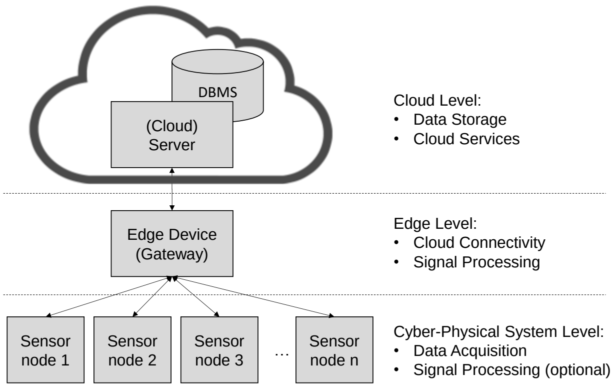

Fig. 2. Overall system architecture

As can be seen from Fig 2., the sensor nodes form the basis of the architecture, since they transform the production system to be monitored into a cyber-physical system. Therefore, sensor nodes have to fulfill further tasks besides data acquisition. Depending on the application, these are typically the following:

- Signal processing,
- Energy management,
- System control, and
- Secure communication, including encryption and decryption.

The schematic structure of a sensor node is shown in Fig. 3 (abbreviations used are explained in Table 1).

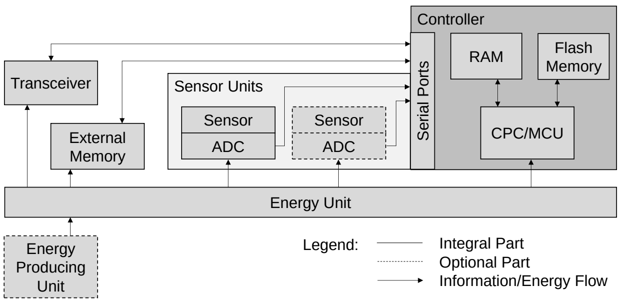

Fig. 3. Structure of a sensor node according to [15]

Table 1 briefly explains the main tasks of the individual components of a sensor node.

Table 1. Main tasks of sensor node components.

Component	Task
Energy Producing Unit	Energy production by means of energy harvesting; Charging the battery
Energy Unit	Autonomous energy supply
Transceiver	Provision of radio standards using diverse communication protocols; Establishing a connection to other devices in the network and organizing communication
External Memory	Persistent backup of measurement data or other data
ADC (Analogue to Digital Converter)	Converting analogue data into digital data
Sensor	Acquisition of analogue physical quantities of the environment
RAM	Storage of data (e.g. variables) during program execution
Flash Memory	Storage of program code
CPU/MCU (Central Processing Unit/ Microcontroller unit)	Execution of program logic and interaction with sensors, external memory and transceiver via appropriate ports
Serial Ports	Provide interfaces like I2C (Inter-Integrated Circuit) or SPI (Serial Peripheral Interface) and allow the CPU/MCU to communicate with external hardware

E. Data Analysis

As already mentioned in the State of the Art section, statistical moments in vibration signals have proven to be suitable features for detecting advancing wear. In particular, the mean value, variance, kurtosis, skewness, and RMS were selected to form the feature vector. Table 1 presents the computational formulas of the selected features.

Table 2. Computational formulas of the selected features.

Feature	**Formula**
Arithmetic mean	$\bar{x} = \frac{1}{n} \cdot \sum_{t=1}^{n} x_t$
Variance	$\sigma^2 = \frac{1}{n} \cdot \sum_{t=1}^{n} (x_t - \mu)^2$
Skewness	$\upsilon = \frac{1}{n} \cdot \sum_{t=1}^{n} \left(\frac{x_t - \mu}{\sigma}\right)^3$
Kurtosis	$\gamma = \frac{1}{n} \cdot \sum_{t=1}^{n} \left(\frac{x_t - \mu}{\sigma}\right)^4$
RMS	$RMS = \frac{1}{n} \cdot \sqrt{\sum_{t=1}^{n} {x_t}^2}$

These features are determined individually for each travel direction and transferred as input data to the model of a Support Vector Machine (SVM), which has been teached using training data. The Random Forest (RF) classifier and the k Nearest Neighbours (kNN) classifier have also proved to be alternative classification algorithms with good results in experiments when monitoring the belt tension of the drive of a grinding spindle. The SVM classifier was implemented using the Python module scikit-learn [16]. The classification is carried out on the Edge Device, which then sends both the feature vector and the classification result to the IoT platform for permanent storage of the data.

IV. EVALUATION

F. Experimental Setup

The evaluation was carried out in the test field of the Berlin Production Technology Centre. The following components were used for the experimental setup:

- Industrial robot Comau NJ-110-3.0, cf. Fig. 4,
- Sensor node Bosch XDK110, cf. Table 2,
- Edge device Raspberry Pi 3 B+, and
- Database Server with Database Management System (DBMS) PostgreSQL.

Fig. 4. Industrial robot (Comau NJ-110-3.0)

Table 3. Specification extract of Bosch XDK110.

Component	Description
Network Communication	Gigabit Ethernet; 2,4 and 5 GHz Wireless LAN; Bluetooth 4.2 low energy
Processing Unit	32-Bit MCU (ARM Cortex M3)
Energy Unit	Li-Ion battery 560 mAh
3D Accelerometer	Bosch BMA280 Measuring range: ± 2 ... ± 16 g Sampling rate: 2 kHz

The sensor nodes were mounted as close as possible to the axis joints by means of magnetic holders in order to record the vibrations emitted by the bearings and gears as undistorted as possible. Fig. 5 shows the mounting positions of the sensor nodes.

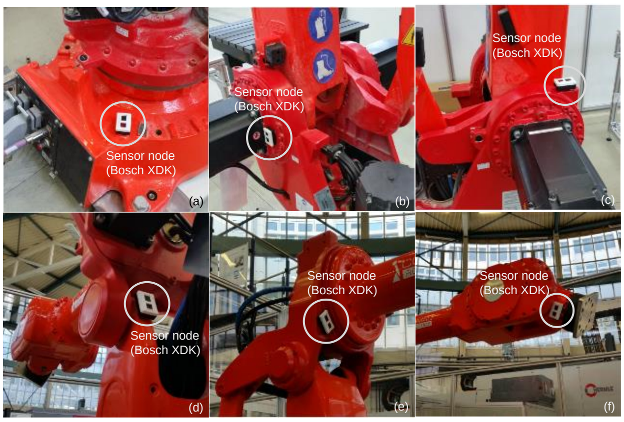

Fig. 5. Mounting positions of the sensor nodes

G. Results and Discussions

The implemented system architecture fully met the set requirements. Data communication using the publish-subscribe pattern via the MQTT IoT protocol proved to be very robust, even when using several sensor nodes in parallel.

Unfortunately there were no differently worn components available for the experiments to evaluate the implemented classifier with real data. Furthermore, no information on the wear condition at the time of the experiments was available. The principle functional validation of the SVM classifier was therefore carried out with synthetic data. In the context of the presented condition monitoring concept, statistical control charts (cf. Fig. 1 and [11]) can be applied if the prerequisites for the use of classifiers are missing. The possibility to detect trends in these charts can already give hints on increasing wear and tear and thus supports the introduction of predictive maintenance with simple means.

V. CONCLUSIONS AND OUTLOOK

In this paper a holistic concept for condition monitoring of industrial robots based on self-tests and MEMS-based sensor nodes was presented. It was shown which constraints have to be taken into account when designing a self-test to determine the wear condition and how a suitable system architecture should be designed. Furthermore, it was discussed how machine learning methods can be used to classify the wear condition, provided that sufficiently labelled historical data are available.

The fact that obviously no labelled case data are available in practice for the application of supervised learning methods in the context of condition monitoring is a serious problem. For economic reasons, industry is not willing to put in the effort to collect case data and label them. Future research activities should therefore focus on how (partially) automated labelling of measurement data can be carried out.

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