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A Hybrid, Distributed Condition Monitoring System using MEMS Microphones, Artificial Neural Networks, and Cloud Computing

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Abstract

Condition monitoring supported with artificial intelligence, cloud computing, and industrial internet of things (IIoT) technologies increases the feasibility of predictive maintenance. However, the cost of traditional sensors, data acquisition systems, and the required information technology expert-knowledge challenge the industry. This paper presents a hybrid condition monitoring system (CMS) architecture consisting of a distributed, low-cost IIoT-sensor solution. The CMS uses micro-electro-mechanical system (MEMS) microphones for data acquisition, edge computing for signal preprocessing, and cloud computing, including artificial neural networks (ANN) for higher-level information processing. The system's feasibility is validated using a testbed for reciprocating linear-motion axes.

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Keywords: Condition Monitoring System; Artificial Neural Networks; Cloud Computing

1. Introduction

Maintenance is a significant cost driver in manufacturing and production [1,2], making related strategic approaches influence company performance [3]. Depending on the industry, the estimated contribution of maintenance to the total cost of goods produced ranges between 15–60% [1] and 15–40% [4]. However, cost allocation practices may skew said percentages [1]. Predictive maintenance (PdM) is a business strategy informed by condition monitoring systems (CMS), which can lower maintenance costs, equipment downtime, and waste. Both PdM and condition monitoring benefit from the ongoing coalescence of the physical and digital world in the context of Industry 4.0. Technologies such as the industrial internet of things (IIoT), big data, artificial intelligence, edge computing, and cloud computing facilitate the development of PdM and condition monitoring systems [5–8]. However, only 15% of production companies questioned in a study have implemented predictive and 4% prescriptive maintenance strategies [9], even though the industry recognizes the benefits of such strategies [10].

Data-driven approaches reduce the challenges model-based and knowledge-based approaches pose to developing accessible PdM and CMS solutions [2,11]. However, developing solutions requires interdisciplinary competencies and capacities for maintenance, data science, and computer

Nomenclature

ANN	Artificial Neural Network
CMS	Condition Monitoring System
IIoT	Industrial Internet of Things
I2S	Inter-Integrated Circuit Sound
MEMS	Micro-Electro-Mechanical System
PdM	Predictive Maintenance

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science. Small and medium-sized enterprises, in particular, often lack sufficient capacities for these competencies. Therefore, new approaches are required to overcome these challenges. The recent year's prize decline in sensors, microcontrollers, and, in parallel, the increasing performance in information processing enable new possibilities for economically beneficial applications of CMS and PdM. Especially, micro-electro-mechanical system (MEMS) based sensors provide increasingly good technological characteristics at a low cost. This paper aims to propose a condition monitoring system architecture based on MEMS microphones, artificial neural networks (ANN), and cloud computing, facilitating the implementation of CMS and PdM solutions.

2. Related Work

PdM strategies aim to schedule maintenance measures based on (predicted) equipment conditions [1,2,5,11–13], while condition monitoring comprises different technologies to determine equipment conditions and potentially predict failures [14]. CMSs include various components for data acquisition, transmission, storage, preprocessing, and analysis [15], organized in a system architecture tailored to the specific application. Typical CMS architectures define the arrangement of components and the allocation and distribution of computing tasks within the system [4,16–24].

In an IIoT context, edge and cloud computing allow flexible computing task-allocation within systems. Light computing tasks are allocatable to on-premise nodes (devices) at the “edge” of a network, while resource-intensive computing tasks occur in the cloud [2,6,7].

Data-driven PdM and condition monitoring often exploit vibration signals [5,11]. Vibration, in general, describes an oscillatory movement [25], which relates closely to acoustic emission, and acoustic signals (sound). Acoustic emission describes the generation of transient elastic waves due to a rapid release of strain energy caused by a structural alteration in a solid material [26]. Sound describes mechanical vibrations in the frequency range perceivable to the human ear. Depending on the medium in which the sound occurs, distinctions are between air-borne, liquid, and structure-borne sound [27].

Exploiting acoustic signals for PdM and condition monitoring poses advantages under certain conditions. Sensors (microphones) to capture acoustic signals do not require placement directly on the monitored equipment [28]. Specifically, MEMS microphones are low-cost and small while offering high sensitivity, a flat frequency response, and a low noise level [29]. MEMS microphones have proven a suitable alternative to conventional microphones for condition monitoring purposes [30–34].

The literature reviewed in the scope of this paper includes multiple valid approaches to PdM and CMS, including different solutions for data acquisition/sensors [2,11] and predictive analysis [2,5,11]. However, there is a lack of accessible technology chains for condition monitoring systems that facilitate data acquisition from industrial operating equipment [5,10,11,24]. Furthermore, time-based prediction approaches are underrepresented compared to classification and fault diagnosis approaches [5,11].

3. Approach

The general approach to the proposed CMS architecture includes a hybrid allocation of computing tasks between the edge and the cloud (Fig.1). The architecture allows flexible distribution of preconfigured edge nodes to various assets facilitating scalable and cost-effective implementations. The hybrid approach enables using capacities at the edge while also leveraging resource-intensive data-driven approaches in the cloud. Multiple distributable IIoT edge nodes enable data

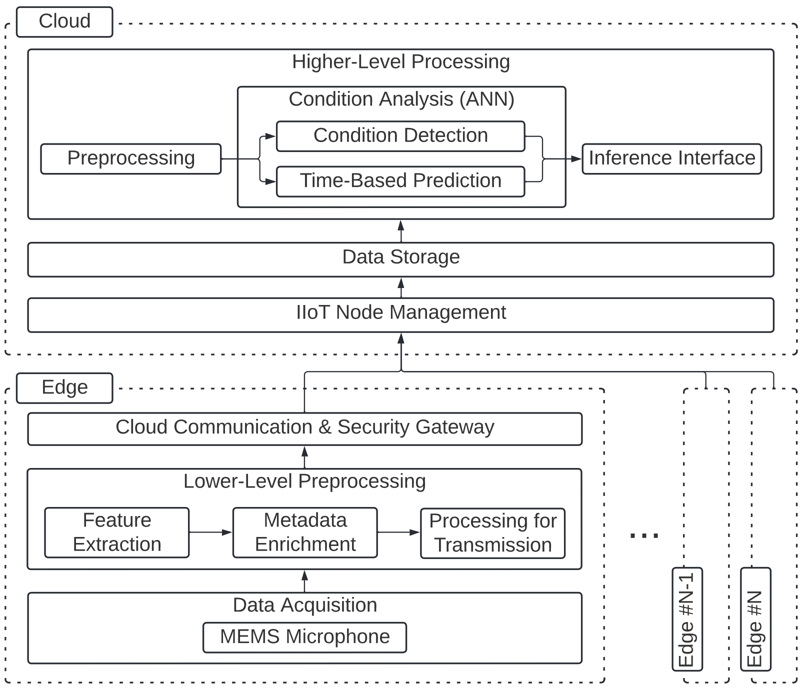

Fig. 1. Condition Monitoring System Architecture.

acquisition and lower-level processing, while the cloud provides edge node management, storage, and higher-level processing (see Fig. 1). The condition analysis capabilities enable condition detection and time-based predictions without data representing the entire component degradation process. In addition, the condition analysis capabilities extend toward covering the entire machinery degradation process with increasing data availability.

3.1. Edge node

Data acquisition for the proposed CMS architecture relies on a MEMS microphone due to the advantages of low cost, small size, the option for remote placement, and technical qualities such as high sensitivity, a flat frequency response, and a low noise level. The technical specifications of the MEMS microphone and the analog-to-digital converter must have adequate sensitivity/resolution to determine differences in equipment conditions. Here, MEMS microphones with a digital interface such as I2S are preferable due to the already integrated analog-to-digital converter. Furthermore, the data acquisition intervals must be granular enough to capture changes in condition over time. A clock on the edge nodes allows localizing measurements in time.

The lower-level processing at the edge includes feature extraction from the recorded audio signals to reduce network traffic, metadata enrichment to facilitate data labeling at a later stage, and data transmission to the cloud. Examples of acoustic-based features include root mean square values, amplitude envelopes, kurtosis, frequency spectra, spectrograms, Mel-frequency cepstral coefficients, and wavelet coefficients. The cloud communication and security gateway provides communication to cloud provider-specific application programming interfaces to ensure authentication and encrypted data transmission between the edge and the cloud.

3.2. Cloud module

The cloud requires an interface to manage and securely authenticate multiple edge nodes and enable data transmission between the edge and the cloud. Storing the transmitted historical data is an essential requirement for higher-level processing. The higher-level processing includes data preprocessing, condition analysis, and an interface for inference purposes and adjacent applications.

Preprocessing applies statistical operations such as outlier removal and normalization necessary to prepare the features extracted during lower-level processing for the condition analysis. Furthermore, the features are labeled to satisfy requirements for implementing both condition analysis approaches.

Condition analysis consists of separate ANN-based approaches for condition detection and time-based predictions. The condition detection aims to determine condition classes, while time-based predictions aim to correlate changes in the extracted features to a time-delta between arbitrarily chosen points (conditions). Therefore, condition detection relies on a classification ANN and the time-based predictions on a regression ANN. Both ANNs train on the same features labeled differently to account for the respective approach. The approaches rely on the premise that the MEMS microphone recordings can reflect changes in physical condition.

The respective ANNs differ regarding their aim, network architecture, hyperparameters, and feature labeling. The architecture of ANNs describes their overall structure, i.e., the organization of neurons, layers, and their connections [35]. The hyperparameters (such as the learning rate, optimizer, and loss function) control the algorithm's behavior during training [35].

Both condition analysis components require a dedicated solution for deployment to make the respective detection and prediction capabilities available to users and subsequent processing in adjacent applications.

4. Implementation & Validation

A prototype with three edge nodes was deployed to a testbed for reciprocating linear-motion axes simulating three different lubrication conditions. The test environment aims to investigate the feasibility and capability of the proposed CMS architecture to determine the condition of machinery components. The profile rails were parallel, and a belt drive reciprocated the guides simultaneously. Three different conditions were simulated by applying 50%, 100%, and 150% lubrication to the rail guides (according to the manufacturer's specification). The edge nodes installed on the rail guides faced the MEMS microphone down towards the profile rail.

Furthermore, the rail guides were loaded with 0.5 kg and continuously reciprocated for an 11-day test period. Each edge node acquired two seconds of audio every five minutes throughout the test period. The following sections describe the implementation of the individual architecture components.

4.1. Edge node implementation

Data acquisition consists of a digital MEMS microphone (Knowles SPH0645LM4H-B on an Adafruit breakout board) recording at 44.1 kHz, 24 bit via the inter-integrated circuit sound (I2S) protocol.

The lower-level processing at the edge (Raspberry Pi 3 Model B) includes applying a fast Fourier transform to the audio and reducing the resulting spectrum by averaging the magnitudes over 10 Hz-wide frequency bands. Reducing the dimensionality of the spectra was necessary to accommodate the 256 kB limit for device-to-cloud messages.

The cloud communication and security gateways authenticate using connection strings uniquely assigned to each edge node to enable data transmission. Afterward, the spectra and corresponding metadata (recording timestamps and edge node identifiers) were serialized and transmitted to the cloud. An additional copy of the data was backed up to a private cloud running an InfluxDB. Data acquisition, lower-level processing, and transmission to the cloud occur fully automated according to specified time intervals.

4.2. Cloud module implementation

The cloud components of the proposed architecture were implemented using Microsoft Azure. The higher-level processing occurred in an Azure-hosted machine learning workspace with allocatable compute instances to account for preprocessing, both condition analysis approaches and the inference interface. Most of the cloud implementation, including higher-level processing, required manual setup and execution.

4.2.1. IIoT node management

An Azure IoT Hub provided the interface and node management to the edge, including authentication and routing incoming data to a specified storage container for the higher-level processing. The individual edge nodes were registered manually and assigned a unique connection string for authentication and secure communication.

4.2.2. Storage

The spectra and metadata were automatically transmitted to the cloud and saved to .avro files within an Azure storage container. The further data transfer from the storage container to the machine learning workspace for higher-level processing required manual execution.

4.2.3. Preprocessing

The data acquired at the edge was split into features and labels. The features are the magnitude values of the spectra, and two labels per feature were constructed from the metadata according to the requirements for the condition detection and time-based predictions. Details for both labeling approaches are presented in the following section.

To account for random noise events, spectra where the mean magnitude across all frequencies exceeds 1.5 times the interquartile range of the entire dataset were removed as outliers. Furthermore, the features for training and testing were scaled to a range between zero and one. The dataset was then split into 80% training and 20% testing data for validation.

4.2.4. Condition analysis

The condition detection and time-based prediction rely on a supervised learning approach. However, the respective ANN architectures and hyperparameters required setup to the specific intended task, i.e., classification for condition detection and regression for the time-based prediction.

The ANNs were implemented in Python using Keras. The architectures and hyperparameters for both ANNs were chosen based on trial and error to enable functionality without focusing on optimized performance and prediction accuracy.

The classification approach aims to predict specific conditions of equipment. Therefore, the features were labeled according to the conditions set in the test environment, i.e., three classes corresponding to 50%, 100%, and 150% lubrication. The trained classification model's accuracy on the test set was 100%, correctly predicting 1898 labels (lubrication conditions) in 1898 predictions. Fig. shows the confusion matrix of the measured conditions plotted against the predicted conditions on the test dataset. The confusion matrix complements the accuracy measure to evaluate the ANN's classification performance, showing the distribution of errors per label (i.e., per lubrication condition).

The regression ANN aims to output a single continuous value suitable for time-based predictions. The recording timestamps allow for labeling the dataset with the respective time-delta of each entry/recording to an arbitrarily chosen point in time within the dataset. After training, the regression ANN predicted the previously unseen test data with a mean absolute error (MAE) of less than 15 hours. Fig. 3. shows the progression of the MAE on the training and the test data over 50 training epochs. The error steeply declines during the first training epochs and progressively converges less steeply towards a gradient of zero. The error progression suggests that further training is uneconomical in terms of computing resources. However, further training might still marginally improve the model as the validation error on the test data does not suggest overfitting.

4.2.5. Inference interface

Both trained ANN models were registered to the machine learning workspace, packaged in separate Docker containers, and deployed as web services hosted in Azure to implement the inference interface. The models are accessible via HTTPS requests using individual inputs matching the format of the spectra used for training. Both deployments answer requests automatically.

5. Conclusions & Outlook

The presented results show the feasibility of the proposed system architecture and implemented technology chain in terms of data transmission throughout the system and the

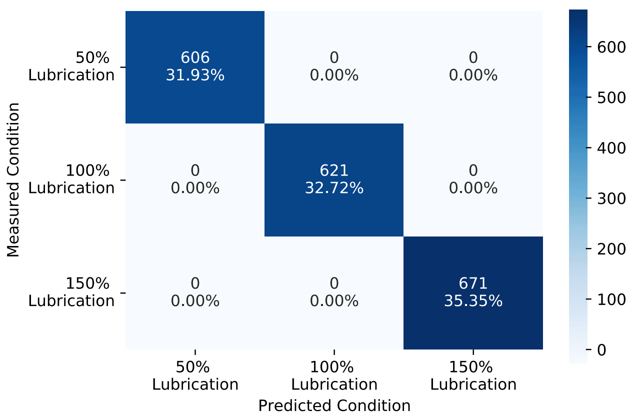

Fig. 2. Classification ANN Confusion Matrix.

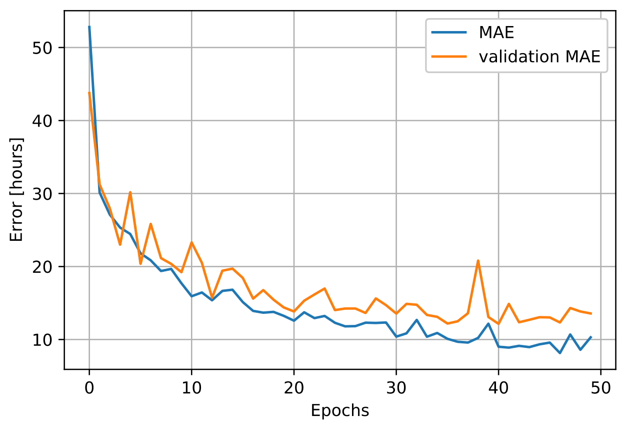

Fig. 3. Regression ANN Mean Absolute Error over 50 training epochs.

limited capability to determine machinery component conditions. However, the capability of both neural networks must not be overestimated regarding their ability to extrapolate and generalize to other implementation scenarios.

The system architecture enables insight into condition classes from a broad perspective, while the time-based analysis enables granular insight on sections within the entire degradation process. Focusing the analysis on initially selected sections allows a limited detection/prediction capability based on small datasets while gradually extending detection and prediction capabilities with additional data.

Future work focuses on optimizing individual components within the proposed system architecture to improve condition detection and prediction capabilities and computational efficiency. Examples are feature selection, (automated) hyperparameter tuning, and collecting data over the entire degradation process of additional machinery.

Possible extensions to the proposed system architecture include full automation of the manual processes in the cloud (preprocessing, training, deployment), including retraining the ANN models on newly acquired data. In addition, allocating lightweight versions of the trained models to the edge enables offline and real-time access to the condition analysis. Furthermore, multiple edge nodes enable sound source localization and noise-canceling opportunities.

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