A Predictive Maintenance Deployment Model for IoT Scenarios

Albana Gorishti¹
Klaidi Gorishti²

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Abstract: The Internet of Things (IoT) concept describes the intelligent connectivity of smart devices using Internet connectivity. In a continuously developing IoT environment, companies try different approaches for predictive maintenance as a solution to reduce costs and the frequency of maintenance activities. Such an environment can natively foster predictive maintenance as it integrates information from different equipment to derive insights and predictions.

This paper proposes a deployment model for predictive maintenance approaches on industrial equipment by processing and analyzing their audio signals. Proper maintenance scheduling is necessary to prevent business costs and maintain the equipment in operational capability. The authors propose a system architecture to make predictive maintenance applicable in different industrial scenarios. The implementation exploits deep learning neural networks to detect anomalies and further classify them into categories. These machine learning techniques enable predictions of equipment’s conditions and thus maintenance services can be performed.

1. INTRODUCTION

Nowadays, the automation and digitalization of industrial production processes are standard in many companies (Liebetrau & Grollmisch, 2017). Liebetrau and Grollmisch explain that an aspect of this automation process is the timely and efficient handling of equipment failures. Considering this, industrial equipment maintenance is an essential process with an impact on the prospect of the businesses. Its primary purpose is to ensure that all the equipment, required for production, is operating at 100% efficiency at all times (Mobley, 2002). Maintenance is considered one of the most important facets of modern industry⁴. According to British Standard, 381¹⁴ maintenance is:

*The combination of all technical and associated administrative actions to retain an item in, or restore it to a state in which it can perform its required function.*

In this work, maintenance is interpreted within the context of industrial environments, with a particular focus on its technological point of view. Therefore, we elaborate about applying maintenance to industrial equipment in an IoT environment. Industrial equipment is a wide range of devices, built and designed to make manual labor faster and easier, in industrial production floors⁵. They handle different industrial processes, such as: production, measurement, components assembly, etc.

¹ Faculty of Economy, University of Tirana; Rr. Arben Broci 1 1001, Tirane, Albania
² Amazon Web Services; Oskar-von-Miller-Ring, 80333 Munich, Germany
³ www.paragon-u.com/the-importance-of-equipment-maintenance
⁴ www.bsigroup.com/en-GB
⁵ www.industrial101.com/equipment
Different categories of equipment maintenance philosophies are currently applied in the industry, including run-to-failure maintenance, preventive maintenance, proactive maintenance and predictive maintenance (Girdhar & Scheffer, 2004). Each approach has its advantages and disadvantages. The division of types of maintenance has the disadvantage that each piece of equipment needs a mix of each of the above-mentioned maintenance types, so we cannot think of applying a single one of them in equipment.

2. PREDICTIVE MAINTENANCE

The focus of this paper is predictive maintenance, considering the benefits and its broad utilization in the industry. Predictive maintenance (PdM) aims to prevent machinery failure by predicting when failures occur and thus performing maintenance services. Its purpose is to periodically monitor and report the status and operational capacity of the equipment by knowing the values of certain parameters, which represent such states and operational ability (Girdhar & Scheffer, 2004).

Using the predictive maintenance technique requires the identification of the physical parameters (e.g. temperature, vibration, audio, etc.), and which state serves as a trigger for the need of the machine’s maintenance. The proposed solution architecture monitors audio signals of the equipment components, thus it is an audio-based system for predictive maintenance.

Predictive maintenance’s benefit is predicting machine failures before they occur (Mobley, 2002). This approach allows one to perform a maintenance service before an erroneous state causes the failure of the equipment. As a result, the offline time of the equipment is minimized, and maintenance financial costs are reduced.

According to Yoskovitz, "Predictive maintenance has been proven to be efficient in reducing maintenance costs by 30%, eliminating 75% of all failures and even reducing energy consumption by up to 20%". However, Yoskovitz further adds that only 12% of commercial facilities are using predictive maintenance in their production lines. As a result, we should focus more effort on predictive maintenance to provide further solutions and make it more accessible in the industry.

3. RELATED WORK

Due to the rapid increase of complexity in engineering systems and the availability of condition monitoring data, predictive maintenance has gained a lot of attention in the last decade (Lee & Pan, 2017). Predictive maintenance approaches use different technologies such as vibration monitoring, thermography, visual inspection, ultrasonic and other testing techniques (Mobley, 2002). The usage of each approach depends on the industrial equipment’s physical and technical features. The application of the same solution for different types of industrial equipment is not possible (Yul Oh & Yun, 2018).

One of the predictive maintenance technologies, elaborated by Liebetrau and Grollmisch, is sound analysis. On this premise, Liebetrau and Grollmisch define two approaches used for monitoring: structure-borne analysis and airborne analysis (i.e. airborne analysis is less common in

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7. www.newelectronics.co.uk/electronics-technology/making-ultrasound-based-predictive-maintenance-accessible/152769
8. Ibid.
real-world scenarios). On the one hand, structure-borne analysis measures the structural vibrations through the sensor mounted on the system under test (SUT). On the other hand, an airborne approach captures the radiated sound of the SUT using contactless microphone sensors (Liebetrau & Grollmisch, 2017).

In addition, Liebetrau and Grollmisch explain: the collected sound data are analyzed using different machine learning approaches such as Support Vector Machines (SVM), Gaussian Mixture Models (GMM) and Deep Neural Networks (DNN). In conclusion, acoustic condition monitoring via airborne sound analysis in conjunction with advanced signal processing and machine learning methods prove to be a powerful tool for early detection of machinery failures (Liebetrau & Grollmisch, 2017).

Saimurugan and Ramprasad propose a combination of the vibration-based analysis with audio signals analysis. As a result, they achieve a higher classification efficiency with the fusion of the two features, compared to both the vibration and sound signal. Additionally, the usage of an artificial neural network performs better than other machine learning approaches. Finally, Saimurugan and Ramprasad observe that the vibration-based analysis gives more information than the audio features (Saimurugan & Ramprasad, 2017).

Zhu et al. propose an approach for sound events classification using convolutional neural networks (CNN) (Zhu et al., 2018). Their work puts the focus on audio data preprocessing (i.e. featurization) using the Fast Fourier Transform algorithm. According to Zhu et al., this process is required to make the data useful for the machine learning algorithm. The neural network architecture which they propose is very similar to the VGG network (Simonyan & Zisserman, 2014).

4. SYSTEM DESIGN

This section focuses on identifying the components of the system and establishing its architecture. In an industrial context, various types of sensors can be used. However, this solution focuses on audio sensors to monitor industrial equipment’s conditions. The system consists of three components: DataCollector, LearningExpert and PredictionExpert. Figure 1 presents the UML component diagram which depicts the subsystem decomposition (Brügge & Dutoit, 2009).

The solution uses a broker architectural pattern to facilitate the communication between its components. The usage of such a pattern ensures the modularity of the components (i.e. thus...
low coupling), as their communication mechanism is decoupled from the implementation. Additionally, the broker pattern enables location transparency because the components do not need to know the location of each other, but they use the broker as a "man-in-the-middle", to transmit messages to other components. Furthermore, considering the decoupling of components, it is easier to add, remove or change them at runtime. Finally, since the subsystems do not directly interact with each other, we achieve platform independence (i.e. components can be implemented with different programming languages).

In this solution, this architectural pattern exploits the MQTT protocol to exchange topic-based messages. However, it is important to emphasize that other protocols can be used instead of MQTT and this is only a design decision for the system.

4.1. Data Collector

The DataCollector component serves for collecting audio recordings and preparing them for analysis. Firstly, it opens the audio stream and writes the audio frames into WAV\textsuperscript{9} files. Secondly, the DataCollector preprocesses the audio recording files and extracts their spectrogram representation. Finally, it uploads the generated audio spectrograms to the cloud storage. The DataCollector consists of five packages, discussed in the following.

- **AudioRecorder**: takes care of the audio recording process.
- **DataAugmentor**: recorded audio files go through several augmentation steps in order to generate noise in the dataset and increase its size.
- **SpectrogramGenerator**: hosts the logic to calculate the frequency spectrum from the amplitude representation of raw audio signals.
- **ClientConnectionManager**: client which publishes/subscribes to an IoT broker.
- **StorageManager**: establishes the DataCollector’s connection to the cloud storage and uploads the generated audio spectrograms in the respective storage components.

4.2. Learning Expert

The LearningExpert component conducts the process of audio data analysis. It focuses on understanding relationships in the audio signal features which serve to build the trained models. The LearningExpert component establishes the knowledge which is used for the prediction phase and maintenance schedule.

- **TrainingManager**: responsible for the training process management.
- **AnomalyDetection**: exploits an autoencoder neural network to provide a residual error-based anomaly detection pipeline.
- **ClassificationPipeline**: trains the classification model.
- **ClientConnectionManager**: responsible for handling the connection and the messaging infrastructure logic.
- **StorageManager**: controls the LearningExpert’s connection to the cloud storage, thus enabling it to download audio spectrograms and upload trained models in the corresponding storage components.

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4.3. Prediction Expert

The *PredictionExpert* component exploits the knowledge stored in the *LearningExpert*’s trained models to make predictions on unseen data. This component analyzes audio recordings to detect anomalies and classify them into categories. Additionally, its features include scheduling maintenance services, based on the prediction results in combination with expert knowledge.

- **InferenceManager**: supervises the inference process. First, the *AnomalyDetector* package analyzes the audio data to check for anomalies. Second, only if an anomaly is detected, the *Classifier* package provides predictions about the anomaly’s classification. Third, based on the anomaly score from *AnomalyDetector* and the classified category from the *Classifier*, maintenance service is performed.
- **AnomalyDetector**: uses *AnomalyDetection*’s model to detect anomalies on new recordings.
- **Classifier**: uses the *ClassificationPipeline*’s trained model to distribute new recordings into known categories.
- **MaintenanceScheduler**: exploits predictions from the *AnomalyDetector* and *Classifier* to determine the needs for maintenance services.
- **FeedbackCollector**: hosts the logic of retrieving industrial equipment operator’s feedback and injecting it during the prediction process.
- **ClientConnectionManager**: allows the *PredictionExpert* to interact with the IoT broker.
- **StorageManager**: facilitates the *PredictionExpert*’s connection to the cloud storage.

5. FOG COMPUTING ARCHITECTURE

Fog computing is a distributed paradigm that provides cloud-like services to the network edge (Dastjerdi & Buyya, 2016). According to Dastjerdi and Buyya, the technology deals with IoT data locally by edge devices near users, to carry out a substantial amount of storage, communication, control, configuration, and management (Dastjerdi & Buyya, 2016). The approach benefits from edge devices’ proximity to sensors while leveraging the on-demand scalability of cloud resources. Such a concept adapts well to the solution domain of AudioForesight system. In this context, AudioForesight contains one or more audio sensors (i.e. one sensor for each drive) attached to industrial equipment. The above-described architecture suggests that the *EquipmentController* machine collects and processes the audio data. As a result, this machine is a single point, which handles the preprocessing of all sensor data. Thus, a single machine uses a considerable amount of computational power.

To relieve the *EquipmentController* machine from the workload, we can use a fog architecture between the edge devices (i.e. the audio sensors) and the cloud infrastructure which further analyzes the data and makes predictions. In Figure 2, we present the UML deployment diagram, which embeds the fog infrastructure concept. In this case, each sensor attached to the industrial equipment connects to a microcontroller chip (e.g. a RaspberryPi device) which hosts the *DataCollector* component. As a result, each edge device (i.e. RaspberryPi) individually executes the collection and preprocessing of the sensor data.

Thus, we alleviate the *EquipmentController* machine from the pre-processing operation and it only takes care of retrieving the data from edge devices and forwarding them to the cloud infrastructure. Such architecture makes it easy to scale the system with new monitored physical parameters, as each sensor has its individual pre-processing unit which is decoupled from other sensors.
6. CONCLUSION

This paper introduced AudioForesight, an audio-based approach for predictive maintenance in IoT environments. This solution allows for the prediction of the need for maintenance services based on the monitoring of operational conditions of industrial equipment. Furthermore, AudioForesight establishes a system architecture that is adaptable to different industrial application domains and types of sensors.

Compared to other approaches which focus specifically on designing and implementing machine learning solutions to deal with predictive maintenance, AudioForesight suggests a system architecture by exploiting several machine learning approaches. While the focus on a single machine learning solution enables it to be more specific with the prediction results and probably even more accurate, using a solution such as AudioForesight has the advantage of providing a broader picture of the industrial equipment conditions and thus more reliable decisions.

AudioForesight is a ready-to-use system and it can be easily deployed on various platforms. We encapsulated its components into Docker containers which make the deployment procedure quick and with little effort required. Since the system hosts online the communication and storage infrastructures, the deployed components need network connectivity to interact. Once the system is successfully deployed at industrial equipment it is available for operation.

7. FUTURE RESEARCH DIRECTIONS

7.1. Adding Other Sensor Types

Extending the system’s architecture with new types of sensors is part of future work. Several alternative types of sensors can be included in the system to improve its predictive maintenance mechanism. Having a broader physical parameter coverage allows for building a more accurate and reliable solution. If we use more sensors, the decision-making regarding maintenance performs analyzes more parameters and thus predictions are more accurate. As a result, we enhance the predictive maintenance approach of AudioForesight.
7.2. Implementing Client Application Interfaces

AudioForesight uses a command line interface to interact with external users. Such a solution facilitates the usage of the system, however, is not very satisfying for the users. To improve the system’s usability, the implementation of better client applications is necessary.

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