Deviation Detection in Industrial Rotary Machinery Diagnostics

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***Abstract*—The industrial Internet of Things (IIoT) applies monitoring of technical state and utilization conditions for rotary machinery. Monitoring is based on multiple sensors that embed or surround the machinery under monitoring. The sensed data are used for diagnostics of machinery operation and utilization. In this work, we consider existing approaches for diagnostics. We focus on construction of a digital profile for the given machinery, on transformation of raw sensed data for further analysis, and on the model of deviation detection in machinery technical state.**

I. Background

The industrial Internet of Things (IIoT) includes technologies that monitor the technical state and utilization conditions for rotary machinery during the production operation. The data come from multiple sensors and the data flows are processed in the real-time mode.

Diagnostics methods analyze the data to detect possible faults or defects as well as analyze possible evolution of detected faults or defects. The diagnostics methods are applied with attention paid to machinery operation, fault detection, and maintenance planning. Basically, the following two approaches are applied in diagnostics [1]:

- Technical conditional monitoring,
- Prognostics and predictive analytics.

The first approach is based on a set of sensors (e.g., vibration sensor, current clamp, thermocouple, tachometric system). The sensors provide data to evaluate the conditional state in real-time. A diagnostics method can use data from a single sensor or the data flows are fused from multiplied sensors. The second approach is focused on making forecast that is based on defect evolution recognized in the historical data.

Among technical conditional monitoring methods, we can outline some of them, which are based on Artificial Neural Network Models (ANN) [2]. The methods can be used for defect classification. For instance, utilizing vibration data from an accelerometer, we can classify bearing ring defects [3]. In that case, the input data form raw vibration signal from an analog-to-digital converter (ADC). The result is the bearing state class:

(0) — healthy bearing,

(1) — outer ring defect,

(2) — inner ring defect.

Classification-based methods require data set for training the model. This model could be trained on the open and general-purposed data set. Examples are Paderborn Bearing Data Set, CWRU: Bearing Data Center, FEMTO Bearing Data Set, MFPT Fault Data Set, Bearing Data Set IMS.

Each machinery unit is unique. Hence, the models have low accuracy when they are trained on the open datasets. Another approach is to collect own dataset for each machinery part. The utilization of this obtained dataset allows the model to increase accuracy in defect classification.

Note that the approach has the following limitations.

1) Time requirements for data collection — it takes time to collect data in different operation modes;
2) Cost requirements for data collection — sufficient healthy and damaged machinery units are required to create a representative dataset;
3) Cost requirements for data collection — at the time of data collection for training, the equipment will not work for its intended purpose. This entails a loss of profit;
4) The dataset should be marked by an expert;
5) The dataset is individual — the replacement of one unit may reduce the accuracy of the model in operation mode;
6) The model must be trained again in case the dataset expanded.

II. Methods

The alternative technical conditional monitoring way is deviation detection in rotary machinery based on referring digital profiles of a unit [4]. The reference digital profile represents a technical state of the unit (normal operation mode). The technique is divided into the following two steps (modes).

1) Adaptation mode. Reference digital profile construction with data from various sensors while the equipment runs under normal conditions. This mode requires the utilization of machinery in all allowed operation modes, like a startup, running under load, etc.
2) Deviation control mode. The model detects deviations by applying a comparison reference profile with the current observation where the last one had made from data obtained with the same sensors.

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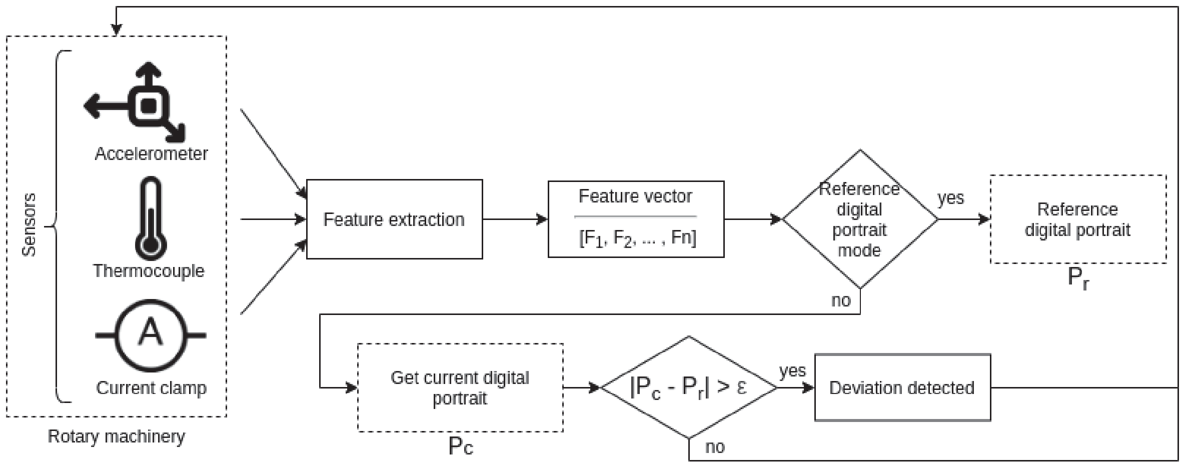

Fig. 1. Data flow for a deviation detection model based on a feature vector

Additionally, let us introduce the ϵ coefficient. If the difference between current and reference profile is more than ϵ, we suppose, the machinery has deviations in the current state. In this way operator attention must be paid. The border ratio ϵ requires tuning for each machinery unit.

Technical conditional monitoring methods are based on digital profiles. In this case, the deviation detection uses matching the current data to the profile. No data markup is required. The process of digital profile construction and update goes automatically without staff and machinery halting.

When the adaptation mode is set a vector of features is extracted from a converted digital signal with n samples. This feature vector used to build a reference digital profile in the adaptation mode.

For rolling machinery parts, like bearings, the data from the vibration sensor could be selected as a base to build the reference digital profile. The analog signal from vibration sensor is converted by ADC (analog-to-digital converter) into x_1, x_2, $\ldots$, x_n digital samples. Each n samples from digital signal are taken to extract N features F_1, F_2, $\ldots$, F_N, like RMS, mean, min and max values, crest factor, variance, etc. [5]. Another approach of data preparation is using spectrogram as input data for making profiles [6].

Deviation detection model application showed in Fig. 1. There are two digital profiles are used: reference — for healthy technical state, current — to compare with the reference profile and detect deviations in machinery unit. Here, a feature vector F is extracted from heterogeneous data, that obtained from sensors. The coefficient ϵ is applied to set detector limits.

Deviation detection digital profile-based method allows to modify reference profile (include new operation modes) without model stop and reconfiguration. These digital profiles could be made with:

- Autoencoders (deep, VAE) [7],
- Hopfield network provides patterns that could be used as digital profiles.
- Complex models can be used for feature vectors as an input, extracted from a raw signal.

III. Conclusion

This work-in-progress paper considered the opportunities of technical conditional monitoring methods for rotary machinery diagnostics. We overview the latest diagnostics methods applicable with the IIoT technologies for real-time monitoring. We identified the basic research problems for selecting a digital profile construction method, transforming raw sensed data, and applying the deviation detection model.

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