Theoretical Background of Predictive Maintenance Models

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Predictive Maintenance (PdM) is one of the most important applications of advanced data science in Industry 4.0, aiming to facilitate manufacturing processes. To build PdM models, sufficient data, such as condition monitoring and maintenance data of the industrial application, are required. Collecting maintenance data is complex and challenging as it requires human involvement and expertise. Due to time constraints, motivating workers to provide comprehensive labeled data is very challenging, and thus maintenance data are mostly incomplete or even completely missing. In addition to these aspects, a lot of condition monitoring data-sets exist, but only very few labeled small maintenance data-sets can be found.

Keywords: welding industry ; predictive maintenance ; maintenance event detection

1. Introduction

Predictive Maintenance (PdM) is one of the most prominent industrial applications of data-driven technologies and key to the smart manufacturing concepts, promising many benefits such as optimized maintenance scheduling, resource optimization, and improved decision support [1]. PdM models are typically used to predict future failures due to the wearing out of components and thus provide the opportunity to perform maintenance proactively. The main reasons for the interest of researchers and industry alike in PdM in recent years are the relevance and influence of maintenance on production cost and quality [2], the increased information base due to the availability of cheap and powerful sensor technology [3], and huge advances in artificial intelligence (AI) [4]. In general, maintenance costs are an aspect that make up the majority of operating costs and can vary between 15% and 60% depending on the type of industry [5]. Consequently, PdM helps to reduce maintenance costs without increasing the risk of downtimes. For instance, Han et al. [6] introduced a Remaining Useful Life (RUL)-driven PdM approach that reduced the maintenance costs by 4% compared to scheduled maintenance.

Building PdM models requires a comprehensive amount of condition monitoring data describing the operation conditions of the machinery and maintenance data documenting maintenance events. Usually, the condition monitoring data are collected by sensors embedded in smart manufacturing systems. Yet, the collected maintenance data mainly consist of feedback from shop-floor workers, and motivating the shop-floor workers to provide this feedback is a big challenge. This is often neglected due to time constraints. Consequently, maintenance data are often incomplete or even completely missing [7][8]. One way to tackle the challenge of missing or incomplete maintenance documentation is to automatically detect the maintenance events based on their manifestation in monitoring data like time series collected from sensors in the machines. Anomaly detection approaches are suitable for these event detection tasks and can be found in many topics within manufacturing including defect detection [9][10], fault detection [11][12], or maintenance event detection [7]. It is to automatically detect performed maintenance actions in monitoring data to create comprehensive data-sets. Subsequently, the completed maintenance and condition monitoring data can be used to build suitable PdM models, which in turn will help to facilitate maintenance scheduling, optimize manufacturing processes, and enhance product quality. It will showed that Change-point detection (CPD) is a promising technique for maintenance event detection.

It was investigated the application of CPD techniques as event detection approaches. CPD is a common and promising approach to tackle this challenge as they aim to detect abrupt changes in time series [13]. The Pruned Exact Linear Time (PELT) in particular is a state-of-the-art offline CPD method that provides accurate event detection outcomes as a result of its binary segmentation and the lower computational complexity it offers compared to exact search methods [14]. The main advantage of PELT is its use of pruning to reduce computational costs without affecting the accuracy of the segmentation results. However, a drawback of event detection approaches in general, and CPD in particular, is their tendency to predict a large number of False-Positive (FP) events [15][16][17]. FP events add additional noise in case the list of events is used as an input for other algorithms. Moreover, a large number of FP events can hinder the application of such models in real scenarios, thus decreasing the usefulness of these approaches [17]. To address this challenge, it was proposed MEDEP as a novel framework based on PELT for multivariate time series. The experimental results are evaluated using two different manufacturing use cases. As a result, MEDEP promises high accuracy event detection results at a low FP rate. The provided low FP rate is a crucial aspect when aiming to integrate these approaches in real-world use cases, and promises increased potential for higher acceptance and trust in these approaches, and in turn a high application rate.

2. Related Theory

In the age of smart industrial diagnostics, multiple sensors are embedded within machines to collect condition monitoring data [9]. This provides the foundation to develop data-driven models to understand, support, and automate manufacturing processes. Despite the huge advances of PdM, many companies struggle to build suitable PdM models. The major reason for this struggle and also the major barrier of introducing PdM in the industry is the lack of suitable data. In particular, the process of collecting maintenance data is challenging as it requires human feedback to document performed maintenance activities. Usually, the shop-floor workers focus on the execution of maintenance actions so that manufacturing continues as soon as possible, and the documentation of their works is only a secondary concern. In many cases, the documentation of maintenance actions is performed retrospectively; thus, a lot of details are not included.

Sensor data are typically more complete than the feedback provided by humans. Based on this observation, several were proposed technical approaches for event detection to overcome the missing human feedback as a major barrier of introducing PdM. The collected sensor data can serve the purpose of anomaly detection in general, defect detection [9][10][18], failure detection [11][12], or maintenance events detection [7] in particular. Event detection for specific components in large machines is challenging due to the high degree of complexity inherent to the large number of components and environmental factors influencing the health state of the machines and their components [1]. Data-driven models are seen as a promising solution to tackle these challenges. Supervised, semi-supervised, and unsupervised machine learning methods have found their applications for anomaly detection in manufacturing.

Supervised approaches are widely applied and usually provide good results. Typical application examples of supervised learning in manufacturing can be found in [9][19][20]. These approaches require large labeled data-sets for their training where the condition monitoring data are annotated with known maintenance events indicating the true health conditions of the machine. However, such annotations are often incomplete and not available in real-world use cases [21][22]. Semi-supervised approaches are a promising way to overcome the challenge of incompletely annotated data-sets [23]. The main characteristic of semi-supervised approaches is the repeated training with a labeled subset of all maintenance events to continuously improve detection or predictive results. For semi-supervised modeling, at least a partly annotated training data-set representing the healthy state of machines and components has to be available. However, this is hard to assure as machines continuously degrade or even crash, and such crashes might affect the condition monitoring system and, therefore, the collected data [24].

Unsupervised approaches can overcome these issues since they learn solely from condition monitoring data and neither require labeled nor only healthy system data [25][26][27]. The focus is targeted towards identifying abnormal patterns that can be exploited for fault detection or event detection knowledge. However, their application in maintenance event detection is less explored. The knowledge acquired in fault and defect event detection models is mostly used as input for maintenance decision making. Nevertheless, anomaly detection for maintenance event detection has been receiving more attention recently [7][8][28]. It was mostly focused on the detection of abnormal patterns using sensor data complemented by a human-in-the-loop setup to validate the detection results. For instance, Moens et al. [7] introduce an interactive dashboard for event detection in sensor data. This is based on a matrix profile as its motif discovery technique and requires human feedback or intervention to label correct maintenance events. This work showed that maintenance events could be detected and correctly labeled with limited feedback from the human expert. De Benedetti et al. [12] proposed an anomaly detection approach detecting anomalies in photovoltaic systems based on artificial neural networks to generate predictive maintenance alerts. Furthermore, Theodoropoulos et al. [29] evaluated Deep Learning-based approaches in a maritime industry sustainability. It was [29] showed that 1D-CNN models can successfully deduce important properties, for example, component decay and status, in different time horizons. In contrast to benchmark ML approaches, the proposed methodology showed efficiency in the detection of defect patterns for small degradations. Susto et al. [30] compared state-of-the-art anomaly detection approaches using different industrial use cases. As a result, Local Outlier Factor (LOF) [31] outperforms other approaches in terms of outlier and event detections.

However, these approaches are not straightforward and require human feedback [7] to validate the detected events that lead to extra effort from shop-floor workers. A common challenge of anomaly detection techniques is the tendency to detect a large number of false positives (FPs) [15][16][17]. The tuning of hyper-parameters in these models helps to reduce the FP rate, but usually at the expense of the sensitivity rate, reducing the performance in the detection of real events [15]

[16]. The detection of maintenance actions requires high accuracy results and, therefore, also low FP rate. High FP rates hinder the application of such models in real-world use cases, thus decreasing the usefulness of event detection approaches [17]. Therefore, MEDEP, presented in this work, is designed as a novel event detection approach that tackles all the aforementioned challenges in the context of maintenance event detection.

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