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Machine Learning-Driven Condition Monitoring and Fault Detection in Manufacturing

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***Abstract*—The manufacturing industry has witnessed a surge in the adoption of machine learning (ML) techniques to enhance various aspects of production processes. One critical application of ML in manufacturing is condition monitoring and fault detection, which play a pivotal role in ensuring product quality, minimizing downtime, and maximizing operational efficiency. This paper presents a comprehensive review of the use of machine learning for condition monitoring and fault detection in manufacturing environments. It also discusses the importance of data preprocessing, feature engineering, and model selection in developing robust and reliable ML-based condition monitoring systems. Furthermore, the paper addresses the case studies, challenges and future trends associated with deploying ML-driven condition monitoring, such as data quality, model interpretability, and integration with existing manufacturing systems. It also highlights emerging trends and future research directions in this domain, including the integration of edge computing, digital twins, and advanced analytics for real-time, predictive, and prescriptive maintenance strategies.**

Keywords—Condition Monitoring; Fault Detection; Machine Learning; Supervised Learning, Sensor- based Monitoring.

I. INTRODUCTION

The evolution of data storage and computational power, together with the democratization of machine learning methods, has widened the scope of what is considered possible within the realm of condition monitoring and fault detection. Algorithms can be trained to detect and predict incipient faults in equipment only from its sensor data. In other words, expert knowledge and rule-based approaches are no longer viewed as the only way forward. This is especially interesting in the current competitive market, where rapid changes in manufacturing configuration and changes in business are inherently welcome. Many owners and service providers are opting for an on-demand, predictive maintenance regime in which prognosis methods play a vital role, in contrast to traditional maintenance methods. In the following, we provide an introduction to predictive maintenance and discuss the feasibility and the potential benefits of doing this with machine learning. [1]

Condition monitoring and fault detection have been at the heart of manufacturing for many years. The goal is to ensure continuous and reliable operation of manufacturing machinery and other devices in the production process, thus preventing equipment damage, production downtime, defective products, and potentially much larger problems. The primary driver for condition monitoring and fault detection in the factory is to replace centralized maintenance schedules with more efficient on-demand maintenance regimes, where repairs and replacements are executed only when necessary. Typically, condition monitoring and fault detection depend on the analysis of historical data, train human experts to monitor the acquired data, and create cause-and-effect models. Methods vary from very simple rule- based approaches to practical but complex engineering models. Implementation is often capital and know-how intensive, time-consuming and only executed by highly trained experts [2][3].

The aim of this paper is to demonstrate the power of machine learning for condition monitoring and fault prediction in discrete event manufacturing systems. It focuses on using machine learning for fault detection, and novel early fault detection is demonstrated. The comparison phase is an important part, and different measures to quantify the performance of the machine learning techniques are suggested. The machine learning tools can be used for intelligent decision support or for dynamic reconfiguration for fault prevention.

II. FUNDAMENTALS OF MACHINE LEARNING FOR MANUFACTURING

The two most important tasks in the field of condition monitoring are fault detection and diagnosis. In most literature and some implementations, they are often used interchangeably. In fault detection, a system aims to detect a sudden change in and/or deviation from the normal behavior of the physical system. In contrast, fault diagnosis aims at identifying the likely cause of the symptoms, i.e., it is the process of identifying the specific abnormal conditions that have occurred. In condition monitoring systems, fault

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detection is inherently a necessary part. However, it cannot be assumed that it is enough. With a proper fault diagnosis system, it can further help the system to decide which components to shut down, predominant influential factors, and prevent unplanned shutdowns. Especially in the predictive maintenance system, more than one detection mechanism is required, since it can foresee the needs for replacement earlier and reduce the risks of in-service failures or accidents [4].

Machine learning consists of a suite of analyses and modeling that have been developed in multiple research fields such as computer science, statistics, chemical engineering, etc., and has become a commonly employed method in scientific and industrial fields. The terms "artificial intelligence" and "machine learning" are often interchangeably used but, in general, the terms refer to subsets of the other. Artificial intelligence has a wider connotation, encompassing all human-like behaviors. It involves "learning from data" which is realized in a few primary classes: (1) Supervised learning - a model to form an input-output map from sets of training data; (2) Unsupervised learning - a model to derive insights from data, without any supervisory inputs; (3) Reinforcement learning - an agent tries to make the best possible sequences of decisions based on the experiences gathered, and when taking actions in an environment, it receives feedback in terms of some reward [5].

A. *Supervised Learning Techniques*

With the classic machine learning approach, every attribute pertaining to an input pattern/data point is explicitly assigned. Instead, deep learning methodologies map the dataset into a modeling feature using computational models composed of multiple processing layers to learn data representation, with multiple levels of abstraction. As a preliminary step, a supervised approach could be tested for identifying the most relevant and discriminative attributes to be configured into the employed Auto-Encoder architectures. The identification of such sets of optimal attributes is often a relevant research question, in particular if the domain deals with small size datasets. Once identified, the subset of meaningful attributes cannot be considered as input to the Deep Learning methods to be used in stage two [6].

In the case of supervised learning, the data available is labeled, i.e., it is tagged with the corresponding category. Training is performed through presenting and testing the machine with a set of examples containing the input and the desired output. A possible set of techniques in the case of structured data, which is the best candidate for our employment as it fits very well with the structure of industrial data, is decision trees. Decision trees require learning and class prediction. Training involves the operation in which a tree is learned from data, while during class prediction, the example must be labeled [7].

III. Techniques For Condition Monitoring And Fault Detection

It is clear that there are numerous situations in different areas of industrial processing, which are of equal or even enhanced complexity, in which relevant data have to be acquired and processed, have to be used to demonstrate their benefit; otherwise, the words machine learning (ML) would not have become some of the most common buzzwords of the current knowledge society. As shown in Section 1, manufacturing use cases related to problems of Research & Development (R&D), such as quality optimization, evaluating morphology or defects, are those use cases related to fast feedback in process monitoring and control. The need for ML in these cases is mainly caused by physical modeling approaches based on system identification, which are widely used to track relatively slowly changing dynamics of manufacturing processes. While these techniques are well suited to predict equipment failures and forecast maintenance requirements in quasi-stationary equipment (parts in a manufacturing process), they might still only partially capture dynamics during fast operation of machinery components, which are only marginally affected by varying deterministic inputs but mainly by occurring and superimposed stochastic disturbances [8].

The need for condition monitoring (CM) and fault detection (FD) in manufacturing processes is discussed in Section 2. In order to satisfy the needs of fast and efficient FD and process optimization in manufacturing, various approaches from the fields of data science, signal processing, and physics have been adopted and adapted for the use of in-line measurements for analog and discrete control signals and, less frequently, for the acquired data from process webs. In this section, a general framework for the stages of data conditioning for these data lunch during production, followed by insights into the structure of processing measures commonly used for monitoring purposes, is given. We then describe the ML techniques to be used with these matrices that have shown the most promising results in the context of FD within production departments and illustrate them with case studies from different manufacturing areas [9].

A. *Sensor-based Monitoring*

The sensors play a key role to keep the manufacturing process in a statistically controlled state, and to monitor and detect actual manufacturing performance. However, it is difficult to monitor the entire manufacturing process through the direct operation of all available sensors. They are expensive to install and maintain for every possible signal, and they are also incapable of measuring an entire signal. There may not even be a direct correlation of the sensor's reading with the feature being measured. Therefore, to select appropriate sensors, the sensors based on methods must be highly efficient and cover as much data as possible. All of the sensor data is stored in a database to be used as the dataset for the developed machine learning algorithms to detect the states or patterns. In order to detect and diagnose signals, during preliminary analyses, manufacturing engineers with the aid of statistical techniques used to reduce the dimension of a large set of data. After that, in an off-line manner, they are correlated with accurate diagnostic strategies [10].

Products are manufactured in various processes which consist of multiple manufacturing operations. The operations generate signals and data from different kinds of sensors attached to machine tools, workpieces, or fixtures, used to provide process-informing data for system equipment, setup, and operations. Sensor-based monitoring in manufacturing is essential to achieve close monitoring, to provide early detection and diagnosis of a broad range of problems that might compromise product quality, to reduce cost, to reduce cycle time, or to optimize system and process performance.

The sensors give important information and process knowledge which is otherwise unavailable. These sensors also improve processing capability and productivity. Sensor-based manufacturing process monitoring, or fault detection is defined as the use of sensors that distinguish unacceptable from acceptable process behavior. The sensors can be contact or noncontact types and can detect variables such as tool wear, magnetic field, electric current, temperatures, forces, visual inspection, power consumption, laser signals, ultrasound, sound signals, and vibrations. The signals that are monitored and collected can be time series data, images, 3D data, and spectra properties [11].

IV. Case Studies In Manufacturing

This chapter discusses the utilization of machine learning for predicting imminent failures by training models on sensor data generated from the machines or other monitored equipment. The sensor data generated from multiple types of sensors, each of a different modality, were concatenated and transformed by Principal Component Analysis (PCA). The transformed data were used as the input to the model. With the PCA transformation, the exercise reduced the model's training time while preserving its performance. The response of the developed model was binary; when it predicts that the monitored machine is about to fail, it triggers a flag. In response, reliability engineers or qualified domain experts intervene and rectify the issue to avoid further damage to the component. Using the acquired knowledge and expertise from the case studies discussed herein this chapter, practitioners in industrial or manufacturing settings can deploy a SCME environment and leverage the insights from sensor data for managing machine condition jointly [12].

This section explains two case studies using condition monitoring in a manufacturing setting. The first case study was conducted using a rolling element bearing, an accelerometer, and a setup of signal acquisition hardware. The third case study maps the noises emanating from drilling into binary classes using a CNN, trained and tested on a labeled dataset. It successfully performs the on- site testing using the SCME. It describes the development and use of the multimodal sensor concept in condition monitoring, which combines the familiar thermography technique with two inexpensive, cheap, and affordable breather pipes. The second case study presents the development and testing of an acoustic emission sensor used in machining on concurrent electro-hydraulic vibration testing.

A. *Case Study 1: Predictive Maintenance in Automotive Industry*

Consider the case of a large automotive manufacturer that operates hundreds of heavy machineries, including milling machines, turning machines, and even automated guided vehicle (AGV) systems. An unexpected breakdown of any such machine not only disrupts potential production schedules but also results in high repair costs and loss of revenue. Hence, predictive maintenance becomes important, but the preventive maintenance or time-based maintenance of such machines may result in unnecessary downtime and increased maintenance cost. To solve this bottleneck, a machine-learning-based predictive maintenance solution was implemented for the milling machines. The real-time features extracted from a simple one-dollar vibration sensor were transformed into higher-level features using the advanced signal pre-processing and feature optimization methods. These higher-level features were then input to the neural network implemented with the LSTM network to predict when the machine would fail. [13]

B. *Case Study 2: Anomaly Detection in Semiconductor Industry*

Small particles are the most common wafer defects, so they are used in the classification process. Eleven contaminants and three levels of shaking particles cause defects. The proposed system has been evaluated on new wafers and has achieved satisfactory results with high accuracy using a combination of classifiers (SVM). As an end-to-end vision system, the findings support the potential of employing deep learning methods to detect surface contaminants on wafers. Due to the high accuracy of 99%, the system can classify the contaminants and isolate the severity level of each detected contaminant. A key challenge is that the localized small percentage of identified dust particles does not accurately reflect the severity of the contamination found. The classification of all the detected particles into the correct class is challenging for real-time detection of the contaminants. [14]

V. Challenges And Future Directions

In a challenging and continuously growing global market and by highly effective production techniques, existing manufacturing firms are constantly working to develop products with modified functionality and minimize manufacturing costs. The Fourth Industrial Revolution is identified and referred to as Industry 4.0. At its heart, this state-of-the-art production revolution is made possible through the integration of the physical world with the internet. For this reason, the term 'Smart Factory' is often used to clarify these digital techniques. Smart, cloud-connected, electric-powered devices, also referred to as cyber-physical systems (CPS) in the literature, are these devices. At its core, the Smart Factory is a blend of physical and virtual engineering processes and technologies, including industrial Internet of Things (IIOT), Augmented reality, Artificial Intelligence (AI), and Machine Learning (ML). Due to the large volume and variety of data collected from intelligent devices, Machine Learning techniques open up significant possibilities to render manufacturing intelligent and capable of accomplishing self-diagnostics. The goal of machine learning in smart manufacturing processes is predictivity. The purpose of such predictive algorithms is to create a control system that can decide the future by learning from past patterns, before it happens, whatever the subject, occurrence, or action. However, the realistic potential of self-diagnoses of machine learning model’s establishment is complicated by five relevant challenges in condition monitoring applications that create communication gaps between the computation aspects and the industrial processes [15].

VI. Conclusion

The adoption of machine learning-driven condition monitoring and fault detection systems has become increasingly prevalent in the manufacturing industry, driven by the growing need for enhanced productivity, quality, and operational efficiency. This paper has explored the key advantages and applications of ML in this domain, showcasing its ability to identify complex patterns, adapt to changing conditions, and provide early warning signals of potential issues. While the implementation of ML-driven condition monitoring and fault detection offers numerous benefits, the review has also addressed the associated challenges and considerations, such as data quality, model interpretability, and integration with existing manufacturing systems. These aspects must be carefully addressed to ensure the successful deployment and long-term sustainability of such systems.

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