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ANALYSIS THE MECHANICAL FITTING FAILURE DATA BY USING AI

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ABSTRACT:
When put into practice in the real world, predictive maintenance presents a set of challenges for fault detection and prognosis that are often overlooked in studies validated with data from controlled experiments, or numeric simulations. For this reason, this study aims to review the recent advancements in mechanical fault diagnosis and fault prognosis in the manufacturing industry using machine learning methods.. Full-length studies that employed machine learning algorithms to perform mechanical fault detection or fault prognosis in manufacturing equipment and presented empirical results obtained from industrial case-studies were included, except for studies not written in English or published in sources other than peer-reviewed journals with JCR Impact Factor, conference proceedings and book chapters/sections. Of 4549 records, 44 primary studies were selected. In 37 of those studies, fault diagnosis and prognosis were performed using artificial neural networks (n = 12), decision tree methods (n = 11), hybrid models (n = 8), or latent variable models (n = 6), with one of the studies employing two different types of techniques independently. The remaining studies employed a variety of machine learning techniques, ranging from rule-based models to partition-based algorithms, and only two studies approached the problem using online learning methods. The main advantages of these algorithms include high performance, the ability to uncover complex nonlinear relationships and computational efficiency, while the most important limitation is the reduction in model performance in the presence of concept drift. This review shows that, although the number of studies performed in the manufacturing industry has been increasing in recent years, additional research is necessary to address the challenges presented by real-world scenarios.

INTRODUCTION:

Machine maintenance, with its impact on machine downtime and production costs, is directly related to a manufacturing companies' ability to be competitive in terms of cost, quality, and performance [1, 2]. The purpose of maintenance goes beyond repairing an equipment after it malfunctions. Its main objective is to maintain the functionality of machinery and minimize breakdowns.As the name suggests, predictive maintenance consists in the early detection of problems. Under a predictive maintenance program, maintenance is performed by monitoring the actual condition of machinery and repairing or replacing components after a certain level of deterioration has been detected, instead of performing repairs after a fault has occurred [3]. This approach has several advantages over reactive and preventive maintenance strategies

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[4, 5], namely:

- Prevention of catastrophic failures.
- Extension of an equipment's useful life.
- Optimization of preventive maintenance tasks.
- Improved management of the maintenance inventory.
- Optimization of equipment availability.
- Improved productivity.

By preventing serious failures, reducing unexpected faults, and maximizing the mean time between failures (MTBF), predictive maintenance helps reduce workplace accidents and their severity, reduces the number of repairs and the mean time to repair (MTTR) and extends the useful life of equipment, all of which results in increased earnings, less maintenance and production costs and more sustainable manufacturing [4, 6]. According to Sullivan et al. [5], the successful implementation of a predictive maintenance program can lead to an average reduction of maintenance costs between 25% and 30% and a return on investment (ROI) of 1000%.

Predictive maintenance is a form of condition-based maintenance [4], which relies on the prediction and detection of incipient faults in the equipment based on parameter measurements that reflect a machine's real condition [7,8,9]. In condition-based maintenance, decision-making is supported by diagnostics and prognostics techniques [7].

Diagnostics, which involves performing fault detection and identification (FDI), is generally performed using hardware redundancy methods or analytical redundancy methods. Hardware redundancy consists in measuring the same parameters using more than one sensor and then comparing the duplicate signals by means of various techniques, such as signal processing methods [10]. Analytical redundancy methods are based on mathematical models of the system and can be divided in quantitative, or model-based, methods and qualitative, or data-driven, methods [10, 11]. Both methods compare predicted or estimated parameters to real, measured values, but while model-based methods estimate the parameters of interest based on a mathematical model of the system under normal operating conditions, data-driven methods employ historical data and artificial intelligence algorithms to predict such parameters or detect anomalous values.

While diagnostics deals with the detection, isolation and identification of faults, prognostics aims to predict faults in the monitored system before they occur [7]. Specifically, prognostics techniques are used to estimate how soon - i.e., estimation of the remaining useful life (RUL) - and how likely a fault is to occur, but most of the literature on machine prognostics focuses on the former type of prediction [7]. RUL estimation methods, which can also be data-driven, aim to predict how long a machine will function before a fault occurs or if the machine is going to fail in a given time interval [7].

Since they don't require additional hardware, analytical redundancy methodologies are less expensive to implement than hardware redundancy methods Given the emergence of Internet of Things (IoT) technologies in industrial settings it is now possible to obtain a real-time digital representation of the production processes and current status of the equipment which has led to an exponential growth of the volume of industrial data Data-driven methods, in particular machine learning and data mining techniques, are well suited to extract knowledge from this wealth of data and have successfully been used in the context of predictive maintenance Moreover, although model-based methods can produce good results if the model of the system is precise, building an accurate mathematical model of a system is an arduous task that makes model-based methods a less viable option for complex

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systems Recent review papers focusing on the use of machine learning techniques for predictive maintenance have identified that commonly used data-driven methods include artificial neural networks support vector machines decision trees (including ensemble methods), k-means and logistic regression among others.
Predicting and detecting faults in industrial equipment are difficult tasks that require the choice of adequate techniques to obtain accurate results. The present study performs a systematic literature review of the machine learning methods used for the detection of mechanical faults and the prognosis of faults in manufacturing equipment in real-world scenarios. It is meant to serve as a foundation for the implementation of predictive maintenance systems and help identify future research opportunities. The literature on mechanical fault detection and fault prognosis is vast, but to the best of the authors' knowledge no systematic literature review on this specific topic of study exists.
The review focuses on the detection of mechanical faults because these types of faults are a leading cause of breakdowns in manufacturing equipment As mentioned above, fault prognosis aims to predict the time left before a machine breaks down and/or the probability of failure, without seeking to identify the type of fault (diagnostics techniques can be used for this purpose) [7]. Therefore, primary studies focusing on both mechanical fault detection and fault prognosis were considered in this review.
Another important aspect of this review is that only real-world industrial cases are considered. When put into practice in the real world, predictive maintenance presents a set of challenges for fault diagnosis and prognosis that are often overlooked in studies validated with data obtained from controlled experiments, testbeds, or numeric simulations. Manufacturing systems are characterized by complex, non-stationary processes where noise and other disturbances are a reality This conditions the choice and applicability of machine learning methods, as do other aspects of practical order such as the absence of historical fault data that occurs frequently in industrial settings and restricts the learning task to unsupervised and semi-supervised methods. For these reasons, this study aims to present an overview of the current landscape of fault diagnosis and prognosis in real-world scenarios using machine learning techniques.
The study here presented was guided by five research questions aimed at characterizing the relevant research in terms of publication sources and scientific fields, as well as examining the state-of-the-art machine learning methods for mechanical fault detection and fault prognosis in manufacturing equipment, their strengths and weaknesses, and their application in the context of data stream learning. A search for eligible publications was conducted in five academic databases, which, after applying a set of criteria, culminated in the selection of forty-four primary studies.

LITERATURE REVIEW:

Equipment reliability analysis is mainly conducted to quantify the probability of equipment failure. Poor reliability of equipment will lead to a high probability of equipment failure. Yang et al. [10] proposed a simple yet effective supervised deep hash approach, which constructed binary hash codes from labeled data for large-scale image search. Makantasis et al. [11] proposed a deep supervised learning-based classification method that hierarchically constructs high-level features in an automated way. These references are the main motivation behind the research work presented in this paper. Deep learning is a method for representing data and for learning data in machine learning. TensorFlow was used to integrate one-dimensional or two-dimensional convolutional neural networks (CNN) in

[12]. Considering the complexity of the reliability analysis model and the objectivity of the equipment data set, we propose a TensorFlow-enabled DNN model to simulate the degradation process of the equipment. According to Zio [1], the knowledge, information, and data available for the modeling, computations, and analyses done in reliability engineering are rapidly increasing. The degradation model for health management of equipment is increasingly made of heterogeneous and highly interconnected elements. Lei et al. [13] proposed an intelligent fault diagnosis method using unsupervised feature learning for mechanical big data. The proposed unsupervised two-layer neural network achieved high diagnosis accuracies for the motor bearing dataset, compared to existing methods. Gal and Ghahramani [14] used dropout as a Bayesian approximation to estimate uncertainty with a DNN model. Compared with traditional reliability analysis methods, machine learning methods (e.g., DNN) have been applied widely with the features of parallel processing, fault tolerance, self-learning and self-monitoring. Time series data are measurement sequences that describe the behavior of time-varying systems or equipment. The application of time series-based prediction methods in the fields of medicine, aerospace, finance, commerce, meteorology and entertainment were introduced in [15], [16]. Khodayar et al. [17] developed a DNN structure based on stacked autoencoder and stacked denoising autoencoder for ultra-short-term and short-term wind speed predictions. The experiment results showed that the DL model was feasible for short-term predictions. Deb et al. [18] summarized state of the art machine learning methods for predicting time seriesbased energy consumption. The authors concluded that a hybrid model comprised of two or more prediction techniques was more effective for time series prediction. Considering the randomness of equipment deterioration, in this paper, we evaluate the risk of equipment failure through short-term and medium-term predictions. The motivation behind the work presents in this paper is to discover the critical time node and support active maintenance when the running status of equipment changes.

IN “MACHINE LEARNING IN MATERIALS INFORMATICS: RECENT APPLICATIONS AND PROSPECTS” Propelled partly by the Materials Genome Initiative, and partly by the algorithmic developments and the resounding successes of data-driven efforts in other domains, informatics strategies are beginning to take shape within materials science. These approaches lead to surrogate machine learning models that enable rapid predictions based purely on past data rather than by direct experimentation or by computations/simulations in which fundamental equations are explicitly solved. Data-centric informatics methods are becoming useful to determine material properties that are hard to measure or compute using traditional methods— due to the cost, time or effort involved—but for which reliable data either already exists or can be generated for at least a subset of the critical cases. Predictions are typically interpolative, involving fingerprinting a material numerically first, and then following a mapping (established via a learning algorithm) between the fingerprint and the property of interest. Fingerprints, also referred to as “descriptors”, may be of many types and scales, as dictated by the application domain and needs.

IN “AN INFORMATICS APPROACH TO TRANSFORMATION TEMPERATURES OF NITI-BASED SHAPE MEMORY ALLOYS” The martensitic transformation serves as the basis for applications of shape memory alloys (SMAs). The ability to make rapid and accurate predictions of the transformation temperature of SMAs is therefore of much practical importance. In this study, we demonstrate that a statistical

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learning approach using three features or material descriptors related to the chemical bonding and atomic radii of the elements in the alloys, provides a means to predict transformation temperatures. Together with an adaptive design framework, we show that iteratively learning and improving the statistical model can accelerate the search for SMAs with targeted transformation temperatures. The possible mechanisms underlying the dependence of the transformation temperature on these features is discussed based on a Landau-type phenomenological model.

IN "A GENERAL-PURPOSE MACHINE LEARNING FRAMEWORK FOR PREDICTING PROPERTIES OF INORGANIC MATERIALS" A very active area of materials research is to devise methods that use machine learning to automatically extract predictive models from existing materials data. While prior examples have demonstrated successful models for some applications, many more applications exist where machine learning can make a strong impact. To enable faster development of machine-learning-based models for such applications, we have created a framework capable of being applied to a broad range of materials data. Our method works by using a chemically diverse list of attributes, which we demonstrate are suitable for describing a wide variety of properties, and a novel method for partitioning the data set into groups of similar materials to boost the predictive accuracy. In this manuscript, we demonstrate how this new method can be used to predict diverse properties of crystalline and amorphous materials, such as band gap energy and glass-forming ability Rational design of materials is the ultimate goal of modern materials science and engineering. As part of achieving that goal, there has been a large effort in the materials science community to compile extensive data sets of materials properties to provide scientists and engineers with ready access to the properties of known materials.

CONCLUSION:

The developed AI highlights the sound applicability of ANN for fatigue failure prediction by exhibiting a mean conservative estimation accuracy of 91.6%. The overall accuracy, considering non-conservative and conservative false statements, of 81.1% is also a satisfying value. Summarizing, one can state that this novel fatigue failure prediction approach may form the basis of an innovative new way to characterize fatigue behaviour. Within this study, applicability is only investigated for machined surfaces.A derived threshold fatigue strength surface, by determining the lowest stress amplitude at which failure is predicted, for any given hardness and defect size combination, enables to evaluate the fatigue strength in dependency of these two parameter. This translation is bridging the gap between AI and actual application in fatigue.Although the amount of data is considered little for training an ANN, satisfying results are btained. Iterative architecture and parameter optimization showed distinct improvement. The effort to produce necessary data is significant but provides future opportunities to further improve the accuracy of presented AI based fatigue failure prediction model. Implementation of additional, substantial influencing factors, such as residual stresses, may cause a more reliable fatigue failure prediction, however its determination is of high expense and cannot be performed after destructive testing due to release of inherent stresses.Provided a data base large enough to cover all significant material groups and as well may feature additional significant input arguments, alongside feasible improvements outlined in this paper, similar AI based methodologies possess the potential to possibly become a leading technology in future. However, this should be supported and validated with other significant quantitative data.

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