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Induction Machine Faults Diagnosis: A State of the Art

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Abstract

Rotary Machines such as motors, compressors, pumps and turbines are of major importance in the industry and keeping them running reliably and efficiently at all time is a number one purpose all of the companies. However, the harsh environment where these machines operate make them expose to many failures that may lead to machinery downtimes and production shutdowns, therefore, predictive maintenance is introduced primarily in the context of industry 4.0 to prevent such catastrophes and increase manufacturing productivity.

Résume

Les machines rotatives telles que les moteurs, les compresseurs, les pompes et les turbines sont d'une importance majeure dans l'industrie et les maintenir en fonctionnement de manière fiable et efficace à tout moment est un objectif numéro un pour toutes les entreprises. Cependant, l'environnement difficile dans lequel ces machines fonctionnent les expose à de nombreuses pannes pouvant entraîner des temps d'arrêt des machines et des arrêts de production. Par conséquent, la maintenance prédictive est introduite principalement dans le cadre de l'industrie 4.0 pour éviter de telles catastrophes et augmenter la productivité de la fabrication.

ملخص

تعتبر الآلات الدوارة مثل المحركات والضواغط والمضخات والتوربينات ذات أهمية كبيرة في الصناعة ، والحفاظ عليها تعمل بشكل موثوق وفعال في جميع الأوقات هو الهدف الأول لجميع الشركات. ومع ذلك ، فإن البيئة القاسية التي تعمل فيها هذه الآلات تجعلها عرضة للعديد من الإخفاقات التي قد تؤدي إلى تعطل الآلات وإيقاف الإنتاج ، وبالتالي ، يتم تقديم الصيانة التنبؤية بشكل أساسي في مسابقة الصناعة 4.0 لمنع مثل هذه الكوارث وزيادة إنتاجية التصنيع.

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1. Introduction

Rotary machinery are the pillars of nowadays industry thus keeping them save are of a major concern, therefore condition monitoring and fault diagnosis plays a significant role in detecting failures in such machines consequently improving productivity, efficiency, and reduction of financial losses.

Industry 4.0 is the new era of the industry that integrates multiple technologies and elements such as: The Internet of Things, Big Data, Cyber-Physical Systems, Machine Learning, Cloud Solutions and Additive manufacturing. This integration revolutionised the diagnosis of the industrial machinery thus internet of things allows machines equipped with smart sensors to communicate and share data inside an organization with the outside world. According to IBM, 1.6 zettabytes (1021bytes) of digital data are now available, and this number is increasing (S. Reis et al, 2017). These huge amounts of data are collected by sensors from multiple sources namely vibration, current, acoustic signals, temperature, and air gap torque, to store them in integrated databases to be, later on, filtered and processed using different signal processing techniques to extract features that serve as fault indicators. The analysis results are used to perform prognosis, which is generally classified as three types: model-based methods that rely on mathematical modelling of physical systems, knowledge-based methods that inquire expert's knowledge and data-based methods are applicable when data is sufficiently abundant and have a relatively low operating cost (Zhong et al, 2019). The complexity of data in terms of its size, variety, and uncertainty in one hand and the need to preventing ahead of time machinery breakdowns in another hand, lead to the use of artificial intelligence techniques that includes machine learning, data mining, and deep learning.

2. Predictive maintenance

Predictive maintenance consists of identifying the equipment failure in machinery head of time before it occurs. This helps in scheduling maintenance, therefore, minimize downtimes and maximize equipment lifetime. The following figure represents a work flow of the predictive maintenance.

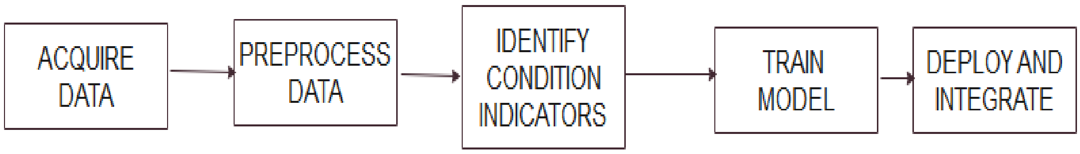

Figure 1: The workflow of the predictive maintenance

2.1 Acquiring data

The first step of predictive maintenance is acquiring data which can be classified into two main types: event data and condition monitoring data while the event data include information about what happened to the asset and which maintenance was applied to it, the condition monitoring data are related to the measurements of the health of the physical asset. Multiple sensors are used to collect a large set of condition monitoring data (vibration, current, temperature, ...), however, in some cases, sensors fail to provide enough information about the state of the machinery, therefore, models are used as alternatives to supplement with synthetic data, that works along with sensor data to develop predictive maintenance algorithm. For the later to be more robust it is important to gather data in varying operating conditions.

2.2 Data Pre-processing

The Data acquired are usually noisy, incomplete, and full of outliers due to human and sensor device factors that may cause errors in data which lead to erroneous mining procedures, therefore, Preprocessing data is an assenting step in predictive maintenance and it can be divided in three procedures: cleaning, transforming and reducing the data. The cleaning process is accomplished using different techniques, for instance, regression techniques can be used to estimate missing values, clustering methods for noise detection and data outliers can be detected using three-sigma edit rule (Jimenez-Cortad et al, 2020). Moreover, in some cases, data can be of a huge amount which can be computationally costly and may increase difficulty in decision making by the machine, to overcome those issues, techniques are used for data reduction, one of the famous techniques called principal component analysis (Jolliffe and Cadima, 2016). Another step in preprocessing is data transformation that includes standardization and smoothing, while standardization is where the data are scaled to a small range and make different signals comparable, the data smoothing consists of filtering from the noise, the best technique for aforementioned is Symbolic Aggregate approximation (Yahyaoui and Al-Daihani, 2019). The data after preprocessing is expected to be pure and of good quality, for assuring correct results when it processed using signal processing methods or when it fed to machine learning models.

2.3 Condition indicators

Condition indicators are features extracted using model-based methods or signal processing methods as figure 2 shows.

These features indicate the condition of the machinery, faulty or healthy, to have more information on the machinery state those features are used to train machine learning models as the following title illustrates.

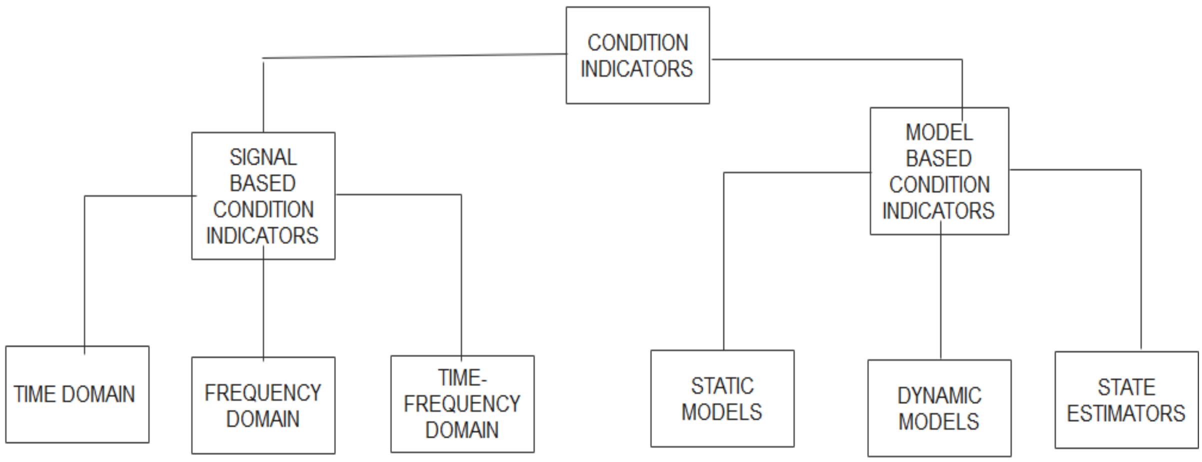

Figure 2: Condition indicators

2.3.1 Signal based condition indicators

There are many signal processing methods used for fault diagnosis of rotary machine among them: Fast Fourier Transform, Short Fourier Transform, Wavelet Decomposition, Empirical Mode Decomposition, Hilbert Huang Transform and Variational Mode Decomposition. The choice of one method over the other essentially depends on its effectiveness, ease of use and speed. (E. Ayaz et al,2014); (Yiqi et al,2017).

2.3.1.1 Fast Fourier Transform

Fast Fourier transform(FFT) is a frequency domain operation that decomposes a time-domain signal into a frequency component that contains a function. Fourier transform can be implemented at high speed using Fast Fourier Transform(FFT) which makes it suitable for digital signal processing systems.

2.3.1.2 Short Fourier Transform

Short Fourier Transform is a windowing technique that overcomes the deficiency of the Fast Fourier Transform as it applies to nonstationary signals by analyzing small sections of those signals at various times and provide some information in both time and frequency domain. However, the only drawback of this method is lack of precision due to the fixed size of the window. (Benbouzid, 2014).

2.3.1.3 Wavelet Transform

Wavelet Transform works on decomposing a signal into wavelets with several frequency bands, it can be applied on nonstationary signals One of the main characteristics of the WT is its compression property. This property keeps the overall characteristics of the original signal in the desired frequency band while decimating the original length by a factor of two for each detail level applied, the drawbacks of which include the need to use a single window function in all frequency components and the acquisition of linear resolution in the whole frequency domain. (Salloum et al, 2011) (Alejandro et al, 2008).

2.3.1.4 Empirical Mode Decomposition (EMD)

EMD is one of the powerful self-adaptive signal processing and time-frequency analysis techniques used for non -stationary and nonlinear signals such as mechanical fault signals of rotating machinery. It is based on decomposing the signal into intrinsic mode functions (IMF’s) which are almost orthogonal components that satisfies the following two conditions: (1) in the whole data set, the number of extrema and the number of zero-crossings must either equal or differ at most by one, and (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero(Yaguo.et al,2012). However, the method suffers from many limitations such as lack of theoretical background, mode mixing, and end effects. Many improvised EMD versions were suggested such as ensemble empirical mode decomposition (EEMD)(Wu et al 2009)) to overcome the mode mixing problem.

2.3.1.5 Hilbert Huang Transform

Hilbert Huang Transform is a novel method invented by (Hung et al,1996) it combines two methods: Empirical Mode Decomposition (EMD) method that works on decomposing the signal into intrinsic mode functions(IMF's) and Hilbert spectral analysis(HSA) method which is applied to the IMF's for extracting instantaneous frequencies. This method preserves the characteristics of varying frequency which makes it more suitable for nonstationary and non-linear time series data signals.

2.3.1.6 Variational Mode Decomposition(VMD)

VMD is a novel time-frequency analysis method which introduced in 2014 by Dragomiretskiy and Zosso. It consists of decomposing the signal adaptively and non-recursively into quasi-orthogonal variational mode functions (Dragomiretskiy et al, 2014). For the method to be more accurate and prevent the loss of information, its parameters must be well selected, among those parameters a mod number that has a great influence on the decomposition results.

2.4 Train the model

The machine learning models are trained using condition indicators to accomplish three main goals: detect anomalies, indicate fault time and estimate the remaining useful life this last estimates time left for the machine to breakdown. There are three common models used for estimating the remaining useful life: similarity model used when historical data of similar models are available, degradation model uses past data to predict the future state of the machinery and survival model is a statistical method used when data of life span of similar component are abundant.

2.4.1 Digital twin

Monitoring the health of the rotary machinery is a crucial aim in modern industry. And now with digitalized world, the monitoring becomes more sophisticated as the machines have virtual replica that models their state and simulate their behavior, this digital representation of the machinery known as the digital twin which will be soon a key predictive maintenance enabler.

A first step in constructing a digital twin is building a geometrical model along with virtual sensors, while the model includes material properties, key equipment dimensions, and assembly relationships among the part such as dynamical behavior, the virtual sensors used to monitor and gather data from the physics-based models during their simulation (Aivalioti et al,2019). The improvement of internet of things technology, digital twin models can receive data in real-time from of a variety of smart sensors (transducers, probes, acoustic emission sensors, temperature sensors, etc.) which are attached to physical machines. This interaction with the two different worlds machines (virtual and physical) what power a 3 D model of a digital twin *(*Shiklo,2018***)***. To ensure a predictive maintenance it is important to include machine learning algorithms such as neural networks that use the historical data of the machine health status and data received constantly from both virtual and real sensors to predict the condition of the machine and prevent future machinery downtimes.

2.4.2 Machine Learning techniques

Automation and smart manufacturing are aspects of industry 4.0, although, it integrates the most recent technologies such as Internet of Things, Cyber-Physical Systems, Digital Twins, Cloud Computing or Big Data Analytics. These technologies serve in predictive maintenance and intelligent condition monitoring of rotary machinery. Thus nowadays machines are equipped with wireless multi-sensors that collect a huge amount of data to be processed and analyzed using machine learning tools such as k-Nearest neighbor, Naive Bayes classifier, and few most common techniques including Artificial Neural Network (ANN), Support Vector Machine (SVM), Deep Learning(DP).

2.4.3 Quantum machine learning

Quantum technology introduced to improve the classical machine learning techniques in terms of speed and complexity reduction. The increase of features space dimensionality leads to constructing a complex machine learning algorithms which are computationally hard to process on classical computers and requires a huge amount of time. In contrast, quantum computers with basic units called qubits that hold quantum properties namely entanglement, parallelism, and superposition perform highly faster than conventional computers counterparts. For instance, with a classical computer 50 bits, can be in exactly one (of 250) state in time, and only operate iteratively. A quantum computer with 50 fully connected qubits can be in 250 states at the same time (Jaroszewski et al,2020). Quantum machine learning algorithms have proven their efficiency in many sorts of ways, for example, in speeding up distance calculation in case of nearest neighbor, and describing stochastic processes using probabilistic theories in case of bayesian theories and Markov models (Schuld et al, 2014). Yet this technology is not well harnessed due to lake of theoretical understanding of its concepts, in one hand,

and a weak of computing exactness of the current hardware, in another hand, which has proven by an experimental conducted by Jaroszewski that remarked, Quantum Neural Network (QNN) performs nearly as well as Neural Network NN (Jaroszewski et al, 2020).

2.5 Deploy and integrate

The final step of the predictive maintenance workflow is choosing where to deploy the algorithm, whether on the cloud, or embedded services or both. When dealing with a huge amount of data it is preferably to run the predictive maintenance on the cloud and the results are delivered through tweets, email notifications, web apps, and dashboards, however, the results are more immediate in case of deploying them on embedded services. The third option consists of extracting features on embedded services and run the predictive maintenance on the cloud. At last, the deployed algorithm is tested and validated under real-life conditions.

2.5.1 Cloud - based prognosis

Cloud computing is an essential element in rotating machinery prognosis, as it allows data gathered in the shop floor by smart sensors to be transferred remotely to the cloud platform and stored in different storage devices where it processed using different prognostic techniques according to the data type and physics of the monitored component (Wang et al, 2016), it also allows m2m communication, in other words, it provides an interconnection between the physical machine and its digital twin. Cloud computing compromises of three different services: software-as-a-service (SaaS)**,** infrastructure-as-a-service (IaaS), and platform-as-a-service (PaaS). This automation provided by cloud computing presents many advantages such as cost savings, increased productivity, speed and performance, and security, improve accessibility and robustness, improve computer efficiency and data storage. the later advantages what helps to achieve an improvement in predictive condition-based maintenance decision making.

2.6 Conclusion

The thesis represents the literature review of the fault diagnosis and prognosis of the rotary machinery. At first, a general introduction on diagnosis and prognosis of rotary machinery is presented. Therefore, preventive maintenance is discussed along with its steps. The first step is data acquisition which is performed using different sensors (vibration, current, temperature and acoustic sensors), the second step is preprocessing the data, the main goal for this step is cleaning the data from outliers and noise, for better results extraction, the next step is processing data using signal processing techniques, to extract condition indicators to feed machine learning modelled. the final step of the prognosis process is deployment on the cloud or embedded services.

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