LONG SHORT-TERM MEMORY AUTOENCODER-BASED ANOMALY DETECTION SYSTEM FOR ELECTRIC MOTORS

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Master of Philosophy

School of Electrical Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

SEPTEMBER 2022

DEDICATION

To my beloved family, and to my lecturers and classmates from Universiti Teknologi Malaysia.

ACKNOWLEDGEMENT

First and foremost, I am truly indebted to my supervisor, Assoc. Prof. Ir. Dr. Kumeresan A. Danapalasingam for supporting my Master of Philosophy (MPhil) project. With his help and permission, I was able to join JCY HDD Technology as an intern, where I was able to gain more knowledge about my project topic. Furthermore, he helped me to understand algorithms that could be effective in predictive maintenance, especially LSTM and autoencoders.

Finally, I would like to thank my parents and my fellow post graduate students for providing me with their endless support and advice in my time of need.

ABSTRACT

Predictive maintenance (PdM) systems have the potential to detect underlying issues in electric motors, and this can allow them to prevent production downtime and loss of manufacturing yield. However, majority of the PdM systems for electric motors that have been proposed so far are unsuitable for industrial implementation, since they require hours of manual data collection and annotation, and are unable to account for more than one type of motor fault. Therefore, this thesis presents an unsupervised long short-term memory (LSTM) autoencoder-based anomaly detection system for electric motors. It analyzes the vibration and current consumption data from motors to detect anomalies, which is sufficient to account for the various motor defects. Aside from this, it can adapt to varying operating conditions. The system is created to autonomously collect vibration and current consumption data from the motor, and then use the data to train the LSTM autoencoder model and deploy it in real-time to detect anomalies. In addition to this, the system comes with several features including personal computer and web user interfaces that enable ease of access as well as remote monitoring of the motor's conditions. To test the system, a hardware test bench using a stepper and a brushless direct current (BLDC) motor is made to simulate defective conditions. LSTM autoencoder models are trained on the data from this setup and deployed once the training is completed. If the system detects increasing rate of anomalies, the users are informed through an email or a short message service notification. The presented anomaly detection system is tested on hardware test bench. Based on the experimental results, as the simulated defect worsened, the rate of anomalies detected by the system increased, with the maximum anomaly rate reaching 7 anomalies per second. Additionally, the LSTM autoencoder technique is also compared with principal component analysis and isolation forest for validation purposes, and it proved to be the most accurate in the case of both the stepper and BLDC motors with accuracies of 66.24% and 86.43% respectively.

ABSTRAK

Sistem penyelenggaraan ramalan (PdM) berpotensi untuk mengesan isu kerosakan di dalam motor elektrik, dan ini boleh menghalang masa henti pengeluaran dan kehilangan hasil pembuatan. Walau bagaimanapun, kebanyakan sistem PdM untuk motor elektrik yang telah dicadangkan setakat ini tidak sesuai untuk pelaksanaan perindustrian, kerana ia memerlukan pengumpulan data dalam masa beberapa jam dan anotasi manual, dan tidak dapat mengambil kira lebih daripada satu jenis kerosakan motor. Oleh itu, tesis ini membentangkan sistem pengesanan anomali berasaskan pengekod auto memori jangka pendek (LSTM) tanpa pengawasan untuk motor elektrik. Ia menganalisis data getaran dan penggunaan arus elektrik daripada motor untuk mengesan anomali, yang didapati mencukupi untuk mengambil kira pelbagai kerosakan motor. Selain daripada itu, ia boleh diadaptasi dalam keadaan operasi yang berbeza-beza. Sistem ini dicipta untuk mengumpul data getaran dan penggunaan arus elektrik secara autonomi daripada motor, dan kemudian menggunakan data tersebut untuk melatih model pengekod auto LSTM dan menggunakannya dalam masa sebenar untuk mengesan anomali. Di samping itu, sistem ini dilengkapi dengan beberapa ciri termasuk aplikasi komputer peribadi dan web yang membolehkan akses mudah serta pemantauan jarak jauh keadaan motor. Untuk menguji keberkesanan sistem, sebuah perkakasan bangku ujian yang terdiri daripada motor pelangkah dan arus terus tanpa berus (BLDC) telah dibina untuk mensimulasikan kerosakan motor. Model pengekod auto LSTM dilatih menggunakan data daripada persediaan ini dan digunakan sebaik sahaja latihan selesai. Jika sistem mengesan peningkatan kadar anomali, pengguna dimaklumkan melalui e-mel atau pemberitahuan khidmat pesanan. Sistem pengesanan anomali yang dibentangkan diuji pada bangku ujian perkakasan. Berdasarkan keputusan eksperimen, apabila kecacatan simulasi semakin teruk, kadar anomali yang dikesan oleh sistem meningkat, dengan kadar anomali maksimum mencapai 7 anomali sesaat. Selain itu, teknik pengekod auto LSTM juga dibandingkan dengan analisis komponen utama dan hutan pengasingan untuk tujuan pengesahan, dan ia terbukti paling tepat dalam kes kedua-dua motor pelangkah dan BLDC dengan ketepatan masing-masing 66.24% dan 86.43%.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
CNN	-	Convolutional Neural Network
LSTM	-	Long Short-Term Memory
MLP	-	Multi-layer Perceptron
MSE	-	Mean Squared Error
MAE	-	Mean Absolute Error
PCA	-	Principal Component Analysis
PdM	-	Predictive Maintenance
RNN	-	Recurrent Neural Network
SVM	-	Support Vector Machine

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Problem Background

Electric motors play several irreplaceable roles in companies. Automations ranging from conveyor belts to robotic arms all require motors to operate. With manufacturing demands on the rise, most machines may be required to run continuously for an entire day. Due to continuous usage motors are no strangers to frequent failures. They may suffer from both mechanical faults, such as worn-out bearings or broken shafts (Guo & Liu, 2018), and electrical faults, whereby there may be open-circuit or short circuit faults in the motor (Lee et al., 2008). If motor faults are not detected on time, they may eventually lead to catastrophic failures. Such disasters may be ruinous for production schedules and consume a significant chunk of financial resources in companies. Furthermore, if motor faults are not treated at an earlier stage, they may inflict damage on expensive equipment, increasing the repair cost (Nandi et al., 2005). Therefore, having a system that predicts possible motor failures could prove to be immensely useful for reducing maintenance costs and to avoid machine downtime. Thus, many industries are in dire need of an intelligent fault diagnosis system that keeps track of motor conditions and predicts any possible failures that may occur (Rahman et al., 2010). In order to build a system which is capable of accomplishing such feats, it is necessary to have an algorithm that mimics human intelligence or can analyse large quantities of data in real-time.

Fortunately, the advent of the fourth industrial revolution has led to vast progress in the fields of machine learning, deep learning, and artificial intelligence (AI). As such, over the past few years many fault classification systems based on machine learning algorithms, like support vector machine (SVM), fuzzy logic inference, etc. have been proposed (Shao et al., 2020). Nevertheless, predictive maintenance models are rarely implemented in industries. Fault classification techniques can be divided into two groups, supervised and unsupervised learning techniques. Most of the proposed state-of-the-art fault diagnosis systems make use of supervised learning, which while effective is not without flaws. In the case of supervised learning, an expert has to spend hours analysing and acquiring data from industrial motors under both normal and faulty conditions. This is much easier said than done, since an industrial motor may suffer from a variety of faults. Acquisition of data under different faulty conditions can be tremendously time consuming. This is also the reason why many of the proposed supervised models are not applicable for detecting multiple motor faults. Additionally, the operating conditions of motors must also be taken into consideration. The vibration and current consumption of motors may vary from machine to machine as they may need to operate at different torque and speed. Supervised models are trained under fixed operating conditions, which means they are not dynamic to change. Considering all these issues, supervised fault classification systems are barely implementable for real-time fault detection of motors in industries. Furthermore, data acquisition and labelling under different conditions require considerable manpower, which most companies cannot afford. Thus, fault classification systems are still very rare in industries.

It is often forgotten that when it comes to fault classification, anomaly detection can also be a technique for finding any possible faults (Vercruyssen et al., 2018). This technique does not always require users to spend hours labelling their data. In fact, it is possible to develop unsupervised anomaly detection techniques. Hence, this thesis proposes a real-time unsupervised anomaly detection system for electric motors.

To save companies the time to acquire data, the presented system (upon implementation) will initially collect current consumption and vibration data from the motor for a certain period of time. After that it will autonomously train a long-short term memory (LSTM) autoencoder model for pattern recognition autonomously, without any manual scripting from operators. The trained model is then used to detect anomalies in the present vibration and current consumption data. A rising number of anomalies on a regular basis would be indicative of a faulty motor. Such a fault detection system would be applicable to a motor without the need to worry about variance in load and motor speed.

1.2 Problem Statement

Electric motors are used in every corner of modern-day industries. However, their frequent usage tends to lead to unexpected motor failures that may interrupt the production cycle and degrade manufacturing profits (Taplak et al., 2016). Motor faults come in many forms, from worn out bearings to short circuit faults in stator windings (Guo & Liu, 2018). Thus, to avoid unexpected machine downtimes, it is necessary to have an intelligent fault diagnosis system that can detect abnormalities at an earlier stage. Unfortunately, while many proposed motor fault classification systems have shown potential, they are quite impractical and are rarely implemented in industries (Lei et al., 2016).

When it comes to training fault classification models, vast data acquisition is an inescapable issue. Most of the proposed systems make use of supervised learning models, as explained by the works of Altaf et al.(2017), Hendrickx et al. (2020), and Song and Shi (2018). They are required to be trained with labelled data collected under different motor conditions (both healthy and defective conditions). Data acquisition coupled with labelling of the multiple issues that may occur in an industrial motor can consume tremendous amounts of time and manpower, something that is unacceptable for companies. Furthermore, these techniques are not dynamic as they were trained on data collected under a fixed set of operating conditions. For example, a model trained on data from a conveyor belt induction motor may not perform well if it is applied to another induction motor used in a brushing machine. Reasons for this could be variation in load or motor velocity. Training fault detection models under all possible conditions is not practical. As a result of such impracticalities, industries still lack effective predictive maintenance systems that can carry out real-time fault detection of electric motors in industrial machines.

What many researchers often forget is that a less tedious way to diagnose motor faults is to simply use anomaly detection techniques, which may not always require users to spend hours labelling the data. In industries, managers only care whether the electric motor is working well, they do not care for a specific fault that may occur. Therefore, a motor anomaly detection system is enough to account for all faults. Unsupervised learning techniques can be used for anomaly detection. The LSTM autoencoder technique (which is an unsupervised learning method) proposed in this thesis has been applied for detecting anomalies from motor data in the works of Principi et al. (2019) and Abdellatif et al. (2019). Although effective, the works did not outline a system to deploy the model on industrial machines. Additionally, they also did not display how the fault diagnosis model would function under different operating conditions. Thus, this thesis presents a real-time unsupervised anomaly detection system that deploys an LSTM autoencoder model to detect abnormalities in electric motors. Upon implementation, the system collects data for a certain period to train the model before deployment. Due to this reason, the system is capable of adapting to different operating conditions.

1.3 Research Goal

Electric motors are used in every corner of present-day industries and are subjects to various defects. Therefore, the primary goal of this thesis is to design an anomaly detection system for electric motors, which can carry out data acquisition, and model training and deployment without supervision. Since the system carries out anomaly detection, it can also account for multiple motor faults, a shortcoming of most proposed predictive maintenance methods, especially the ones proposed by Altaf et al.(2017), Hendrickx et al. (2020), and Song and Shi (2018).

The most important step to create any machine learning model is to collect data. As a procedure to train and test the proposed system, this project involves creating an experimental setup using industrial motors (for this project stepper and BLDC motors will be used). The motors are run with different load conditions and speed. Vibration and current consumption of the motors is collected under simulated conditions from the setup. The data for the anomalous conditions are gathered by simulating a motor bearing defect in the setup. Since the motor data plays a crucial part in this project, it is necessary to study the current and vibration patterns of the stepper and brushless DC motor. The amount of horsepower they provide and the maximum rotations per minute (RPM) the motors operate on has been recorded.

The core part of the proposed anomaly detection system is the unsupervised LSTM autoencoder model. Without it, the anomaly detection system will be ineffective. The model will basically filter anomalies by reconstructing familiar input signal patterns. Therefore, a great deal of research is done on LSTM autoencoders to determine how good they are at reconstructing time series data. Finally, the anomaly detection system is designed such that it is capable of adapting to different motor operating conditions. To make that possible, the system is programmed to automatically collect data for a period, so that it is able to capture variations in current and vibration of the electric motor. Therefore, this project involves a software architecture that automates the data collection, training and deployment phase for the machine learning model.

1.3.1 Research Objectives

The primary objectives of the research are:

(a) To develop LSTM-based autoencoder models that can detect anomalies by analysing the patterns of vibration and current consumption data from electric motors.

(b) To design a real-time and unsupervised anomaly detection system that can be calibrated or recalibrated to give accurate results based on changing motor operating conditions such as different torque and speed.

(c) To compare the LSTM autoencoder algorithm with other anomaly detection techniques for validation purposes and to analyse the performance of each method.

(d) To implement an anomaly detection system that enables users to keep track of motor fault conditions as determined by the rate of anomalies through a web application.

1.4 Research Scope

The entire motor anomaly detection system is made in such a way that it can operate autonomously. The system can carry out data acquisition and model training automatically without the need of manual scripting from operators. As such, the overall anomaly detection system will be unsupervised.

The project proposed in this thesis involves much research regarding anomaly detection of motors. For this project, the long-short term memory (LSTM) autoencoder technique will be used for pattern recognition. LSTMs can analyse sequential data and autoencoders are a type of neural network architecture that can reconstruct familiar signal patterns. By using the mean squared error (MSE) between the original signal and its reconstructed counterpart as a threshold, it is possible to filter anomalies. As part of the scope, in depth research must be carried out on LSTM autoencoders. A novel LSTM autoencoder model architecture will be created for this project. The model will be trained using the current consumption and vibration data from the motor.

The motor anomaly detection should be applicable to detecting defects in two types of electric motors: stepper motor and brushless DC (BLDC) motor. To test the effectiveness of the system, an experimental setup is built to accommodate experiments for each motor. The setups will be used to simulate motor bearing defects, to test whether the anomaly detection system can truly detect faults or not. The experimental setups must be made to simulate variance in load conditions as well as the velocity of the motor. The specifications of the two motors that will be used in this project are displayed in Table 1.1.

Table 1.1: Specifications of motors that will be experimented on.

Motor Type	Input Voltage (V)	Max Torque (N/m)	Max Current (A)	Max Speed (RPM)	Weight (kg)
Stepper Motor	12 V (DC)	400	1.7	300	0.28
BLDC motor	12 V (DC)	1961.33	5.2	3000	1.3

Majority of the code for this project, will be written in Python, since it has the most contemporary libraries for machine learning. The code must be written such that the system collects data for a certain period of time after the sensors are initially connected to a motor. The microcontroller board which will be interfaced with the current and accelerometer sensor, should be programmed in C++.

For this project, an LSTM autoencoder model will be trained for pattern recognition, so that it may detect anomalies from the current consumption and vibration data from the motor. It should, however, be noted that there are other algorithms can carry out similar operations like LSTM autoencoders and are applicable for anomaly detection. Thus, algorithms such as principal component analysis (PCA), and isolation forest can be used for anomaly detection as well. Hence, the LSTM autoencoder method will be compared with other techniques.

Last but not least, the anomaly detection system should enable the user to remotely monitor the condition of the motor. The user should be able to observe the number of anomalies the system detected in the motor. If the condition of the motor degrades too far, the user will receive a warning notification to change the motor. For this purpose, a simple web application is created to enable remote monitoring of the electric motor's conditions. Aside from this, the system also comes with a PC user interface (UI), which eases the use of the anomaly detection system.

1.5 Thesis Outline

This document is divided into five chapters. The first chapter includes an overall introduction to the requirement of fault diagnosis techniques for industrial motors. The vital requirement of a motor fault detection systems are explained under the Problem Statement. The sub section also goes in depth about why most of the proposed predictive maintenance techniques are not implementable in industries.

The second chapter, Literature Review, includes previous research on fault diagnosis of motors. All the algorithms and predictive maintenance techniques proposed for motors are described in this section.

The project methodology has been illustrated under Chapter 3, this includes the block diagram and flowchart of the anomaly detection system. It also includes description of the LSTM autoencoder model. It is also explained how the model is used to filter the anomalies. as well as detailed explanations of the experiments that have been carried out for the preliminary results. The calculations used to separate the abnormal data from the normal ones are shown as well.

The results of conducted experiments are illustrated in Chapter 4. The outcomes are also explained in detail. Finally, Chapter 5 provides the conclusion of this thesis.

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