

BEAUTIFUL TITLE, ENGLISH

– SUBTITLE, ENGLISH

VÄLDIGT FIN TITEL

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Abstract

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1 Introduction

Maintenance of devices/vehicles/systems/machines (hereinafter referred to as “units”) is generally done by planned scheduling. Typically this is done when some parameter of the system reaches a threshold value. For example, car maintenance can be scheduled after 30,000 kilometres, after a year or perhaps after a certain number of operating hours. One problem with planned scheduling is the reliance on experience and statistics from many units. For a single unit, the planned scheduling will either be executed too early (could have waited longer before service) or too late (problems encountered before threshold reached).

Internet of Things (IoT) permits the streaming of continuous data from multiple units. The data is typically the state of the unit in the shape of many different variable values. A rule framework can be built incorporating the continuous data. The framework can then give an informed service alert based on the actual state and need of a unit.

Machine Learning (ML) models can be used to, for example, capture dependencies in large-scale data sets (ref needed), anomaly detection (ref), clustering (ref), image recognition (ref), and decision making (ref). Anomaly detection could be used together with continuous real-time data from a system to find unusual changes or behaviour, which could be the basis for a service alert and/or the gathering of new knowledge about a system. ML-algorithms can also be used to perform Predictive Maintenance (PdM).

1.1 Background

Maintenance Techniques

There are different techniques to carry out maintenance work, each with various drawbacks and benefits. Corrective Maintenance (CM) is the technique to identify, isolate, and solve faults. The aim of CM is to restore the faulty equipment to working conditions. CM can only be done after a fault has been detected and is a reactive approach to maintenance. The fault detection can be carried out without the need of expensive, or extensive, equipment to monitor the health of a system. On the other hand, such equipment can help during the fault identification and isolation steps. The faults typically require costly repairs or equipment replacement, as small failures might not be detected until a major fault occurs.

source

Another technique is Preventive Maintenance (PM). PM focuses on proactive maintenance of equipment by carefully monitoring and servicing equipment by expert personnel. The goal

is to maintain satisfactory operating conditions of the system by solving minor faults before they cause major ones. PM requires good knowledge about the system and regular, systematic inspections to be carried out.

The technique which will be explored in this thesis is Predictive Maintenance (PdM). The aim of PdM is to optimise scheduled maintenance work and minimise, or even prevent, unexpected equipment failures. Equipment is directly monitored and measured to understand the actual maintenance need. Maintenance can then be scheduled for a specific equipment, based on the actual need.

Internet of Things

The rise of Internet of Things (IoT) applications in various industries indirectly solve the problem of data gathering and equipment monitoring. For example, data is typically integrated in IoT applications to provide direct system control, statistical features, localisation or planning.

1.2 Problem Description

Systems with a Corrective Maintenance (CM) policy typically suffer from expensive repairs and system downtime due to faults. Preventive Maintenance (PM) can suffer from premature repairs and replacement of equipment. Premature repairs and replacements do not only lead to greater costs but also a larger environmental stamp. Predictive Maintenance (PdM) aims at solving both issues. By monitoring the actual need of a system, premature maintenance can be avoided and minor faults detected and solved. However, PdM requires direct monitoring of equipment, which might not be easily achievable in traditional industries. Internet of Things (IoT) applications solve the monitoring problem by continuously gathering data and collecting it. This work focuses on the usage of IoT data to realise PdM. The goal is to implement PdM to reduce costs associated with repairs of faulty equipment, premature replacement of equipment, and unnecessary maintenance services.

1.3 Aim

The aim of the work is to perform a case-study on how Machine Learning (ML) algorithms can be used on Internet of Things (IoT) data for Predictive Maintenance (PdM). The study shall compare at least two different ML algorithms. The goal is to implement the ML algorithms and use real-world data from an existing IoT system. The case-study shall also compare how well PdM performs against the Corrective Maintenance approach used in the IoT application today.

1.4 Research Questions

This work explicitly answers the following questions:

1. What methods can be used to detect anomalies in a dynamic real-time system?
2. How can the need for maintenance be detected from real-time processing of domain-specific data?
3. How can Predictive Maintenance be achieved by processing real-time domain-specific data?
4. How many days in advance can maintenance be predicted?
5. How can Predictive Maintenance be evaluated and compared to Corrective Maintenance?
6. How can faults be identified and isolated using Predictive Maintenance?

The RQs below are just an initial draft.

7. What data is required to realise fault identification and fault isolation in Predictive Maintenance?

1.5 Limitations

The data available is from an existing IoT application mainly used to control units. The available sensors in the application can not be changed and additional sensors can not be added.



2 Theory

3 Related Work

Predictive Maintenance (PdM) approaches have been studied and tested for many different industries. This chapter covers some of the approaches proposed in the literature.

3.1 Multiple Classifier Approach

In [2], Susto et al. propose a multiple classifier approach to PdM. They use the approach to predict problems which stem from the "wear and tear" effects of equipment used for semiconductor manufacturing. Each classifier is trained on a different failure horizon m , which results in a different classification problem for each classifier. The failure horizon is the number of iterations in a maintenance cycle where the fault has taken place. In a traditional R2F (Run to Fail) environment only the last iteration would be faulty ($m = 1$). Instead, the dataset is transformed for each classifier so that the last m iterations are marked as faulty. A larger m reduces the skewness of the dataset and enables a more conservative PdM policy. The multiple classifier approach thus enables the implementation of a cost optimisation policy as well as a fault prevention policy.

Results of the Multiple Classifier approach?

Requirements in order to use it? (type of data, dimensionality, environment (R2F), supervised/unsupervised etc.

3.2 Framework based on ARMA and data-driven techniques

Baptista et al. propose in [1] a different approach to PdM utilising usage data instead of sensor data. A framework is built in order to predict the next fault event based on previous events. The usage data (past failures and past scheduled events) is given to the Auto-Regressive Moving Average (ARMA) model, which outputs predictions on future failure events. The predictions from the ARMA model is fed to the data-driven model and transformed, using statistics features and PCA, in order to output a more informed prediction. The data-driven model trains five different classifiers: k -nearest neighbours (k-NN), random forest (RF), neural networks (NN), support vector machines (SVM), and generalised linear regression model (GLM).

The framework is then compared against a baseline approach using a standard life usage (LU) model with the Weibull distribution. Baptista et al. show in their case study [1], that almost all data-driven models outperform or perform comparably with the LU model. The only model to perform worse was the NN model, due to over-fitting [1]. The SVM model

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achieves the best results in almost all metrics which, according to Baptista et al. [1], proves that it is possible to build more sophisticated and improved models than the LU model.

3.3 title

Vi kan nog inte använda denna approach, eftersom det inte riktigt är den typ av data som vi har tillgång till. Vi har tillgång till sensor data (och kanske även lite usage data). Dock är usage datan baserad på den tidigare statistiska modellen, så man vet ju inte riktigt ifall alla scheduled events of failure events hände precis då som de står i loggen. Det hade kanske varit intressant att undersöka huruvida man kan kombinera sensor data med usage data?



4

Method



Bibliography

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