Fault Severity Estimation using Weak Supervision with Language Based Labels and Condition Monitoring Data*

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1 Introduction

Condition monitoring (CM) is widely used in process industry to maximize equipment availability, uniform product characteristics, safety in the work environment, and to minimize production losses and material waste. The value of the machine CM market is estimated to SEK 26 billion with an annual growth rate of 7% according to MarketsandMarkets. A major challenge is to accurately estimate the severity of faults identified with modern condition monitoring systems and recommend effective maintenance policies. This presently requires human experts with years of training. Substantial information about the severity of faults is represented in the annotations written by experts that monitor the development of faults, sometimes over several months until a maintenance decision is made. Can natural language processing (NLP) methods be used to automatically estimate the severity of some faults using this data in combination with machine learning methods for processing of condition monitoring data?

Current methods for decision support in industry rely on signal processing, kinematic knowledge and rule based systems to alert human experts on where in the vast amounts of data to focus. The signal processing and kinematics give analysts a feature space to navigate in, but the algorithm offers no decision support beyond the kinematics in the frequency domain. By automating simpler tasks and providing strong decision support for more difficult tasks, efficiency and scalability can be improved. Deep learning (DL) approaches have become increasingly popular for time series analysis, and several reviews on deep learning for condition monitoring have been written in recent years (9)(16)(6)(14)(8). However, while the field of fault *classification* is well discussed, fault *severity estimation* (FSE) is significantly less explored, as stated in (5). In particular, the possibility of utilizing NLP for FSE, as proposed here, is unexplored.

2 Fault Severity Estimation

Estimating the severity of a fault is a considerable challenge even for humans; the severity of a fault is not perfectly portrayed by the change in vibration signals, and its evolution has a stochastic behaviour, partly due to the physical complexity of faults, and partly

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due to changes in operational parameters. Furthermore, a deep learning algorithm for FSE requires labels which indicate the severity of the fault. To create datasets where the condition of the fault can be better estimated, lab set-ups where faults are forcefully induced are used. This allows for the state of components to be more directly measured through invasive measures, which gives insight for researchers and allow for strong labels. However, it is difficult to generate datasets that are both realistic large datasets that are needed for DL. Additionally, algorithms trained on lab-generated data perform transfer poorly to real industry settings, as stated in (10).

Therefore, training DL FSE models on real world industry datasets is desirable. Given a large amount of labeled data from an industry environment, an algorithm can be trained which should perform well when applied to that industry. Obtaining a dataset with labelled industry data is challenging though, and many attempts utilize data where only the maintenance history is available as labels. This data is sufficient for classification, but as the labels carry little to no information on the severity or the evolution of the faults, it is insufficient for severity estimation. Consequently, there is either a need for industry data with stronger labels (expensive), or new methods that enable weakly supervised training on existing industry data.

3 Approach

This project utilizes a new dataset and aims to develop FSE methods to amend the above mentioned issues. The dataset is obtained through the combined effort of LTU, SKF, Smurfit Kappa and SCA Munksund. It features real world CM time series measurements from the Kraftliner factories of Smurfit Kappa and SCA Munksund. Additionally, notes written by human experts are available, which carry information on bearing faults and, when applicable, severity and proposed maintenance policy. For every fault that is discovered, a note is written with information regarding the fault. For faults where no intervention is needed yet, multiple notes will be available for the same fault, showing the evolution of the severity. Once a fault is considered severe enough, maintenance is scheduled and noted.

Using state of the art NLP methods, notes will be transformed to embeddings to serve as context and labels. As the notes do not precisely describe the state of the machinery, weak supervision methods will be used to allow training with incomplete and uncertain labels. To transform the notes to labels, we desire an algorithm which embeds fault type, severity, time relation and resulting policy. Two methods for this are investigated: sentence embedding (1) and hierarchical vectors, where each fault is one dimension, which in turn contains sub-dimensions with additional context.

Besides transforming labels, the challenges consist of analysis time series data. Time series analysis has been explored extensively in literature (2). Historically, it has been done through time, frequency and time-frequency analysis (15). In deep learning, a model can be either end-to-end or in a feature space with reduced dimensionality. In end-to-end models, methods that automatically encode information such as CNNs have been used (7). To extract features, unsupervised learning algorithms are first utilized (11), such as encoders (13), echo state networks (12) and dictionary learning (3)(4). Supervised learning is then applied to the feature space.

The project is thus a combination of time series analysis, understanding language through natural language processing, and integrating the two using weak supervision models.

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