Domain Contextual and Relational Graph Model for Predictive Maintenance

Robert Schiller*
Deloitte & Touche LLP
USA
roschiller@deloitte.com

Trupti Chavan*
Deloitte & Touche Assurance & Enterprise Risk Services India Private Limited
India
trchavan@deloitte.com

Akshay Kakkar
Deloitte & Touche Assurance & Enterprise Risk Services India Private Limited
India
akshkakkar@deloitte.com

Viraj E
Deloitte & Touche Assurance & Enterprise Risk Services India Private Limited
India
eviraj9@deloitte.com

Don Williams
Deloitte Transactions and Business Analytics LLP
USA
dowilliams@deloitte.com

Derek Snaidauf
Deloitte Transactions and Business Analytics LLP
USA
dsnaidauf@deloitte.com

Edward Bowen
Deloitte & Touche LLP
USA
edbowen@deloitte.com

Deepak Mittal
Deloitte & Touche Assurance & Enterprise Risk Services India Private Limited
India
deepamittal@deloitte.com

Sunil R. Tiyyagura
Deloitte & Touche Assurance & Enterprise Risk Services India Private Limited
India
sutiyyagura@deloitte.com

***Abstract*—The rotating machine is one of the common components which is examined under predictive maintenance across different industry sectors. Failure of bearings and gear boxes in such rotating machines are typical problems and their inspection is done using multiple sensors such as vibration, ultrasound, torque and temperature. The existing machine learning (ML) methods for bearing fault detection include traditional ML approaches and advanced deep learning algorithms. Nevertheless, these approaches often fail to account for the domain context and relationships between features, which are essential for building generalized, knowledge oriented, and trustworthy models. This work attempts to incorporate these aspects using a domain contextual and relational graph model (DCRG). It involves a graph convolutional network which is constructed with domain inspired features and their relations based on domain knowledge. The proposed method has been inspected using open-source bearing datasets such as Franche-Comté Électronique Mécanique Thermique et Optique (FEMTO), and Xi'an Jiaotong University (XJTU) bearing dataset. DCRG achieves stronger F1 scores (improvement by 5-10%) than the baseline machine learning approaches.**

***Index Terms*—predictive maintenance, bearing failure, graph neural network, domain context, relational learning**

*equal contribution

I. Introduction

Predictive maintenance (PdM) aims at a significant improvement over condition monitoring and preventive maintenance approaches. It is a critical component of modern maintenance planning. It comprises various predictive tasks, including early failure warning and remaining useful lifetime estimation, which efficiently addresses challenges in maintenance related activities [1], [2]. It has been found to be beneficial in the reduction of capital costs involved in maintenance processes across different industries such as; manufacturing, logistics, transportation. This class of approaches use sensor data from Internet of Things (IoT)-based assets, and requires data preprocessing, data modeling, and maintenance alert generation. Bearings in rotating machines are one of the commonly supervised components in this maintenance process across various industries.

There are two primary approaches for bearing failure prediction: traditional machine learning (ML) methods with feature engineering and deep learning models [3] [4]. These methods have been able to extract useful features, but they lack in establishing domain driven causal relationships between sensor readings and faults. Knowledge graph based approaches [5] [6]

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are presented to handle these issues. The ontologies defined in these techniques are highly complex and are restricted to a specific domain. Moreover, there are only a limited number of open source data sets available to test these architectures. The majority of this work has been done using four primary open-source PdM datasets [7] [8] [9] [10]. There are graph based algorithms which focus on bearing fault detection. Xia L, et al. [11], attempted to address the maintenance planning for an oil drilling rig in order to repair or prevent system damages. They introduced a link prediction network to explore relations in the knowledge graph. A question-answer system was also included to reduce the communication gap between an engineer and knowledge graph terminology. This method focused more on the user interface to provide maintenance recommendations than on failure prediction.

An attempt to model the correlation information in spatial and temporal domain was done in temporal-spatio graph (TSG) [12] to analyze bearing health. A short term periodogram was applied on raw vibration signals and then the spatio-temporal graph was generated. This graph was further used for mapping of periodogram to graph mapped spectrum which had the principal frequency related to the healthy bearing. The type of fault was identified using the k-nearest neighbor classification of spatio channel graph. In this study, graph modeling was employed for feature extraction, while traditional approaches were utilized for fault diagnosis.

In [13], a graph theory motivated spatio-temporal feature extraction technique called SuperGraph was presented for fault diagnosis of rotating machines. This method was experimented with a very small sample dataset namely Case Western Reserve University (CWRU) [7].

A multi-receptive field graph convolution network (MRF-GCN) [14] was proposed in which relationships between data samples were captured by converting data samples into weighted graphs and different receptive fields were applied for feature learning. It was observed that the number of receptive fields impacted the training duration and model stability. Gao Y., et al. [15], proposed graph shift regularization with directed graphs (GSR-D) to analyze rolling bearing faults. A directed graph was defined by considering each sample as a node, and edges and edge weights were established by obtaining k-nearest neighbors using cosine similarity between the nodes. While it was demonstrated using the CWRU dataset [7], the approach was limited to individual bearing classification and did not demonstrate generalizability of the model. A domain adversarial graph convolutional network (DAGCN) [16] was introduced by modeling class label and domain label. A classifier was used to model class label and domain discriminator was used to model domain label. A convolutional neural network (CNN) was applied for data structure alignment.

Summarizing the above graph based methods in literature, it is seen that knowledge graph based approaches are limited due to availability of data sets needed to define the ontology and are very specific to a particular domain. The methods motivated by graph networks use time or frequency features and attempt to capture relations between the features by defining edges based on their similarity. However, this is limited due to lack of domain relations between various components and their fault identification signatures. This paper highlights these aspects of the fault behavior modeling. The contributions of the proposed work are as follows:

- We have introduced a domain contextual and relational graph architecture for failure prediction of bearing.
- We have extracted revolutions per minute (RPM)-based vibration features to add domain context, which brings additional explainability and trust to the proposed model.

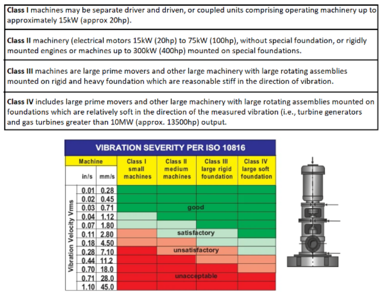
The rest of the paper is organized in the following sections. Out of these sections, the details of the proposed domain contextual and relational graph model are described in Section II. Section III presents different experiments conducted and their results. The overall study is concluded in Section IV.

II. Proposed Method

This section describes the proposed method in detail. The graph based approach involves a crucial step of defining the ontology of graph. Nevertheless, in graph related PdM research, a lot of the work is done to define the temporal dependency of vibration signals. There is very little work done to include the domain contextualization of the raw signal. To address this limitation, we propose the domain contextual and relational graph neural network which is explained in the following subsections.

A. Background for Domain Contextuality

The causal relationships between vibration signals and failure of a machine are presented in this section. There are various standards and studies in literature [17], [18], [19], [20] that explain the reasons for rotating machinery failures, as presented in Fig. 1. It is a common practice in industry to use this information to build simple condition based monitoring models for failure detection. International Organization for Standardization (ISO) 10816 shown in Fig. 1a is one of the earliest and extensively evolved standards which describes how failure severity is related to vibration root mean square (RMS) values for different rotating machine classes. Similarly, some of the studies (for example Fig. 1b) focus on standardization of failure detection based on frequency analysis of vibration signals. Different categories of failures are related to different frequency bands. The frequency bands are expressed as a factor of the rotational speed measured in RPM of the machine. The condition based modelling uses rule-based thresholds for these features but has mixed success due to the noise present in the signals in an industrial setup. Several practical factors, like the placement of sensors, impacts of nearby machines, and other noise, might cause the vibration signatures of real machines to deviate from these standards; indeed in our work we noticed significant variation in our vibration signatures compared to the standards, complicating the ability of a failure prediction model to generalize across assets. We have attempted to address these challenges by incorporating domain-related knowledge into our proposed graph topology, as explained in the section below.



(a) ISO 10816 for vibration severity analysis [18]

Spectral parameter	Bandwidth
Imbalance, missalignment, looseness, rub and belt wear.	1.5 to 2.5x RPM
Missalignment and looseness.	1.5x to 2.5x RPM
Looseness, missalignment and BSF.	2.5 to 4.5x RPM
First harmonics of the bearing fault frequencies BPFO, BPFI and BSF.	4.5 to 20.5x RPM
Higher bearing fault frequencies harmonics and presence of frequencies related to electrical issues.	20.5 to 50x RPM
High frequency spectral band, in units of acceleration (G's). Alarm parameter in case of early bearing deterioration stage, presence of cavitation or lack of lubrication.	1 to 20 kHz

(b) Bearing failure analysis based on Spectral bands [19])

Fig. 1: Standards and studies conducted to analyze vibration failure patterns for predictive maintenance

B. Ontology of Domain Contextual and Relational Graph Model

The ontology of proposed method shown in Fig. 2 is motivated by the domain knowledge. The orange sample node is a single time segment for which we have a binary label. The feature vector for the sample node contains the feature set derived from the signal, as well as intrinsic information about the rotating machine. The green colored nodes in Fig. 2 represent the RPM-based features; each sample node is connected to its own RPM-based feature nodes, and each feature node contains a scalar value. Finally, the blue nodes are bucket nodes, and there is just one set of these for the overall graph. The graph is constructed as a node classification problem where each sample node undergoes failure classification. While we have not included multi-modal signal features in this study, it is straightforward to see how additional features such as ultrasound, temperature, etc. may be added to this architecture.

From the discussion in Section II-A it is seen that the failure behavior is reflected in certain frequency bands of vibration signals and these frequency bands are related to the RPM harmonics. To maintain consistency with the typical units used in PdM, we refer rotational speed as RPM.

Although much of the literature considers the vibrational velocity, the raw signal comes from an accelerometer sensors

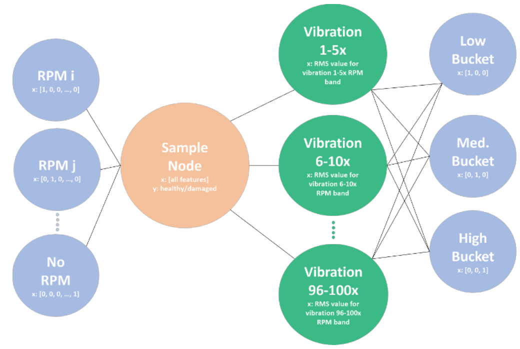


Fig. 2: Ontology of the proposed DCRG model, where each orange sample node has its own green feature nodes. The blue bucket nodes are a single set of nodes for the entire graph, which is the primary way in which sample nodes connect to one another.

which measures acceleration. In our proposed work, we have acceleration data which is preprocessed by removing low frequency noise and converted to a velocity signal using (1). In general, velocity is the time integration of acceleration; however, this requires chaotic windowing and filtering operations, which is why we have used a power spectral density (PSD) based conversion [18].

$$\begin{aligned}\text{velocity PSD} &= \frac{\text{Acceleration PSD}}{\omega^2} \\ &= \frac{\text{Acceleration PSD}}{(2\pi f)^2}\end{aligned} \tag{1}$$

where ω is the angular frequency, f is the frequency and PSD represents power spectral density.

Using the pre-processed acceleration or velocity signals, RPM based band features are extracted. If modalities other than vibration are available, the nodes corresponding to these modalities could be added in the graph.

The standards have thresholds on velocity RMS values for normal, degraded and failure states of a rotating machinery. Hence, we have created high, medium, and low buckets based on the distributions of these features and thresholds considered in standards. The bearing wise and overall feature distributions are analyzed to understand separation among failure and non-failure signals. The thresholds used to bucketize the feature are selected based on this analysis. The band feature values that fall into the high bucket are very likely failures, and band feature values in the low bucket are very likely normal. Fig. 3 shows the impact RMS buckets for one bearing in the XJTU dataset [9]; the thresholds for each feature bucket are fixed across different bearings, and the feature falls into the mid and high buckets as the bearing approaches failure. For each feature, there is a single set of bucket nodes for the entire graph, and each sample will connect the corresponding feature to one of these three bucket nodes. Thus, the primary way we interconnect samples is via these bucket nodes.

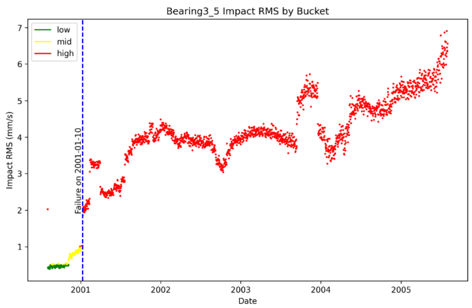


Fig. 3: Visualization of bucketing impact RMS for bearing in the XJTU dataset [9]. Blue color denotes failure point.

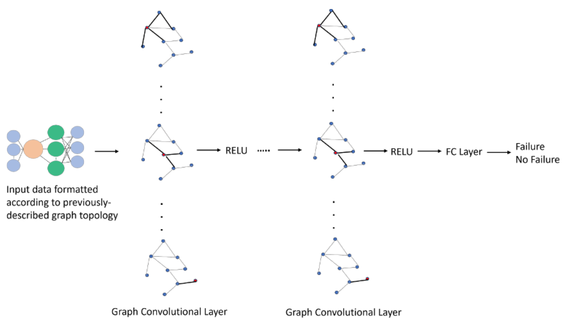


Fig. 4: Architecture of proposed model, where graph convolutional layers are applied on the topology as defined in Fig. 2.

C. Architecture of Domain Contextual and Multimodal Relational Graph Model

The architecture presented in Fig. 4 of the proposed method is elaborated in this section and we elaborate on how the ontology mentioned in above section (Section II-B) is consumed in a graph neural network.

The proposed Graph Neural Network (GNN) architecture consists of a GraphSAGE (SAmple and aggreGatE) [21] convolutional operator which inductively leverages node information to learn contextual relationships between the features based on the dataset. This in turn builds a more generalizable model. Unlike the signal similarity based graph topology defined in literature, the similarity and temporal relationships are established automatically by the message passing layers of the GNN using domain inspired feature bucket nodes in our architecture. This is a novel way of introducing domain knowledge into the graph, thereby making learning more correct. In this work, four GraphSAGE convolution layers are considered for message passing. Each layer is followed by a rectified linear unit (ReLU) activation function. For classification, a sigmoid function is applied at the output layer.

III. Experimental Results

This section discusses the datasets used, as well as experimental results.

A. Datasets

The proposed method is experimented using datasets such as FEMTO [8], and Xi'an Jiaotong University (XJTU) bearing dataset [9]. Both the datasets are run to failure, i.e. each bearing has been measured throughout its transition from normal to faulty.

The FEMTO dataset [8] provides the vibration data acquired during the PRONOSTIA experimental platform's accelerated bearing failures. The collection contains horizontal and vertical vibration recordings from 17 bearings that were subjected to three different operational conditions. A vibration signal was set to one sample per ten seconds at a sample rate of 25.6 KHz for 0.1 second intervals, yielding 2560 data points per waveform. During our examinations, we have taken into account only horizontal vibration data that shows identifiable changes linked with failures.

The XJTU dataset [9] introduced in 2018 is another more modern collection of vibration data collected during accelerated bearing failures. This dataset contains data from 15 bearings that were subjected to run-to-failure studies under three separate operational settings, spanning a variety of bearing failures. The vibration signal was recorded for each minute at a sample rate of 25.6 kHz across 1.28 seconds intervals, yielding 32,768 data points per waveform.

The training and testing set is created by exclusively dividing data based on bearing. 4-fold cross-validation is performed to endeavour robustness of evaluation.

B. Comparative Study of Proposed Method

The proposed method is compared with traditional ML algorithms and various feature engineering methods. The baseline traditional ML models include Naïve Bayes, Linear SVM, Kernel SVM and random forest. We have extracted time-based, frequency-based, and domain-inspired RPM features for the models. The time domain features used in this work are number of zero crossings, kurtosis, RMS, number of peaks, mean, absolute median, standard deviation, skewness, energy, Shapiro test, KL divergence, and crest factor [22]. In the frequency domain feature set, we used real-valued fast fourier transform (RFFT) features [22]. For the RPM-based features, we considered non-overlapping frequency bands in multiples of 5 or 10 times the revolutions per second of the motor, i.e. the RPM divided by 60, with the goal of capturing vibration information at higher harmonics of the rotational speed. In each RPM band, we took the RMS value by using a bandpass filter on the raw signal and then computing the PSD. The differences in manufacturer, bearing type, operating conditions may cause different distributions in sensor data across various bearings which raise the model generalization issue. To handle this, we experimented with data transformation techniques such as standard scaler and median centering. The standard scaler is the mean-standard deviation normalization. Whereas, in median centering, the distributions of different bearings are centered using the median of feature corresponding to healthy signal state. The results for the FEMTO [8] and XJTU [9] dataset using random forest models and different feature

TABLE I: Results for FEMTO Dataset [8]

S. No.	Model	Features	Median Centering	Average Precision	Average Recall	Average F1
1	RF	Time domain features	No	0.29	0.80	0.37
2	RF	RFFT	No	0.62	0.74	0.56
3	RF	RPM (5x)	No	0.62	0.79	0.62
4	RF	RPM (10x)	No	0.66	0.80	0.64
5	RF	Time domain features	Yes	0.36	0.97	0.44
6	RF	RFFT	Yes	0.70	0.82	0.73
7	RF	RPM (10x)	Yes	0.73	0.90	0.79
8	**DCRG**	**RPM (5x)**	**No**	**0.94**	**0.91**	**0.92**
9	**DCRG**	**RPM (10x)**	**No**	**0.93**	**0.89**	**0.90**

TABLE II: Results for XJTU Dataset [9]

S. No.	Model	Features	Median Centering	Average Precision	Average Recall	Average F1
1	RF	Time domain features	No	0.95	0.94	0.94
2	RF	RFFT	No	0.83	0.94	0.88
3	RF	RPM (5x)	No	0.91	0.94	0.92
4	RF	RPM (10x)	No	0.90	0.94	0.92
5	RF	Time domain features	Yes	0.95	0.95	0.95
6	RF	RFFT	Yes	0.84	0.95	0.89
7	RF	RPM (10x)	Yes	0.91	0.95	0.93
8	**DCRG**	**RPM (5x)**	**No**	**0.99**	**0.99**	**0.99**
9	**DCRG**	**RPM (10x)**	**No**	**0.99**	**0.98**	**0.98**

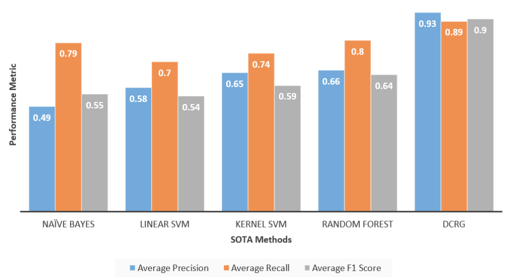


Fig. 5: Comparison of various traditional ML models for FEMTO dataset [8]

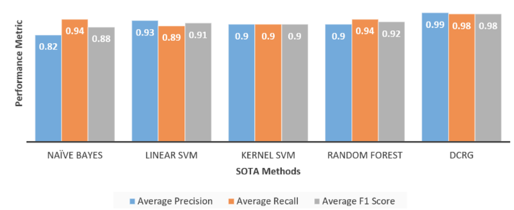


Fig. 6: Comparison of various traditional ML models for XJTU dataset [9]

engineering methods are presented in Table I and Table II, respectively. From these tables, it is seen that the performance of domain inspired RPM features has shown improvement compared to other feature extraction methods in spite of what type of ML model is used. The precision, recall and F1-score are improved by using median centering; however, DCRG achieved higher metrics than the RF models without needing median centering.

The performance of various traditional ML models is compared with DCRG and is given in Fig. 5 and Fig. 6 for FEMTO and XJTU dataset, respectively. From these figures, it is observed that the performance of proposed DCRG model is significantly better than the existing traditional ML approaches.

IV. Conclusion

This work presents a domain contextualized and relational graph model which incorporates domain inspired RPM features and relationship mining through graph modeling. It is a standard practice to observe the specific harmonics relevant to failure of rotating machines and this principle is used to extract domain inspired RPM features in the proposed method. The relationships among the signals are explored using the proposed graph topology which includes sample nodes, band feature nodes and feature bucketization nodes, and the GraphSAGE aggregation model performs relationship mining. The experimental study used open-source datasets namely, FEMTO, and XJTU. DCRG has demonstrated better performance compared to the traditional ML and feature engineering methods. Further, the ability of DCRG to generalize to test set without the need for median centering is significant for its practical usability on new data in the field.

This architecture proposes an elegant way to embed domain knowledge into the graph and have a generic way to represent different asset types and capacities by basing the feature design on machine RPM. The graph topology presented is naturally extendable to incorporate more modalities such as temperature and ultrasound signals.

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