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Semi-Supervised Machine Learning for Motor Eccentricity Fault Diagnosis

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Abstract

Eccentricity is one major indicator of mechanical faults in electric machines and needs to be detected early to avoid machine failures. Data-driven techniques based on machine learning and deep learning algorithms have been proposed in recent years for motor fault detection. However, the majority of these methods use supervised learning algorithms and require large, labelled datasets, which can be challenging to obtain. In this paper, we propose a semi-supervised learning method based on a deep generative model using a variational auto-encoder for eccentricity fault quantification. Good prediction accuracy can be achieved when only a small subset of training data has labels.

1. Introduction

Eccentricity is one kind of fault that commonly happen in rotating electric machines when the air gap between the stator bore and the rotor is not uniform anymore (Benbouzid, 2000). Eccentricity fault can occur in different forms: static eccentricity occurs when the center of the rotor is displaced from the stator bore central axis, while the rotor rotation center is still aligned with the center of the rotor; dynamic eccentricity occurs when the rotation center and the stator bore central axis still aligns, but the rotor center is displaced; mixed eccentricity is a combination of both static and dynamic eccentricity effects. Eccentricity can be caused by several different reasons: there can be a small level of eccentricity due to deviation from the perfect circle and imperfect alignments during the manufacturing phase; eccentricity can also evolve and increase over time during the operation of the machine, due to degradation of the mounting structures and bearings (Nandi, Toliyat, & Li, 2005). High air gap eccentricity can induce unbalanced magnetic pull, cause rubbing between stator and rotor, impact the normal operation of the motor, and even lead to failure of the machine. Therefore, eccentricity faults need to be detected and corrected at an early stage to protect the asset and avoid serious damages.

Several different sensing technologies have been widely investigated and implemented for the detection of mechanical anomalies including eccentricity and bearing faults, such as vibration (Harmouche, Delpha, & Diallo, 2015), acoustic emission (Kang, Kim, & Kim, 2015), and motor phase current (Zhou, Wang, Lin, Inoue, & Miyoshi, 2021). Indeed, the unsmooth rotations of the electric machines due to mechanical faults will cause an increased level of vibration and acoustic emission, and induce additional components in the stator current spectrum. A lot of efforts have been put into the theoretical understanding and physical modeling of the faults (Nandi, Ahmed, & Toliyat, 2001; Akar, 2013; Wang, Albader, Inoue, & Kanemaru, 2022). Based on these physical models, detailed spectral analysis can be applied to the measured sensor signals to identify the fault conditions of electric machines. In practice, however, it can be challenging to accurately detect eccentricity faults based solely on physical models. For example, vibration signals can be affected by noises from other sources, such as the mechanical unbalance of the motor, and excitation from external sources in factories. The sensitivity of vibration signals also highly depends on the specific location of the sensor installation. Detection based on stator current signals has the advantages of simple implementation and low cost, but it also suffers in accuracy due to the low signal-to-noise ratio of the frequency components related to the eccentricity faults (Zhou et al., 2021).

On the other hand, data-driven approaches have been a recent research focus for machine fault detection, thanks to both the availability of measurement data in the internet-of-things (IoT) era and the advancements in machine learning and deep learning techniques. A large number of publications in recent years have proposed and implemented various algorithms for the detection and classification of motor faults (Zhang, Zhang, Wang, & Habetler, 2020). A commonly taken approach is the collect data measured on different fault conditions, and train supervised learning algorithms with these data for fault classification tasks.

While many of these algorithms can achieve extremely high accuracy trained with the publicly available dataset, in real-world applications the measured data can be quite different. In many industrial applications, data is collected automatically without intervention using sensors during the machine operation. However, the labelling of these data can be time-consuming and expensive (R-Far et al., 2019). In addition, we cannot afford to run machines and collect data under faulty conditions for an extended period due to the potential danger. Therefore, labelled data, especially under fault conditions, are almost always scarce. This poses a great challenge to the many available supervise learning schemes.

One promising approach to address this challenge is semi-supervised learning, which utilizes both limited labelled data and a large amount of unlabelled data for improved fault detection and classification accuracy (C. Liu & Gryllias, 2020; Chen, Wang, Zhang, Jia, & Qin, 2018; Verstraete, Droguett, Meruane, Modarres, & Ferrada, 2019). A number of semi-supervised learning algorithms have been proposed for fault detection, such as support vector data description method (C. Liu & Gryllias, 2020), graph-based method (Chen et al., 2018), and generative adversarial network (H. Liu et al., 2018). A recent work evaluated and compared various semi-supervised learning techniques for bearing fault classification, and showed variational auto-encoder (VAE) based semi-supervised models have advantages in training stability and achieved accuracy compared with supervised models and other semi-supervised models (Zhang, Ye, Wang, & Habetler, 2021).

In this paper, we investigate a VAE-based semi-supervised learning scheme for the eccentricity fault detection and its fault severity prediction for electric machines, and quantify the accuracy with experimentally measured data. We show that the semi-supervised learning model can achieve much better accuracy when only a small fraction of the data are labelled.

2. Experiment Setup

In this work, we investigate the eccentricity fault problem of a 0.75 kW, three-phase squirrel-cage induction motor. In order to quantitatively study the behavior at different eccentricity levels, a few modifications have been made to the motor. As shown in Fig. 1, mounting structures are custom-made and replace the original bearings in the motor to support the rotor (only the mount on the load side is visible in the photo), through the extended rotor shaft and a pair of new bearings installed on the mounting structures. The stator assembly of the motor is mounted on a linear stage, whose position in the horizontal direction, hence the eccentricity level, can be accurately adjusted using two pairs of micrometers mounted on each side of the linear stage. The load to the motor under test is provided by a power brake. A pair of accelerometers are installed in the horizontal direction and the vertical direction, respectively.

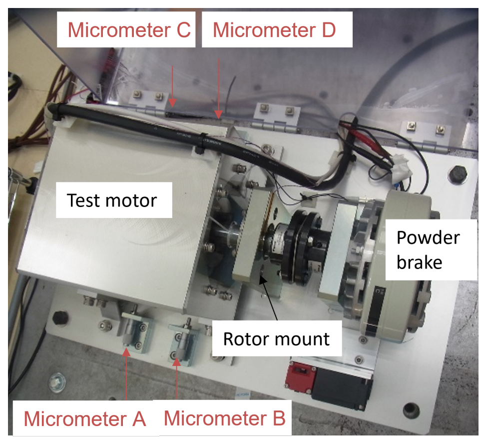

Figure 1. The experiment setup for the study of induction motor eccentricity.

With this experiment setup, different eccentricity levels can be created in the horizontal direction by adjusting the micrometers. In our experiment, a total of 5 eccentricity levels were created in the motor: 0%, 11%, 25%, 43%, and 56%, where the percentage is defined as the ratio between the maximum air gap deviation and the nominal air gap size. Data from the accelerometers were recorded for each eccentricity level at 10 kHz sampling frequency under 8 different load conditions: 0 N·m, 0.3 N·m, 0.5 N·m, 0.9 N·m, 1.4 N·m, 2.0 N·m, 2.7 N·m, and 3.5 N·m.

Depending on the mounting location of the accelerometer, the measured vibration signals can have different features. The signals under different eccentricity conditions can be more distinguishable at certain locations than others. Without loss of generality, we examine the signals obtained with accelerometers mounted in the vertical direction, while the eccentricity fault occurs in the horizontal direction. Fig. 2 shows the measured time-domain vibration signals under the

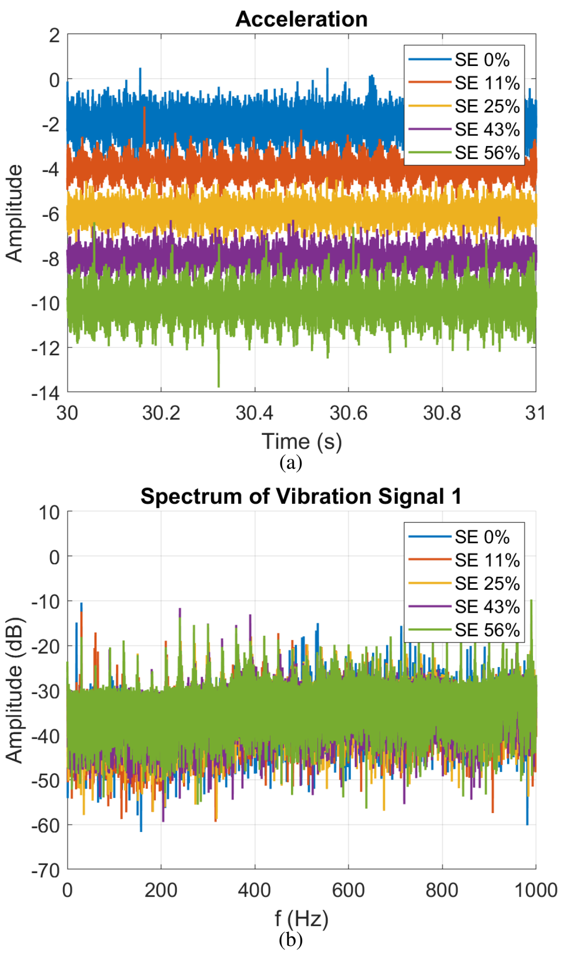

Figure 2. (a) The measured vibration data under different eccentricity levels at no-load condition, shifted in vertical direction for clarity, and (b) the corresponding frequency spectrum.

no-load condition for different eccentricity conditions, and the corresponding frequency spectrum obtained with Fourier transform. As can be seen from Fig. 2(a), the time-domain signals are quite complicated and the vibration amplitude does not change significantly under different eccentricity conditions. It is not straightforward to distinguish difference eccentricity conditions based on the frequency spectrum either,as shown in Fig. 2(b).

3. Semi-Supervised Learning Model for Eccentricity Fault Detection

A variational auto-encoder is a deep generative model whose architecture is similar to a standard auto-encoder, which is composed of an encoder and a decoder, and trained to generally minimize the reconstruction error between the input data and the encoded-decoded output data. The training of VAE is regularized to avoid the overfitting problem, by first encoding the input as a distribution over the latent space instead of

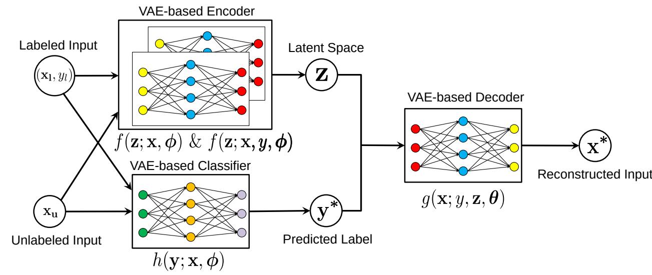

Figure 3. Illustration of the semi-supervised generative model based on VAE.

as a single point, then sampling a point from the distribution, which is then decoded with the decoder. The reconstruction error is then calculated and back-propagated through the VAE network. Probabilistic framework and variational inference are the theoretical foundations of the formulation, and they provide the powerful generative power of VAE.

Semi-supervised generative models based on VAE have been proposed (Kingma, Mohamed, Rezende, & Welling, 2014) and applied for bearing fault classification accuracy improvement (Zhang et al., 2021). Detailed descriptions of the models including theory and formulations can be found in these references. Here a high-level introduction of the model structure is provided.

As shown in Fig. 3, the model takes in both labelled input (x_l, y_l) and unlabelled input data (x_u). Two independent VAE-based encoders are constructed, one for each type of data, with the same network structure, and embed the high-dimensional input data as a set of low-dimensional latent features z. A classifier network is also constructed and trained to make predictions of the fault level y^*. The decoder part of the model is the reverse of the encoder model, which takes in both types of data and reconstructs the input data as its output. Both x_l and y are considered as input for labelled data, and the output will be the reconstructed x_l^* and y^*; for unlabeled data, the input is x_u only and the output is reconstructed x_u^*. The reconstruction error of the VAE model and prediction error of the classifier are minimized during training. During inference, the trained classifier is used to make predictions of the eccentricity level for a given input data. The implementation process of the model can be found in previous work (Zhang et al., 2021).

4. Eccentricity Fault Level Prediction

We then proceed to build machine learning models for eccentricity fault level prediction.

In addition to implementing a semi-supervised VAE model, popular unsupervised learning schemes such as principal component analysis (PCA) and auto-encoder (AE), as well as the supervised convolutional neural network (CNN), are also trained for comparison. Hyper-parameters for these models are either selected to be consistent with the VAE model or are obtained through parameter tuning. A PCA model is trained for dimension reduction of input data into a feature space of 64. Support vector machine (SVM) is applied subsequently as a classifier, with radial basis function (RBF) kernel and regularization parameter $C = 10$. The AE model is configured similarly to the PCA model and also uses SVM as an external classifier. For the CNN model, each time-series vibration data of length 1,024 is first transformed into a 2D 32×32 matrix before feeding to the network, which is a commonly used technique for fault detection (Wen, Li, Gao, & Zhang, 2018). The CNN model has two convolution layers with ReLU as the activation function, each with 2×2 convolutions and 32 filters, followed by a 2×2 Max-Pooling layer and a 0.25 dropout layer. A fully-connected hidden layer follows with a dimensionality of 512, then the output of which is fed into a Softmax layer. The cross-entropy loss is adopted, and the batch size is set to 10, which is also obtained via parameter tuning.

For the semi-supervised VAE, two independent networks are used, one for labeled data and the other for unlabeled data. They have same network structure built on CNN, but different input and output, as well as loss functions. Specifically, the encoder network has 2 convolutional layers, 1 fully-connected layer using ReLu activation, and batch normalization and dropout layers. The decoder network consists of 1 fully-connected layer followed by 3 transpose convolutional layers, where the first 2 layers use ReLU activation and the last layer uses linear activation. Fhe classifier network has 2 convolutional layers and 2 max pooling layers with dropout and ReLU activation, followed by the final Softmax layer. The hyper-parameters of the model are selected empirically. We fix the latent space dimension as 128, and use a batch size of 200 is used for training. We use RMSprop as optimizer, with a 10^{-4} initial learning rate.

The measurement data first need to be pre-processed before they can be used for the machine learning study. Since we have 5 different eccentricity conditions, and measurements are taken at 8 different load conditions, a total of 40 measurements are recorded. Each measurement is 60 s long, with a sampling rate of 10 kHz. These vibration signals are segmented into data samples of equal length with 1,024 data points each and a sliding rate of 0.5. After segmentation, we have 1,170 data samples from each measurement, and a total of 46,800 data samples are obtained for the whole dataset. These data samples are then shuffled and split into training and test data sets with an 80:20 ratio. Classical standardization techniques are also implemented in the training and test dataset to ensure the vibration data have zero mean and unit variance, which is enabled by subtracting the mean of the original data and then dividing the result by its standard deviation.

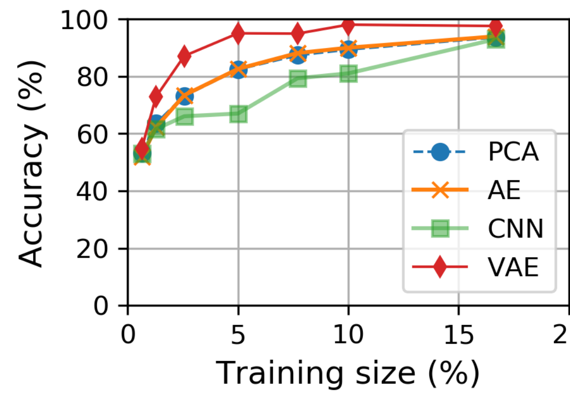

Figure 4. Eccentricity level classification accuracy with models trained on different percentages of labelled training data.

After processing the measurement data, we first train models to perform classification tasks, which are required to train a model and make predictions on which class of eccentricity level (out of a total of 5 levels) a data sample belongs to. Each model is trained on a subset of the training data that are labelled with corresponding eccentricity levels. For each case, the rest of the training data is considered unlabelled. For each trained model, the same test dataset is used to examine the classification accuracy, and the results are shown in Fig. 4. The benchmark models, including PCA, AE, and CNN cannot make use of the unlabelled portion of the training data, and the classification accuracy is generally worse, especially when the ratio of labelled data is small. With an increasing number of labelled data, all models can achieve a classification accuracy of over 95%. On the contrary, the semi-supervised VAE model utilizes both labelled and unlabelled data of the training set, and it achieves higher classification accuracy even when the labelled portion is small. A high classification accuracy of 95% on all the test datasets is achieved when only 5%, or 1,872 data samples from the training data are labelled.

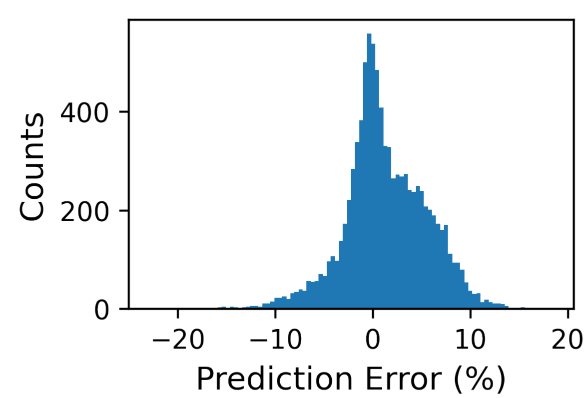

Figure 5. Histogram of the eccentricity level prediction error.

We can also train models to perform regression tasks, which are required to train a model and make predictions on the eccentricity level for a given data sample. Instead of having 5 nodes at the output layer of the model with SoftMax activation function for classification task, only one node is assigned at the output without activation for the regression task. Similar to the classification task, good prediction accuracy can be achieved on the regression task. As shown in Fig. 5, the histogram of the prediction error for all test data samples is centered around 0, and is within a few percent of the ground truth for most test cases. The calculated root-mean-square error (RMSE) over all test samples is around 4.4%, which is well below 10%, which is considered a threshold value for practical applications.

We should point out that in the test, all conditions in the test data are included in the training dataset. The regression task can be considered as interpolation problem. When some of the fault conditions are not included in the training data, a model needs to be trained to make predictions on unseen data. Machine learning models often fail to perform well in such extrapolation problems. We have tested our regression model for extrapolation task, by training the model with data samples from three eccentricity levels, and make predictions for test data sampled from the other two new eccentricity levels. The prediction errors are much higher than 10%. As a future research direction of data-driven fault detection, efforts should be made on such extrapolation tasks, where the trained model can handle unseen new data and make reasonable predictions.

5. Conclusion

In summary, we presented a semi-supervised learning scheme for motor eccentricity fault prediction using a variational auto-encoder-based generative model. We built an experimental setup to measure the vibration data of an induction motor at different eccentricity levels, and trained data-driven models for eccentricity level prediction. We show that the semi-supervised learning model can achieve superior accuracy when only a small amount of data is labelled.

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BIOGRAPHIES

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