An Analysis of Vibrations and Currents for Broken Rotor Bar Detection in Three-phase Induction Motors

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Abstract

Selecting the physical property capable of representing the health state of a machine is an important step in designing fault detection systems. In addition, variation of the loading condition is a challenge in deploying an industrial predictive maintenance solution. The robustness of the physical properties to variations in loading conditions is, therefore, an important consideration. In this paper, we focus specifically on squirrel cage induction motors and analyze the capabilities of three-phase current and five vibration signals acquired from different locations of the motor for the detection of Broken Rotor Bar generated in different loads. In particular, we examine the mentioned signals in relation to the performance of classifiers trained with them. Regarding the classifiers, we employ deep conventional classifiers and also propose a hybrid classifier that utilizes contrastive loss in order to mitigate the effect of different variations. The analysis shows that vibration signals are more robust under varying load conditions. Furthermore, the proposed hybrid classifier outperforms conventional classifiers and is able to achieve an accuracy of 90.96% when using current signals and 97.69% when using vibration signals.

1. Introduction

Being the origin of motion, electric motors play a vital role in rotary systems. Due to the ease of operation, affordability, and structural simplicity of induction motors, they are the most commonly used type of electric motor in the industry (Tsypkin, 2017; Kanović et al., 2013). Rotors in induction motors are manufactured to be quite robust nowadays, but there are still various faults expected, including Broken Rotor Bar (BRB) (Kanović et al., 2013). BRB faults share same starting stage, where there is simple crack in the rotor bar (Ferrucho-Alvarez et al., 2021). In case this fault is not diagnosed and the essential corrective actions are not taken, BRB with serious severity and probably other faults are unavoidable (Wang et al., 2019).

In addition, the essentially of simultaneously low cost and reliable production has resulted in a paradigm shift in rotating machinery maintenance strategy, from corrective to preventive maintenance(Yan, Gao, & Chen, 2014). One of the preventative maintenance methods that has gained increasing attention in recent years is data-driven methods. In order to provide data for such methods, different physical properties may be utilized. As current and vibration signals are two of the most commonly used properties for BRB detection (Gritli et al., 2012), it is crucial to understand how these two signals can be used to detect the BRB from a data-driven perspective.

Furthermore, the induction motors, in general, have the advantage of being able to operate under variable loads(Sonowal, Gogoi, Boruah, & Barman, 2019); however, this feature poses a challenge to data-driven methods. This challenge originates in the fact that every variation of loading condition would also vary the dynamics of the machine; resulting in different sample distributions, which adversely affect the performance of a data-driven model (Sonowal et al., 2019). Therefore, when constructing a data-driven model, it is important to take into account load variations. This subject comes to higher level of importance regarding the BRB diagnosis, where most approaches require the operation of the motor on heavy load (Ferrucho-Alvarez et al., 2021).

In this paper, we analyze the current and vibration signals to detect BRBs. To accomplish this, we compare the accuracy of fault prediction models trained on current and vibration signals. By taking into account the various load variations, we develop a classifier to mitigate these changes; subsequently, we evaluate the performance of the classifiers trained on the current and vibration signals. This evaluation enables us to compare the effectiveness of current and vibration signals to detect BRBs.

2. Background

2.1. Contrastive learning and Siamese Neural networks

Contrastive Learning focuses on set of learning strategies and techniques involving learning by the comparing available samples and through their similarities and differences (Le-Khac, Healy, & Smeaton, 2020). These methods are great approaches to take, specifically in problems that construction of a feature space with noticeable separation of classes over the feature space. Siamese Neural Networks can be used to employ Contrastive Learning to extract such a feature set. A Siamese network consists of a pair of absolutely identical feature extractors that are supposed to derive embedding corresponding to an arbitrary pair of inputs. The network is trained in a manner which pairs with samples from dissimilar classes (negative pairs) orient far apart from each other, while pairs with samples belonging to similar classes (positive pairs) are mapped most closely to each other. Referenced training process would result in a fairly separable feature space in the embedding provided by the feature extractor.

Contrastive Loss can be used to train a siamese network. Its mathematical definition can be seen in the Equation 1. In this equation, Y is the label of a given pair (0 for negative pairs and 1 for positive pairs), D_w is a similarity index describing the similarity between the embeddigs of the samples present in the pair and m is parameter known as margin. This function is consisted of two terms; the first term is supposed to represent observations of similar classes as closely possible, while the second term is responsible to increase the dissimilarity of the observations from different classes up to the highest extent (Jadon, 2020).

$$ContrastiveLoss = (1-Y)\frac{1}{2}D_w^2+(Y)\frac{1}{2}(max(0,m-D_w))^2 \tag{1}$$

3. Related Works

Taking advantage of intelligent methods to analyze the motor vibrations for BRB detection is a well established approach and various studies can be found regarding this matter. For example, in (Su, Chong, & Ravi Kumar, 2011) Artificial Neural Networks are employed to implement an induction motor fault detection system, by analyzing vibrations of the machine. Similarly, in (Khan, Kim, & Choo, 2020) Dialated Convolutional Neural Networks are used to detect bearing faults in induction motors. In (Sadoughi, Ebrahimi, Moalem, & Sadri, 2007), Artificial Neural Networks and set of features derived from frequency spectrum of vibrations are used to detect the BRB problem in induction motors.

Intelligent methods are widely used in the study of induction motor current signals for fault detection purposes too. For instance, in (Godoy, da Silva, Goedtel, Palácios, & Lopes, 2016), various intelligent methods including Artificial Neural Networks and Support Vector Machines are employed to both detect and classify the broken rotor bars in a three-phase induction motor. In (Bessam, Menacer, Boumehraz, & Cherif, 2016), a BRB diagnosis approach is proposed where Hilbert transform is used to extract features from stator current envelope; extracted features are then fed to a Multi-layered Perceptron to report the number of broken rotor bars, from zero to two. In (Valtierra-Rodriguez et al., 2020), short-time Fourier transform derives a time-frequency representation from motor current signals through its startup and Convolutional Neural Networks are employed to detect BRB problem.

4. Comparison of Currents and Vibrations for BRB Detection

In this section, we discuss the method that we use to compare the three-phase currents and vibrations, as describing modalities of BRB problem in induction motors. We aim to evaluate the separability of the different induction motor health classes from BRB point of view (including no broken rotor bar to four broken rotor bars), based on current and vibrations. Therefore, we can determine which modality is more effective for detecting BRB. To this end, we employ conventional deep neural networks initially; We train two multi-layer perception neural networks for BRB Detection using current and vibration signals, respectively. The results of the evaluation describes the separability of different health classes in each modality. The reason is that the classifiers are unable to detect samples that belong to different classes but overlap with each other. However, the overlapping of different classes can be because of the variations in loads. Therefore, we design a hybrid classification method that is able to compensate for load variations; Using this method, we are able to compare vibration and current signals after the effects of variations in load have been eliminated.

The figure 1 illustrates the proposed hybrid classification method in order to compensate for load variations. At first, we pair samples from different loads. Two paired samples taken from the same classes, regardless of the loads, are considered as a positive pair and two samples taken from different classes, regardless of the loads, are considered as a negative pair. Using the positive and negative pairs called *training pairs*, we train a Siamese neural network with Contrastive Loss. As a result of this training, a function as feature extractor called FE is generated. The FE maps the samples to a new embedding space. In the embedding space, positive pairs will be placed close together. It means that the samples with same classes, regardless of their loads, will be grouped. Additionally, the negative pairs will be distant from each other. As a result, different loads will be aggregated in this embedding. We then add a softmax layer to the FE and retrain it using the

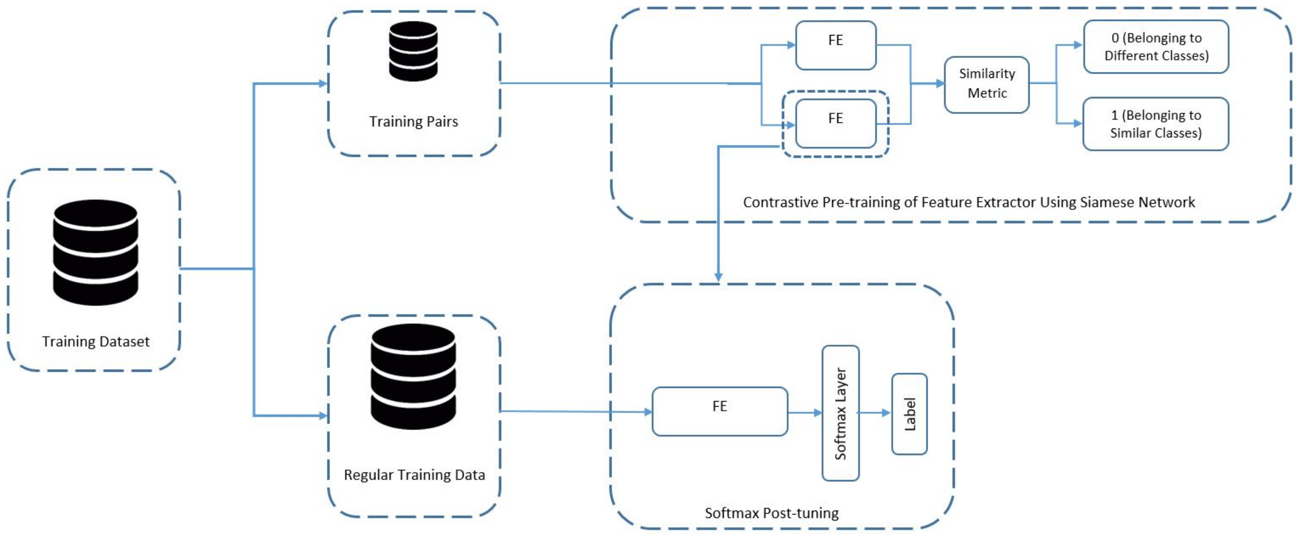

Figure 1. Visual demonstration of the Hybrid Classification Approach

available samples, similar to a conventional classifier. Using the current and vibration signals we train two classifiers using hybrid approach and evaluate the results for the purpose of comparing current and vibration signals.

5. EXPERIMENTS

5.1. Dataset

The experimental dataset for detecting and diagnosing rotor broken bar in a three-phase induction motor is used to conduct the comparative study that this paper aims to carry out(Treml, Flauzino, Suetake, & Maciejewski, 2020). This dataset includes three-phase voltages, three-phase currents and vibrations signals, collected from various locations of the motor, in various loading conditions. In addition to healthy operation of motor cases involving 1 to 4 broken rotor bars are included in this dataset. Moreover, the dataset contains eight levels of mechanical torques as loading conditions, from 12.5% to 100% of nominal load (4 N,m), to evaluate the effect of load variation. In our study, we took advantage of four load levels, including 12.5%, 50%, 62.5% and 100% of nominal load.

5.2. Data Pre-processing and Preparation Procedure

Original time domain signals in both current and vibration modalities are split to time domain signals with lengths of respectively 6667 and 1024 points long signals. Consecutively, Fast Fourier Transform is employed to alter the time domain observations to frequency domain records, as BRB is easier to detect in frequency domain. For each loading condition referenced previously, the training and testing splitting process is done using random selection. Test size of 25% is employed. Random states are preserved to assist the reproducibility of results. Moreover, the load-specific training splits are summed up to make the mixed-load training split. The mixed-load testing split can also be summed up, similarly. Feature scaling, as an important step of data preprocessing is done, using Min/Max scaling.

5.3. BRB Detection using Conventional Deep Classifiers

The first set of experiments conducted on this dataset involves training deep classifiers on both current and vibration modalities, separably. The classification problem to be solved involves detecting the number of broken rotor bars, from zero to four, given either three-phase current signals or vibrations signals. Due to the difference in the size of concatenated three-phase currents signals and its vibration counterparts, networks used for each modality is different from the other. In Table 1, the size of each network is included. Except for the last layer in each network, which is supposed to be a Softmax layer in multi-class classification problems, rest of the layers in both networks employ Hyperbolic Tangent as the activation function. As a conventional loss function for multi-class classification problems, Categorical Cross-entropy is used as the loss function to train classification networks. Moreover, the Adam optimizer is used to minimize the loss function during the training process, where the learning rate is chosen to be 0.000001 and decay is fixed as the division of learning rate by number of epochs. For the sake of training both currents and vibrations, 400 epochs provided well-stabilized training procedure, therefore same value used for both of them.

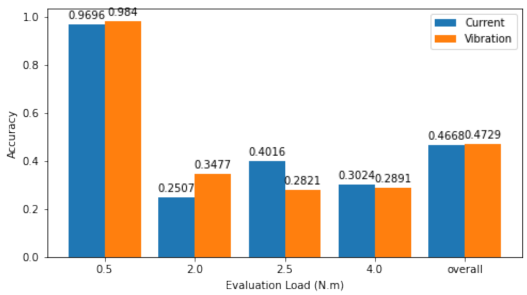

Figure 2. The results of a conventional classifier trained with the samples from load 0.5

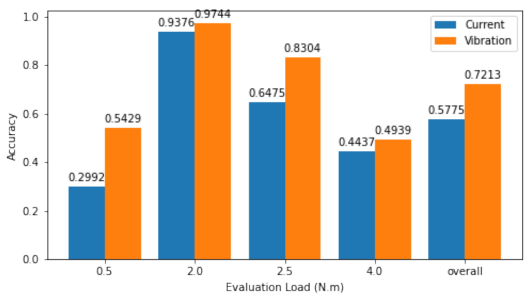

Figure 3. The results of a conventional classifier trained with the samples from load 2.0

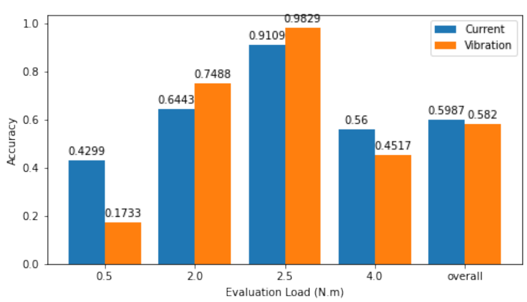

Figure 4. The results of a conventional classifier trained with the samples from load 2.5

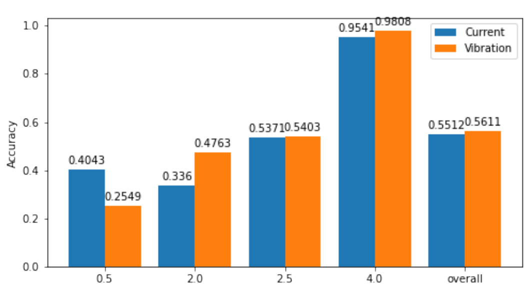

Figure 5. The results of a conventional classifier trained with the samples from load 4.0

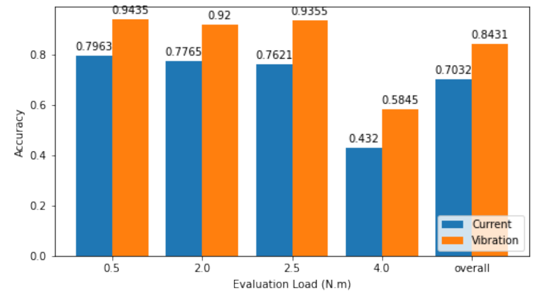

Figure 6. The results of conventional classifiers trained with the current and vibration samples from all load

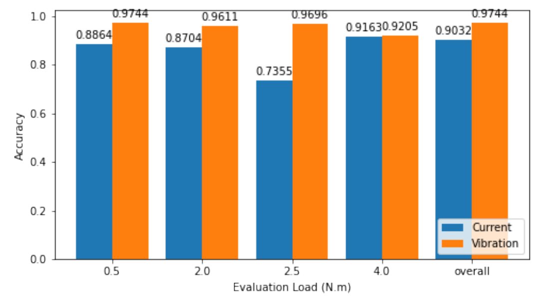

Figure 7. The results of hybrid classifier trained with the the current and vibration samples from all load

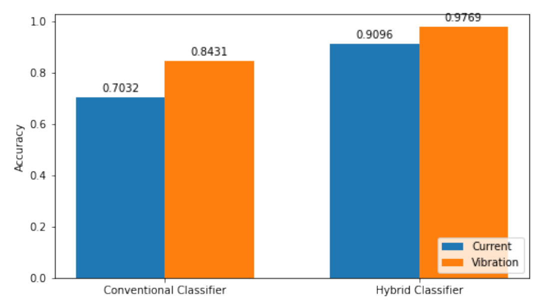

Figure 8. The effectiveness of contrastive pre-training in hybrid-classification approach on the improvement of mean classification accuracies in mixed-load scenarios

The generalizability of what is learnt by classifiers on each load over different loads is quantified by evaluating its performance over not only the training load, but other three loads and the mixture of them. Results obtained by three-phase currents classifiers and vibrations classifiers are gathered in the Figures 2 to 6. To compensate for the effect of randomness, experiments in this section are repeated over 5 trials and the mean classification accuracy is summarized . The figure 2 shows the results of a conventional classifiers that is trained using the samples from load 0.5. Likewise, figures 3 to 6 show the results of the classifiers that are trained using the samples from load 2.0, 2.5, 4.0, and mixture of all loads, respectively. Based on the results provided, it is clearly understood that both modalities perform acceptable in solving the classification problems, when the evaluation load is identical

Table 1. The Structure of Network for each Modality

Modality to be used	Neurons per Layer
Three-phase Currents	9999-7500-6000-4500-3000-1500-750-500-250-50-5
Vibrations	2560-1280-640-580-512-256-128-64-5

to the training load, however, both modalities experience severe decrease in the classification accuracy when classifiers are evaluated on loads, rather than training load. It is also obvious that in most cases, the farther evaluation load is from training load, the more drastic would be the referenced decrease. In addition to those, vibrations offers higher classification performance in mixed-load scenario, in comparison with the currents.

5.4. Hybrid Classification Approach to Overcome Data Drift due to Load Variation

Based on the results available in the Figures 2 to 5, conventional classifiers fail to perform well in mixed load scenarios, no matter which modality is used. Therefore, we evaluate the effectiveness of the proposed hybrid classifier; it means we evaluate the effectiveness of a Contrastive Representation Learning pre-training step to make the feature extraction section(classification network, excluding the softmax layer at its end) of the classification networks, to derive a more robust feature space to load variation. To this end, we use 25% of the training data available for this step. Networks employed in this section follow the exact same architecture of the networks, discussed in the previous section. Number of positive and negative pairs used during the pre-training is kept equal to preserve the pre-training step a balanced training process. Moreover, the number of pairs per each observation in training set used during the pre-training are found by increasing the number of pairs until there is no significant improvement in validation accuracy by increasing the number of pairs, in which 10 and 4 were found as optimum number of pairs for vibrations and currents, respectively. The loss function employed during the pre-training is Contrastive Loss and Adam optimizer is used as the optimizer. Learning rate is fixed at 0.00001 and 100 epochs provided sufficient iterations of training process. Similar to previous experiments, the division of learning rate by number of epochs, is used as the decay parameter of the optimizer. Afterwards to the Contrastive Representation Learning pre-training, a softmax layer is added to the feature extractor and the whole network (feature extractor and the softmax layer) is post-trained, using the remaining 75% of the training data. The post-training procedure of the whole network involving the addition of softmax layer and retraining of the whole network, employs exactly the same set of parameters used during the previous experiments. Similar to the results from previous experiments, these experiments are conducted over 5 trials to exclude the effect of randomness through training process.

According to the Figure 7, contrastive pre-training improves the classification performance significantly for all loads. In addition, the obtained accuracies per load are almost identical; it means that the hybrid classifier is able to aggregate the different loads and consequently makes higher levels of classification accuracy achievable. In addition, similar to the previous set of experiments, still vibrations outperforms currents in the classification performance. To be able to compare the the vibration and current signals using both conventional and hybrid classifiers, figure 8 summarizes the results. We can clearly see that vibration signals can be more effective for detecting the BRBs.

6. Conclusion

This paper studies the robustness of currents and vibrations towards mechanical load variation, for Broken Rotor Bar problem detection in squirrel cage induction motors. Our experiments proved that vibrations is less sensitive towards mechanical load variation. Moreover, we assessed the effectiveness of a contrastive representation learning pre-training in the reconstruction of a feature set in which data drift due to load variation is compensated. Contrastive learning-based pre-training offered significant improvement in the classification accuracy in both modalities. The superiority of vibrations over current in BRB detection is still noticeable, even afterwards of the employment of the pre-training step. Comparison of the robustness of current and vibrations towards mechanical load variation in the detection of other faults of induction motors can be considered as the subject of future work.

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