### **Anomaly Detection Using Motor Current Signature Analysis**

Motor current signature analysis can detect induction motor related faults.The ease of deployment, non-invasive installation, and relatively low cost combined with high detection accuracy are the main advantages of MCSA. For some applications, MCSA is often the only feasible and practical method.

MOTOR CURRENT SIGNATURE ANALYSIS AND FAILURE TYPES:

MCSA is based on the idea that certain electrical and mechanical faults introduce harmonics in electric current, which *can be detected through a combination of signal processing and machine learning methods*. The healthy motors work with a 50 Hz fundamental frequency (60 Hz in the US). However, during the machine’s fault development, different harmonics other than 50 Hz start to appear.

The current is measured by attaching current probes to power supply wires, which makes it relatively convenient and inexpensive to install and maintain. The range of faults detected by MCSA includes stator winding breakdown, broken rotor bar or electric bearing problems.

INDUCTION MOTOR-BASED FAULTS:

i) BROKEN ROTOR BARS

Broken rotor bars faults cause *speed oscillations in the rotor*, leading to premature wear of bearings and other components . The condition can be detected using MCSA and can be artificially generated by drilling holes in rotor bars.

ii) BEARING

In the presence of a bearing fault, the rolling elements (balls) *pass over the defect area periodically*, producing impulses with a certain frequency, which can be detected by MCSA . The condition can be artificially generated by drilling holes of various diameters.

iii) STATOR WINDING

A stator winding fault produces *unbalance in the motor currents* when anomaly occurs.

METHODS:

1)MACHINE LEARNING METHODS:

a) NON-DEEP LEARNING

b)DEEP LEARNING

2) NON-MACHINE LEARNING METHODS:

There are several solutions that do not use ML at all, despite utilizing MCSA.

TRANSFORMATIONS:

1) FOURIER TRANSFORM( time-frequency analysis)

DFT is mainly used in digital spectral analysis, filter simulation, and more.In the signal processing domain, FT decomposes a signal into frequency components.

The formula for Fourier Transform is

X(ζ ) = Z +∞ −∞ x(t)e −2πiζ t dt (1)

where x(t) ∈ C, t is time and ζ is frequency.

There are several ways to observe the motor’s fault with FFT: Short-time Fourier transform (FFT over time) and frequency over samples. They are ways to visualize the fault developing over time.

2) WAVELET TRANSFORMS(it is a time-frequency based transformation)

The signal is decomposed to multi-resolution by filters of cut-off frequencies.

The DWT is defined as

DWT (j, k) = 1 √ 2 j Z x(t)ψ( t − 2 j k 2 j )dt

3) HILBERT TRANSFORMATION(signal’s demodulation operations)

With Hilbert transformation’s usage in fault signature, instantaneous frequency and amplitude can be extracted. Therefore, faulty component induced signal’s modulation can be showed.

The Hilbert transform is defined as:

H(x(t)) = 1 π Z +∞ −∞ x(τ ) 1 1 − τ dτ

Essentially three phase motor signatures are provided to Hilbert transform and to obtain Aa, Ab, Ac, φa, φb, φc where A is amplitude modulation and φ is phase modulation respectively for phases a, b and c.

4) PARK TRANSFORMATION

The Park transform is the conversion of a three-phase system to a two-phase system to describe three-phase IM phenomena with Park’s vector .

xd (t) = r 2 3 xa(t) − 1 √ 6 (xb(t) − xc(t)) (4) xq(t) = 1 √ 2 (xb(t) − xc(t)) (5)

The space vector: xs(t) = q x 2 d (t) + x 2 q (t) (6)

where xd and xq are Park’s vector components

that are made of weighted three-phase components and subtractions from each other.

*After Park transformation*, the healthy motor DQ pattern shows a *circular shape*. *When a fault is introduced, the shape becomes* *elliptic*.The method is applying Park transform on three phases then taking vector modulus. The normalization is done by the dividing phase current by Park’s vector modulus.

1) NON-DEEP LEARNING

a: SUPPORT VECTOR MACHINES

Support vector machines (SVM) is a *supervised learning model* which is used in *classification* tasks.SVM’s are used mainly in detection problems with both vibration and MCSA based data.

Centrifugal Motor Faults Oriented Solutions:

They use line-current probes and accelerometers to collect time domain-based data and convert it to the power spectrum. They compare and choose the best suitable features: Mean, standard deviation and 1/ standard deviation . Then they train and test with a multi-support vector machine (MSVM). They find that every fault alters the flow patterns with a unique effect on signatures.e. Finally, the final obtained test classification accuracy for the same speed training/testing is 83.2% which gets worse if based on a different speed instead or gets better if more resolution is used.

Induction-motor Faults Oriented Solutions:

IM faults based paper authors use multi-class SVMs to focus on the cage induction machines’ rotor fault diagnosis with five conditions: Healthy, broken bar, broken end-ring, static eccentricity (EC), dynamic EC. The test rig created is 1.5 kW, 50 Hz, 220 V and one pair pole cage induction machine.

We can use FFT to derive stator current signal’s frequency spectra and extract other features. With wavelet transformed data ,neural network synthesizing scheme gave the best result but has worse performance with random hidden neurons. The mixture matrix synthesizing scheme is favored with great accuracy and a lower time cost. In the end, mixture matrix/SVM has significantly less training time despite its very small lower accuracy as per the literature survey.

In another research, Toma and Kim use MCSA IM data from a university dataset. Their dataset consists of two current signals with 180 degrees of phase difference and has 17 different combinations of metadata such as but not limited to: bearing, damage in the inner ring. The dataset was labeled with 3 main labels: Healthy bearing, inner ring or outer ring failure. To classify 10 features (e.g. mean, median, variance, skewness) a random forest, SVM, K-Nearest Neighbor (K-NN) algorithms were used. The data was partitioned to 70:30 and 80:20 which are named as training:testing respectively. The performance of random forest, RF and K-NN algorithms is compared using precision and recall metrics. The reported accuracy of SVM and KNN using GridSearch method was 99% and RF has 98% respectively. On top of that, the authors observe that SVM performs slightly better than KNN with a higher recall (99% against 98% respectively).

There are other types of transformations that can be used with MCSA data as well. With the implementation of Hilbert Park transforms, Hilbert modulus current space vector (HMCSV) and Hilbert phase current space vector (HPCSV), the faults like broken rotor bars, supply voltage.asymmetry, air-gap eccentricity and outer raceway ball bearing can be detected with SVM.As per the literature survey SVMs in fault detection utilize vibration data instead.

b: MULTI-LAYER PERCEPTRON

MLP has three core elements: Input connections with ‘‘weights’’ and ‘‘sum’’ functions to gather results and an activation function. MLP/ANN uses feed-forward neural network architecture, and its neuron weights are updated (aka trained) by the backpropagation algorithm.

INDUCTION-MOTOR FAULTS ORIENTED SOLUTIONS:

The loss is calculated with MSE and the correlation factor.the current spectrum increases as applied load increases, and RMS, kurtosis features provides a good indication about the bearing’s state.

MLP’s in fault detection can also utilize vibration data.

c: RANDOM FOREST

Random forest (RF) is an ensemble classifier that is made of a collection of a tree-structured classifiers. RF uses bootstrap sampling to select k samples from the training dataset, creates k decision tree models based on these samples and gets k classification results. After k classification results, the classifiers vote for the final decision.

INDUCTION-MOTOR FAULTS ORIENTED SOLUTIONS

fault detection can also utilize vibration data

2) DEEP LEARNING

a: CONVOLUTIONAL NEURAL NETWORK:

CNN is a deep learning method that uses signals or images as inputs. The whole network is built by several convolutional layers that compute the dot product between the input image and set of convolutional filters .

CNN is also used to detect broken rotor bars in induction motors. Valtierra-Rodriguez et al. It uses CNN’s image classification ability to detect the faults that appeared on the short-time Fourier transform-based time-frequency (STFT) plane, and also uses MCSA for current signals in the transient state. Four induction motor cases are used: half-broken rotor bar, one broken rotor bar, two broken rotor bars, and a healthy rotor.

b: RECURRENT NEURAL NETWORKS AND LONG-SHORT TERM MEMORY

Given that motor current signatures changes over time, the usage of recurrent neural networks (RNN) or long-short term memory (LSTM)s are not uncommon.

LSTMs and (1D -) CNNs detect the fault from different perspectives, Khan et al. [55] investigate their performance on fault detection separately.4 layered LSTM got 83% accuracy which is lower than (chosen optimal model) seven-layered CNN that got 99% accuracy as per the literature survey.

SUMMARY AND PERFORMANCE COMPARISON:

Most successful methods to classify CP/IM faults are CNN, RF and MLP with their over 95% success rates.Therefore, with features used appropriately, near-perfect accuracies can be obtained.

PRACTICAL CHALLENGES:

As much as MCSA is an attractive method, just like VSA, it has its own challenges and shortcomings for successful implementation.

A. DATASETS

The research of machine learning algorithms for fault detection and condition monitoring invariably requires access to large amounts of accurate current data.

Given that the motors can have linear degradation in performance or sudden drops , it is crucial to have a reliable and correctly annotated dataset and a model. Collecting such dataset can be extremely challenging as any monitoring system has to be operating for a long enough time to detect its degradation over time and its eventual failure.Any resulting dataset would be imbalanced and dominated by healthy signatures with a very small proportion of faulty data. Invariably, the datasets from such experiments could be limited, and not all faults could be captured and isolated (especially in real-time).

B. ROBUST DATA COLLECTION

Even though MCSA is a non-invasive method, which is much easier to install and operate compared to vibration based or pressure-based methods. The installation usually involves putting current clamps around the cables with the data fed into a microcontroller or a single board computer. However, deploying and operating a robust data collection system can still be challenging for multiple reasons. The control panels, where MCSA hardware is attached can be in areas with no or poor wireless connectivity. Even if Internet access is available, missing packets or any other hardware problem can still happen to disrupt the system. On top of that, the captured data can be noisy and make it hard to extract the desired features. Processing this data locally requires either a relatively high-performance system or a reliable wireless connection. Besides, processing and monitoring the data in real-time require a system with a specific software installation which can further increase the cost.

CONCLUSION

Having described the relevant machine learning methods, data acquisition techniques and metadata, it can be concluded that CNN and MLP based neural network solutions (when paired with a good training algorithm or transformation) perform better than SVM or other solutions (e.g. LSTM).These ML developments in the future have a great potential in terms of both prediction accuracy and resource requirements.

REFERENCES

<https://www.artesis.com/motor-current-signature-analysis/#:~:text=To%20identify%20the%20exclusive%20current,a%20combination%20of%20these%20faults.>