Introducing a new comprehensive model for fault detection and condition monitoring of rotor bars of large induction motors based on MCSA and ZCT methods

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Abstract

In this research, a model is presented to detect and monitor the rotor bar's condition of large motors. This proposed model uses two diagnostic methods MCSA and ZCT, to extract the fault components. The input of the proposed model is only the motor current at two levels of 80% and 100% of the nominal motor load, which by using the two methods MCSA and ZCT and making changes in how to use them can be the disadvantages of other methods such as incorrect detection of rotor bars in Large motors with variable load, the harmonical stator voltage (or the presence of the drives) and asymmetric conditions. The extracted components are classified using neural network, instead of experimental and human resources constraints. Using this classification algorithm is high accuracy and the ability to implement in conventional processors. The proposed model has been trained and tested using currents of real large motor data and 96.87% accuracy using neural network to detect faults and monitor the online status of the rotor bars. On the other hand, the proposed model has been implemented in the industrial environment (Firoozkooh Cement Factory) and has been able to correctly determine the rotor bars of 4 large suspicious motors announced by the factory technicians.

Index Terms

condition monitoring, faulty rotor bar detection, large induction motor, , neural network, classification, MCSA, ZCT.

I. Introduction

ELECTRIC machines play a very important role in generating electricity and generating the driving force needed for various industrial and non-industrial applications. There are more than 300 million electrical motors in the world known as workers in the modern world. Large motors are essential members of electric machines that play key roles in various industries such as petrochemicals, food, cement, steel, and so on[1].

Large electric motors play a very important role in various industries. There are many problems in diagnosing and monitoring the condition of these large engines. One of these problems is the lack of laboratory facilities due to high costs and inefficiency in creating intentional defects in them and analyzing engine variables. On the other hand, the huge difference between real and laboratory conditions, such as the effects of other electrical devices on the motor and changes in power supplies, makes it impossible to match the fault components in real and laboratory conditions.

Due to the effective and undeniable role of these machines is vital and sensitive industries, their correct and uninterrupted operation is always one of the most important concerns of industry owners.

Lack of proper operation of these motors causes heavy repair and competitive costs in the production process of manufacturers, so the first and most important step to prevent these problems is to predict and detect possible faults in electric motor operation. Other important effects that these defects can cause are adverse effects on the power supply line that can severely affect power quality indicators, the most important of which are: creating harmonic and between harmonics, voltage imbalance and voltage drop, etc., which causes negative effects on the performance of other devices and costs due to the loss of power quality indicators, and its continuation becomes much more harmful. Doing this requires periodic and permanent monitoring of motors. The most important steps are to select the most effective variable for electric machine monitoring. This choice can pave the way for analysis because the accuracy of these analyzes is inevitable due to the high cost of repairing and compensating for these defects[2].

A. Research Statement

Rotor bars are one of the components of large electric motors that are always prone to fault and breakage. Engine asymmetry, variable loads, and erosion are the most important reasons for this defect[3].

Monitoring the electrical condition of the motor has many advantages over other monitoring methods. The most important of these benefits is the online monitoring and uninterrupted operation of the electric motor. If there is a defect in the rotor bars, if the breakage in the bars is not so great that the motor has a problem in its operation, it can continue to work, but if the fractures are more than a certain extent, the motor must be stopped the repair, so monitoring the condition of the rotor bars is much more important than detecting them at different times[3].

If condition monitoring is done, they need correct and practical analysis, which due to the great importance of power quality indicators, the most appropriate method of analyzing this type of monitoring is power quality analysis, which in this study tries to detect errors. Defects of large electric machine monitoring methods based on power quality indicators.

There are many ways to monitor the condition and troubleshoot different electric motors, but in the case of large electric motors this is very rare. The main reason for not monitoring the permanent condition in the industry on electric motors is the high cost of technical inspections and disruption in production[2]. As a result, periodic inspections only lead to electric motor troubleshooting. On the other hand, there is no reliable and reliable way to monitor the condition and diagnose defects of large engine components.

B. Related work

There is a lot of research to diagnose and monitor the condition of induction motor rotor bars[4]. The methods of use in this field are both steady state and transient. Due to the fact that large induction motors are started in different ways, it is not possible to fully implement the transient state analysis, so the steady state analysis is considered. Various methods are used to detect defects in rotor bars. The most important are Motor current signature analysis (MCSA), Park vector analysis(PVA), Instantaneous power analysis(IPA) and Zero-crosses tracking technic (ZCT)[5], [6], [7]. MCSA method widely used in troubleshooting and monitoring the condition of various components of electric motors. On the other hand, ZCT method has been used in some studies due to its advantages[5], [7]. In addition to their advantages, each of these methods has disadvantages that cannot be used alone. The MCSA and ZCT methods are widely used in the detection of broken rotor bars[5], [7], [8], [9], [10]. Researches using MCSA and ZCT methods have mostly been done for low and medium voltage induction motors. However, in monitoring the condition of large motors or high voltages, researches have been done at the level of case reporting and diagnosis using simulation data [3]. On the other hand, fault detection of rotor bars is done using the proposed and experimental range. However, recognizing and classifying the status of components based on collected data and using learning-based algorithms leads to better results [4]. Machine learning is one of the most effective methods in classification issues. Algorithms have been used to detect the condition of the rotors and have good results. The first step to having a proper classifier is to define effective features. In[11], using the collected data, induction motors in laboratory conditions and their classification with algorithm have achieved 92.87% accuracy. In this research, only the data of a healthy motor is given to the algorithm and the number of poles and the speed of the motor are considered as diagnostic features. But this feature does not provide the algorithm with any specifications of the motor and working conditions of the motor. In [12], a multi-layer artificial neural network is used to classify input data and their properties. In another study, artificial neural network and fuzzy algorithm have been used [13]. This combination of the two methods increases the time and volume of calculations, and on the other hand, the features are given to the network in an unsupervised manner. In [14], [15], [16], various unsupervised methods such as deep learning and fuzzy algorithm are used, but because the properties are obtained only based on the computational method, they can not achieve high reliability.

II. THEORETICAL APPROACH

Various methods are used to detect defects in rotor bars. The most important are Motor current signature analysis (MCSA), Park vector analysis(PVA), Instantaneous power analysis(IPA) and Zero-crosses tracking technic (ZCT).

In addition to their advantages, each of these methods has disadvantages that cannot be used alone. The MCSA and ZCT methods are widely used in the detection of broken rotor rods. The advantage of the MCSA method is the ease of calculating the fault components using the short-time Fourier transform (STFT). On the other hand, to calculate the fault components, motor current, rotor speed and supply voltage frequency are required. This method in the situation that the supply voltage of the rotor has harmonics and the connected mechanical load is variable, the fault components obtained from this method are changed and the values of the fault components are not reliable.

The frequency of fault components of the MCSA method is obtained from equation 1 that fs is main frequency of stator voltage and s is slip of rotor.

$$f_{brokenbar} = f_s * (1 \pm 2ks), k = 1, 2, 3..., n \tag{1}$$

On the other hand, the fault components obtained from the ZCT method do not change with the change of the mechanical load connected to the rotor, but the effect of the harmonics of the input voltage and its frequency is still present. In addition to extracting the fault component of the rotor bars, this method also provides motor slip values, which is a very important advantage that has only stator current. The frequency of fault components of the ZCT method is obtained from (2*s*fs) frequency.

1) Data collecting: Data collection from large electric motors is one of the most difficult parts of research due to their inflexible working conditions. In the case of small and medium electric motors, it is possible to take data from them with different loads and conditions in laboratory conditions, but in the case of large motors, their working conditions determine the type of data.

As mentioned before, data collection and condition monitoring should not interrupt the operation of the electric motor. Therefore, in this study, for data collection and monitoring of the status of rotor bars from current samplers and only using current clamps, data collection There have been.

The stator currents of 23 real motors used in steel and rolling, cement, petrochemical and transportation industries are sampled in 80% and 100% of the nominal load. The rotor bars of these motors are classified into 4 classes: healthy (0), with a fraction in one bar (1), with a broken bar (2) and with more than one broken bars (3).

A summary of the general characteristics of the sampled electric motors is given in Table I.

Input voltage	3-6 kV	**Rotor voltage**	1-1.6 kV
Input current	200-500 A	**Rotor current**	600-960 A
Input power	1.9-4.5 MW	**Power factor**	0.86-0.88
Frequency	50 Hz	**Rotor speed**	988-994 RPM

Table I: the general characteristics of the sampled electric motors[17]

To complete the data, along with the real data, a large electric motor simulated in ansys elctromagnetics software is used. This electric motor is designed based on the specifications of ABB large electric motors and is simulated in different conditions of Table II. The motors are named SM1 to SM12 (simulated motor).

Motor name	**Status**	Motor name	status
SM1	healthy	SM2	healthy *
SM3	fracture in one bar	SM4	one broken bar
SM5	one broken bar*	SM6	one broken bar and fracture in another bar*
SM7	2 broken bars	SM8	2 broken bars*
SM9	2 broken bars and fracture in another bar*	SM10	more than 2 broken bars (3 symmetrical broken bars)*
SM11	more more than 2 broken bars (3 asymmetrical broken bars)*	SM12	more more than 2 broken bars (6 asymmetrical broken bars)*

Table II: simulated motors in different conditions of

The condition of the rotor bars of the all sampled electric motors is as shown in Table III.

Motor bar status	Assigned number	Frequency
Healty	0	10
Fracture in one rotor bar	1	9
One broken rotor bar	2	9
More than one broken bar	3	7

Table III: The condition of the rotor bars of the all sampled electric motors

2) Description of the proposed model: Considering that most of the large motors installed in the factory are operated using the drive and on the other hand the input voltage of the motors and drive from the distribution lines is harmonious, the proposed method must be compatible with the stator input voltage. In order to eliminate the disadvantages of MCSA and ZCT methods, optimal use of the output components of these two methods and matching the condition of rotor bars of large induction motors with their real conditions using artificial intelligence, the proposed model is presented according to Figure 1. The input of this model is only a current sampling device. On the other hand, the sampling rate of the sampling device should be such that the signal spectrum in the middle band range can be obtained from the current signal. Current sampling devices on the market are compatible and can be operated.

The reason for using the stator current waveform at 80% and 100% of the rated load is the effect of the fault components by changing the motor load. Changing the motor load causes the motor speed to change as a result of slipping and fault components of the rotor bar. On the other hand, these changes lead to disturbances in the motor current, which leads to a decrease or increase in the fault component. Simultaneous use of motor current at different loads causes the model to adapt to different load modes of its motor and minimize the impact of load changes.

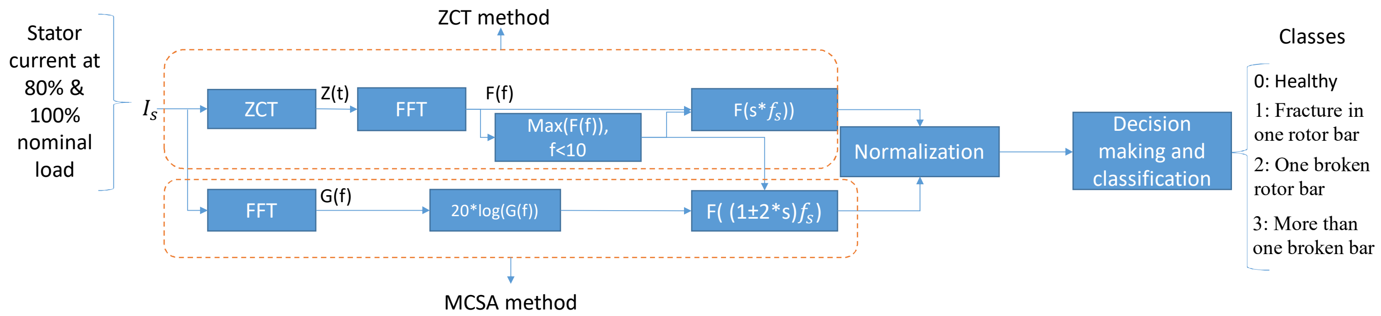


Figure 1: The proposed model

On the other hand, the choice of 80% and 100% of the nominal load is because according to experts in this field, large motors are often used in this load range due to economic issues and their efficiency, as a result of data extraction from the motor. Different in these two levels and real conditions can be done easily and the fault components show themselves well in these two levels.

The motor stator current is applied in two modes of 80% and 100% load in two parallel branches. In the upper branch of the waveform, one of the phases enters the ZCT block and its time signal Z(t) is obtained. In the other block, the Fourier transform is taken from the Z(t) signal to obtain the spectrum of this signal for analysis.

The resulting Fourier transform enters the next block, which is responsible for obtaining the exact frequency of the power line and the amount of slip. In this way, the frequency frequency of the largest component value in the range of 0 to 10 Hz gives the value s*fs. The reason for using the range 0 to 10 Hz is the stable range of slip frequency in induction motors.

In addition to the accuracy of slip values and source frequency, the main advantage of using these values is the lack of use of measuring equipment such as speedometers and frequency meters, which is inexpensive and easy to use. The value of s*fs in the next block gives the value of the component of the broken rotor rod by ZCT method. This component is expressed in dB. This component completely covers the changes in the load and speed of the motor and does not disrupt the error components in this method.

In the lower branch, the current of one stator phase enters the Fourier transform block and using s*fs obtained from ZCT method, the values of rotor bar fault components are obtained in MCSA method. This minimizes the disadvantages of the MCSA method in affecting the harmonic conditions and perturbations in the stator power supply. Using the main frequency of the stator power line by ZCT method, the effects of the drive and frequency changes are also eliminated.

The fault components obtained from both ZCT and MCSA methods have different sufferings that due to the use of machine learning methods, it is necessary for each component to be normalized to its values. Failure to normalize the data leads to inadequate learning of decision-making methods, which impairs the efficiency of the model in diagnosing the defect.

One of the suitable methods for data preprocessing is data normalization by MAX-MIN scaling method. This method is compatible with all methods of machine learning and according to experimental results, leads to desirable learning and diagnosis. Data are normalized by MAX-MIN scaling using Equation 2.

$$X = \frac{x - x_{\min}}{x_{\max} - x_{\max}} \tag{2}$$

Various ranges have been proposed to classify the condition of rotor bars, but these ranges are based on experience alone and cannot be used for large motors in real conditions. In real conditions, the input voltage of the motor has different harmonics and is not completely balanced, thus affecting the fault components and erroneously falling within the usual range and causing misdiagnosis.

As a result, learning-based methods are used to diagnose the accuracy and compatibility of the diagnosis with the real conditions of the motor and to consider all the problems mentioned. This method covers the human error and changes caused by environmental conditions.

In the last and most important part, the block is the decision maker or classifier. Due to the fact that large motors are not able to monitor the situation for various reasons such as the cost of equipment or lack of expertise, in this study, a learnable neural network is used to monitor the rotor bars.

The normalized fault components are divided into two parts: test and training data. The best state of the neural network is obtained to monitor the condition of large motors, and the weights obtained are stored for use in industrial environments.

In order to easily implement the model in common processors, an attempt has been made to select the fastest and simplest configuration for the decision block. The configuration used, in addition to being simple, has the ability to detect and monitor the condition of rotor bars with high accuracy. The number of output layers is equal to 4 classes and the number of hidden layers is equal to 1000. The general structure of the decision block is shown in Figure 2.

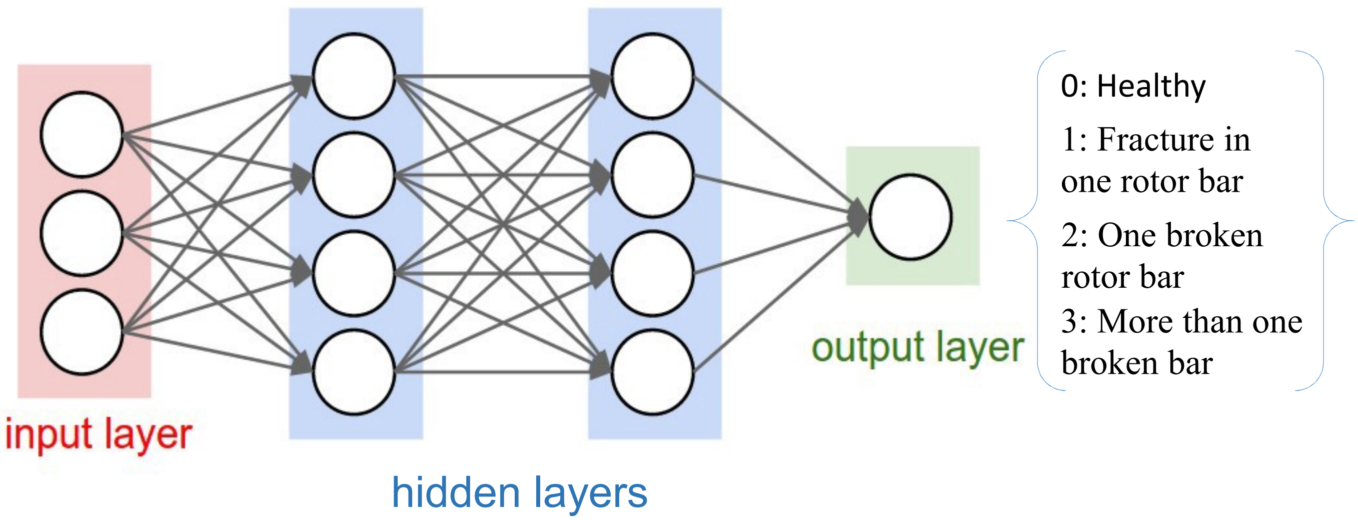


Figure 2: The general structure of the decision block

III. Result

First, by applying the collected data at two levels of 80% and 100% of the nominal load to the proposed model, the neural network is studied. 75% of the data is dedicated to learning and the remaining 25% to network testing. 4 classes considered as: The rotor bars of these motors are classified into 4 classes: healthy (0), with a fraction in one bar (1), with a broken bar (2) and with more than one broken bars (3). The normalized fault components obtained from the model using the MAX-MIN scaling method are shown in Figure 3. The confusion matrix in the learning and testing phase of the model is shown in Figure 4.

To compare the methods used, statistical indicators (metrics) used in machine learning methods should be used. The most important of these are:

$$Recall = \frac{Tp}{(Tp + Fn)} \tag{3}$$

$$Precision = \frac{Tp}{(Tp + Fn)} \tag{4}$$

$$F1 = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \tag{5}$$

Tp: is the number of cases that have been correctly detected.
Fp: The number of incorrectly detected cases.
Fn: is the number of correct cases that have been misdiagnosed.
Table IV shows the statistical indicators mentioned in the models used.

Precision	Recall	F1
96.87%	95.83%	96.06%

Table IV: the statistical indicators of the model in training and test phase

IV. INDUSTRY APPLICATION

To validate the model in real and industrial space, it is necessary to implement the model in an industrial environment where large engines are used.

As mentioned in former, the input of this model is just a current sampling device. The sampling rate of the sampling device should be such that the signal spectrum in the middle band range can be obtained from the current signal. Therefore, the model presented in this research is compatible with all current sampling devices on the market. Can be exploited. On the other

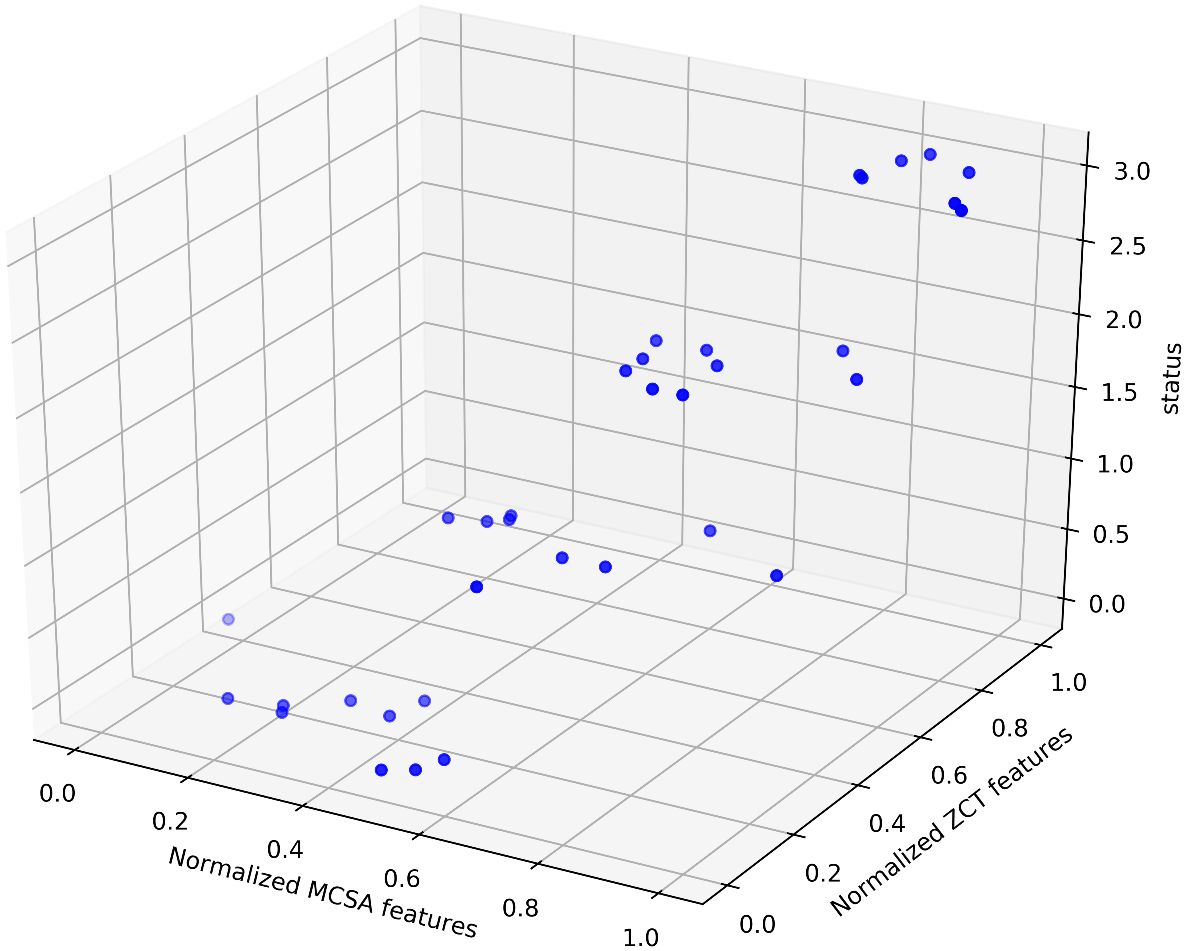


Figure 3: The normalized fault components obtained from the model using the MAX-MIN scaling method

hand, the electrical connection between the proposed model and the motor and its components is not established, which causes interference in the operation of the motor.

Four motors from a cement factory in Iran (Firoozkooh Cement Factory) have been selected for sampling and testing. These motors are for raw material milling, ventilation, cement milling and curing, and ventilation of cement curing motor. The currents of all four motors are sampled in two modes, 80% and 100% of the rated load. The collected data include the compensation of motors fed with harmonic voltage (THD$<$0.04) and motors with variable load[17]. The specifications of the sampled motors are given in Table 11.

The collected data is entered into the model in raw form without any change in sampling rate or other current signal characteristics. In the following, separate methods are applied and then the presented model is applied to the data collected from the motors[17].

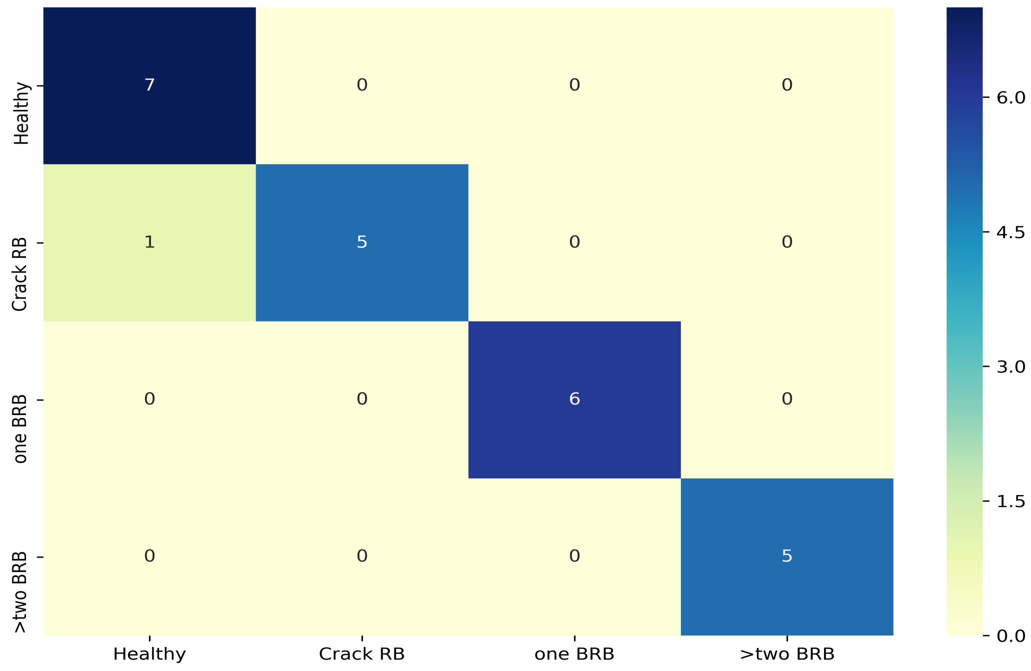
The results of applying the sampled current signals from the motors by MCSA, ZCT methods and the proposed model are shown in Table V.

V. Conclusion

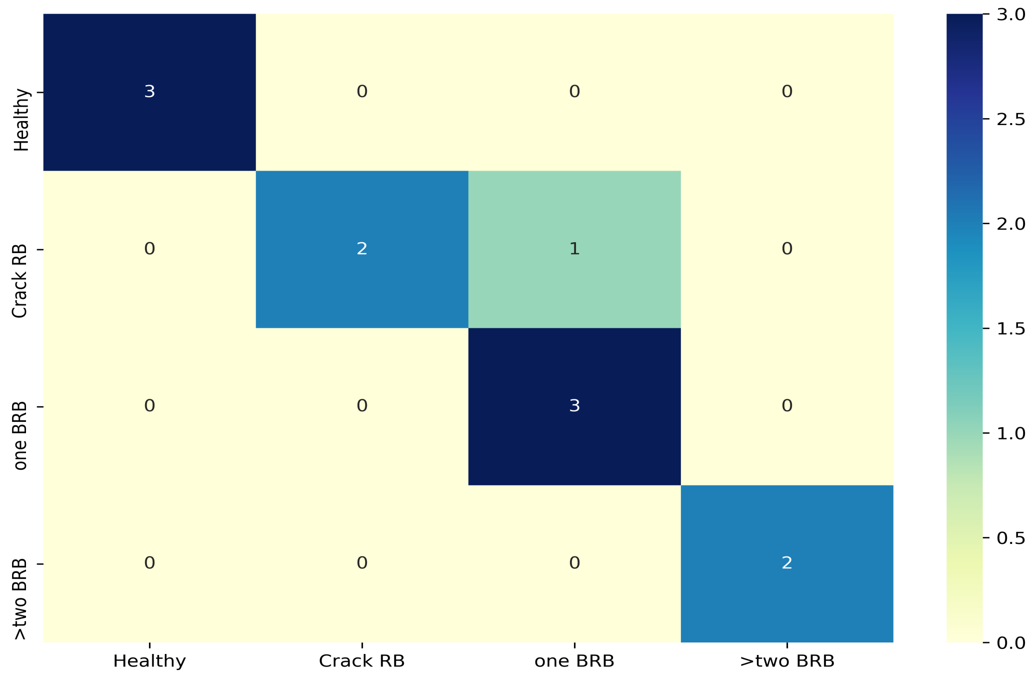
Due to the fact that the ranges provided to detect the fault of the rotor bars of induction motors are purely experimental and the conditions and specifications of the motors are not considered, in this study, learning-based algorithm (neural network classifier) has been used.

By properly combining MCSA and ZCT methods and intelligently using their output components, the disadvantages of the methods can be eliminated and the fault diagnosis can be minimized.

The problem of changing the motor speed and source frequency around the distribution network frequency (presence of electrical motor drives) is eliminated by online frequency extraction and slip using the ZCT method and by sharing it by the MCSA method.



(a) The confusion matrix in the learning phase



(b) The confusion matrix in the testing phase

Figure 4: The confusion matrix in the learning and testing phase of the model

Motor name	ZCT diagnosis	MCSA diagnosis	Proposed model	Actual status
raw material milling motor	fracture in one bar	fracture in one bar	healthy	healthy
ventilator	fracture in one bar	fracture in one bar	fracture in one bar	fracture in one bar
cement milling and curing motor	one broken bar	More than one broken bar	More than one broken bar	More than one broken bar
cement curing ventilator	healthy	healthy	healthy	healthy

Table V: The results of applying the sampled current signals from the motors by MCSA, ZCT methods and the proposed model

On the other hand, feeding the model with motor currents at two load levels of 80% and 100% of the rated load eliminates the problem of changing the fault components with variable load levels.

According to Table 444, the model can monitor the condition of large motor rotor bars with very high accuracy of 96.87% in completely real conditions and under variable loads and diagnose their faults.

Due to the lack of stator current data of large motors and many problems in collecting these data, in addition to the validity of the model with real and simulated data under real conditions, by implementing the proposed model in an industrial environment and completely actual, the model is validated. As the results are presented, the proposed model can well monitor the condition of the rotor bars and detect defects in the rotor bars of the motors that are used in real conditions well, while the use of conventional methods alone is associated with error.

References

[1] "High-efficiency motors." http://www.impelmotors.com/efficiency-overview/. (Accessed on 02/02/2021).

[2] P. Zhang, Y. Du, T. G. Habetler, and B. Lu, "A survey of condition monitoring and protection methods for medium-voltage induction motors," *IEEE Transactions on Industry Applications*, vol. 47, no. 1, pp. 34–46, 2010.

[3] A. Shaeboub, *The Monitoring of Induction Machines Using Electrical Signals from the Variable Speed Drive*. PhD thesis, University of Huddersfield, 2018.

[4] O. E. Hassan, M. Amer, A. K. Abdelsalam, and B. W. Williams, "Induction motor broken rotor bar fault detection techniques based on fault signature analysis–a review," *IET Electric Power Applications*, vol. 12, no. 7, pp. 895–907, 2018.

[5] M. Messaoudi and L. Sbita, "Multiple faults diagnosis in induction motor using the mcsa method," *International Journal of Signal and Image Processing*, vol. 1, no. 3, pp. 190–195, 2010.

[6] K. Bacha, S. B. Salem, and A. Chaari, "An improved combination of hilbert and park transforms for fault detection and identification in three-phase induction motors," *International Journal of Electrical Power & Energy Systems*, vol. 43, no. 1, pp. 1006–1016, 2012.

[7] Y. Wang, *The ZCT method of induction motor failure prediction and speed monitoring.* PhD thesis, University of Sussex, 1997.

[8] W. T. Thomson and M. Fenger, "Current signature analysis to detect induction motor faults," *IEEE Industry Applications Magazine*, vol. 7, no. 4, pp. 26–34, 2001.

[9] I. Ahmed, *Investigation of single and multiple faults under varying load conditions using multiple sensor types to improve condition monitoring of induction machines.* PhD thesis, 2008.

[10] H. Çalış and A. Çakır, "Rotor bar fault diagnosis in three phase induction motors by monitoring fluctuations of motor current zero crossing instants," *Electric Power Systems Research*, vol. 77, no. 5-6, pp. 385–392, 2007.

[11] U.-G. Krebel, "Pairwise classification and support vector machines," *Advances in kernel methods: support vector learning*, pp. 255–268, 1999.

[12] G. Singh *et al.*, "Development of an intelligent diagnostic system for induction machine health monitoring," *IEEE Systems Journal*, vol. 2, no. 2, pp. 273–288, 2008.

[13] W. Xu, D. Wang, Z. Zhou, and H. Chen, "Fault diagnosis of power transformers: application of fuzzy set theory, expert systems and artificial neural networks," *IEE Proceedings-Science, Measurement and Technology*, vol. 144, no. 1, pp. 39–44, 1997.

[14] T. Ince, "Real-time broken rotor bar fault detection and classification by shallow 1d convolutional neural networks," *Electrical Engineering*, vol. 101, no. 2, pp. 599–608, 2019.

[15] S. Abdellatif, C. Aissa, A. A. Hamou, S. Chawki, and B. S. Oussama, "A deep learning based on sparse auto-encoder with mcsa for broken rotor bar fault detection and diagnosis," in *2018 international conference on electrical sciences and technologies in maghreb (CISTEM)*, pp. 1–6, IEEE, 2018.

[16] I. Chouidira, D. E. Khodja, and S. Chakroune, "Fuzzy logic based broken bar fault diagnosis and behavior study of induction machine," *Journal Européen des Systèmes Automatisés*, vol. 53, no. 2, pp. 233–242, 2020.

[17] A. Attar and h. Mokhtari, *Large motor condition monitoring using PQ indices*. PhD thesis, Sharif university of technology, 2021.