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# Broken Rotor Bar Fault Identification using Current Signature Data and Deep Learning

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**Abstract:** Three-phase induction motors (IMs) are used widely used in industrial and transportation applications owing to its cost-effectiveness, simple construction, and high efficiency. However, extensive use of IMs without maintenance causes operation failures and economic losses. The broken rotor bar (BRB) is one of the most occurring faults in rotating machines. To avoid this fault an efficient condition monitoring system is required for diagnosing BRB fault in motor. This paper presents, a BRB fault identification method based on Deep Learning (DL) models. The proposed system acquires the data using non-invasive current sensors through the myRIO board, which offers efficient data acquisition due to its FPGA capabilities in it. The acquired data is used to train DL models and then it is utilized to test the models in order to determine the motor condition. Among the employed DL models, the Long-Short Term Memory (LSTM) achieved best with 100% classification accuracy with raw data. This proposed approach provides an effective and robust BRB fault detection.

**Keywords:** Broken Rotor Bar, Condition Monitoring, Current Signatures, Deep Learning, FPGA

# 1. Introduction

Three-phase induction motors (IMs) are employed in several industrial, transportation, and home based applications because of their low cost, smooth operation, and ease of maintenance. Broken rotor bars (BRB) are one of the most common motor failures, it has a share of almost 9% of all faults which occur in IMs [1-3] as depicted in Fig. 1. Because of the small air gap, the motor is vulnerable to an imbalance of magneto-motive force and magnetic pull force. Significant thermal and mechanical stress is applied to the rotor bar which results in rotor bar failure. There will certainly be fatalities and severe financial losses if the motor breaks during the production process [4-6].

Condition monitoring of IMs is crucial as faults like BRBs affect performance with continuous degradation. BRB fault causes consumption of additional current which ultimately heats the IM under operation. When there are faults with the rotor bar in IM, the starting and tripping torque of the IM are both lowered [7, 8]. Therefore, Condition monitoring is a continuous procedure that assists in the prevention of unexpected system breakdown. The primary reasons for using condition

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monitoring are enhanced availability, damage avoidance, and increased dependability. Its use results in the development of prognostics, which allow for the prediction of the system's future health [9]. Condition monitoring methods based on Artificial intelligence (AI) have been extensively used for fault detection and classification in electrical systems like IMs. Deep Learning (DL) as an emerging subdomain of AI, has also been explored for condition monitoring of industrial systems [10, 11]. To make better use of deep learning's robust and intelligent nature; practical ways such as condition monitoring systems that can be successfully used in industrial applications must be created [12].

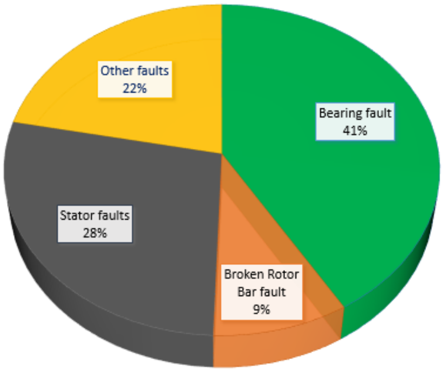


**Fig. 1** Induction motor fault classification

Generally, IM failures are caused by a lack of ventilation, high loads at low speeds, repeated start-stops, and external influences [13]. Because of their versatile application options, low maintenance, and robustness, three-phase Squirrel Cage Motors (SCIM) is the driving force behind the 4.0 Industrial Revolution. It is used in a variety of industries, including mining, oil, cement, textiles, and many others [14, 15]. Broken rotor bars, stator faults between revolutions, and bearing failures are all common causes of failure in machines of this type. These can lead to fault with disastrous consequences. The fault occurs in the rotor that causes to damage the motor and becomes rough. The rotor fault may cause heating and long-term usage without maintenance [16-18].

For effective motor faults identification, different DL models are being widely explored for effective condition monitoring of industrial motors and have yielded effective results [19, 20]. Relating to this, the authors of [21] have worked on BRB fault detection in induction motor operated under low load. They have used Hilbert transform (HT) with Artificial Neural Network (ANN) to detect the BRB condition of the motor. The proposed approach effectively detected the correct number of BRB faults using the current data obtained via HT as the diagnostic signal. K. Edomwandekhoe and X. Liang [22] have investigated ANN and Support Vector Machine (SVM) models for BRB fault classification in motors. The Fast Fourier Transform (FFT), Yule-Walker Estimate by Auto Regression (YUL-AR), and Matching Pursuit (MP) methods were employed for feature selection from stator current signatures. The SVM model yielded 100% accuracy compared to the ANN which achieved 95% accuracy. Similarly, authors of [23] have proposed ANN and HT based method for BRB fault classification under varying load conditions. The proposed method yielded minimum classification mean square error with FFT transformed three-phase current features. M. V. Rodriguez et al. [24] have implemented two-dimensional convolutional neural networks (2D-CNN) model to BRB fault classification. They employed Short-Time Fourier Transform (STFT) to extract features from current signature data and then converted the features into 2D images. The proposed method achieved 100% accuracy in BRB classification. Different from the existing research, this research attempts to detect and identify BRB faults using deep learning models and raw time-series current signature data. The methods can classify the motor condition even with noisy current signature data without any feature extraction technique.

The remaining paper is organized as follows: Section 2 reports system design and methods employed for motor condition identification, Section 3 describes the DL models used in this research, Section 5 reports and discusses the obtained results, and Section 6 concludes the research.

# 2. System Design and Research Methodology

The data acquisition system is developed using current sensors, a three-phase IM, and a myRIO board. The flow diagram in Fig. 2 depicts the procedure of the data acquisition and the fault identification method. System component and design steps are described as under:


**Fig. 2** Flow diagram of the proposed system

## 2.1 Three Phase Induction Motor

A 3-phase squirrel cage IM of 0.5 HP is employed for the experimentation. The motor has a rated speed of 1450 RPM. It has a rated current of 3A. The motor is operated under healthy and different faulty conditions. The experimental setup is shown in Fig. 3 which also includes the 3-phase IM.

## 2.2 Current Sensors

In this project, three SCT-013-005 current sensors are utilized to collect three-phase current signature data from the IM. This sensor operates on the same principle of a transformer. When a voltage is applied to the primary coil, a magnetic flux is formed in the coil, which causes induces a current in the secondary coil due to an electromagnetic effect. This sensor is manufactured by the YHDC. The current sensors are interfaced with the myRIO board and the data is sampled through the internal analog to digital converter (ADC) of the board. For later usage, the collected current data are saved into a comma separated values (CSV) files.

## 2.3 National Instruments myRIO

The current sensors are connected with the myRIO board. The NI myRIO board from National Instruments. It combines the Field Programmable Gate Array (FPGA) with a general-purpose processor. It has a pre-configured Linux-based real-time operating system (RTOS). The data acquisition system is built on LABVIEW which is integrated with the myRIO development board. The output provided by the sensors connected to each phase of the motor is analog and needs conversion that is processed through the built-in ADC of myRIO board. For this purpose, the data is stored in a CSV file. The plot of the 3-channel current data acquisition in the LabVIEW is depicted in Fig. 4.

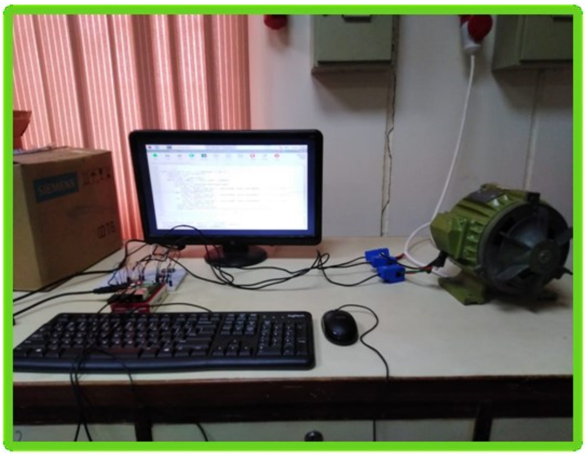

**Fig. 3** Experimental Setup

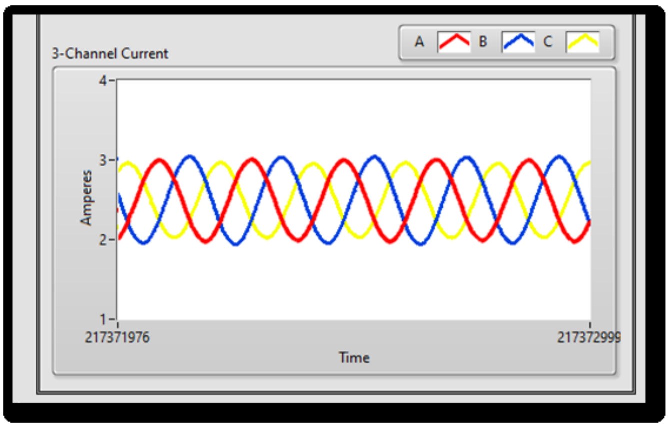


**Fig. 4** Three-Phase current data on LabVIEW front panel

## 2.4 Broken Rotor Bar Faults

To conduct the proposed experimentation, a BRB fault of 2mm diameter and 6mm depth is introduced in the rotor of three phase induction motor as depicted in Fig 5(a). While, two BRB faults of the aforementioned size are introduced in the rotor shown in Fig 5(b).

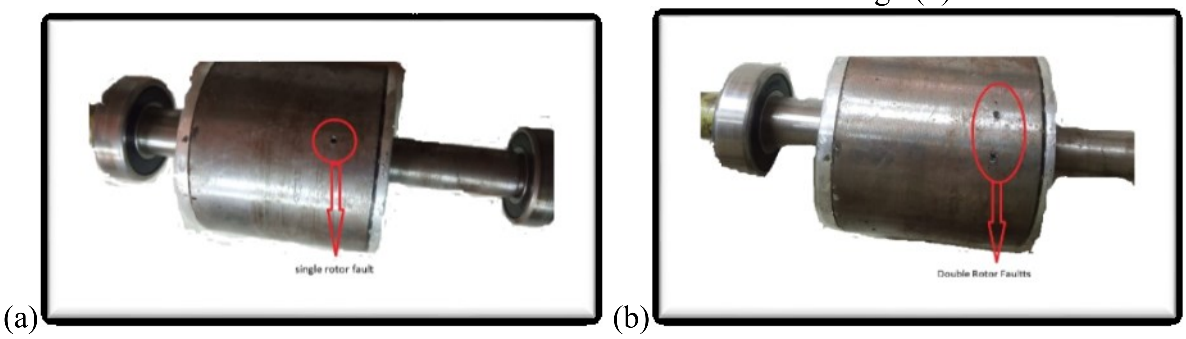


**Fig. 5** Rotor broken bar faults (a) Single BRB Fault and (b) Double BRB Fault

## 3. Deep Learning Models and Experimental Configuration

The classification of the motor conditions is performed using the DL models including MLP, LSTM, and 1D-CNN. The reason for employing three DL models is to perform the comparative investigation and achieve better motor fault identification results. The architectures of the employed models provided in Table 1, 2, and 3. The models are implemented using DL frameworks including

Keras and Tensorflow. A GPU-based workstation with the Python 3.6.13 version is employed for the model training.

**Table 1** Structure of MLP

| Layer Type | Units |
|---|---|
| Dense | 128 |
| Dense | 128 |
| Dense | 64 |
| Dense | 64 |
| Dense | 32 |
| Dense | 32 |
| Softmax | 3 |

**Table 2** Structure of LSTM

| Layer Type | Units |
|---|---|
| LSTM | 128 |
| LSTM | 64 |
| LSTM | 32 |
| LSTM | 16 |
| Softmax | 3 |

**Table 3** Structure of 1D-CNN

| Layer Type | Units |
|---|---|
| 1D-Conv | 256 |
| 1D-Conv | 128 |
| Max-Pooling | 128 |
| 1D-Conv | 64 |
| 1D-Conv | 64 |
| Max-Pooling | 64 |
| Dropout | 0.1 |
| Flatten | 32 |
| Dense | 100 |
| Softmax | 3 |

The hyper-parameters that are used for the models mentioned above are:

- Batch-size = 64
- Number of samples = 3, 00, 000
- Number of epochs = 500
- Learning rate = 0.0002
- Data-split = 6:20:20 as training set, validation set, and cross-validation set, respectively.

## 4. Results and Discussion

The developed data acquisition system allowed to efficiently acquire the time-series current of the motor operated under various conditions. The stored raw data was used to train, test, and validate the performance of the implemented DL models for effective BRB fault identification. The achieved results have demonstrated the effectiveness of the DL models in fault classification with the raw and noisy data. The training and testing accuracy obtained from each DL model is given in

Table 4. The performance of the models was evaluated based on accuracy which is expressed as in Eq. (1):

$$\text{Accuracy} = \frac{Tp+Tn}{Tp+Tn+Fp+Fn} \tag{1}$$

**Table** Error! No text of specified style in document. Training & Testing accuracies of three compared models

| | **LSTM** | **MLP** | **1D-CNN** |
|---|---|---|---|
| Training Accuracy | 100% | 63.66% | 71.00% |
| Testing Accuracy | 100% | 62.85% | 68.19% |

The performance of the models in terms of individual class can be summarized through confusion matrixes which are given in Fig. 6. It can clearly be observed from the above table and confusion matrixes that the LSTM has yielded the best performance among all three models for the provided parameters.

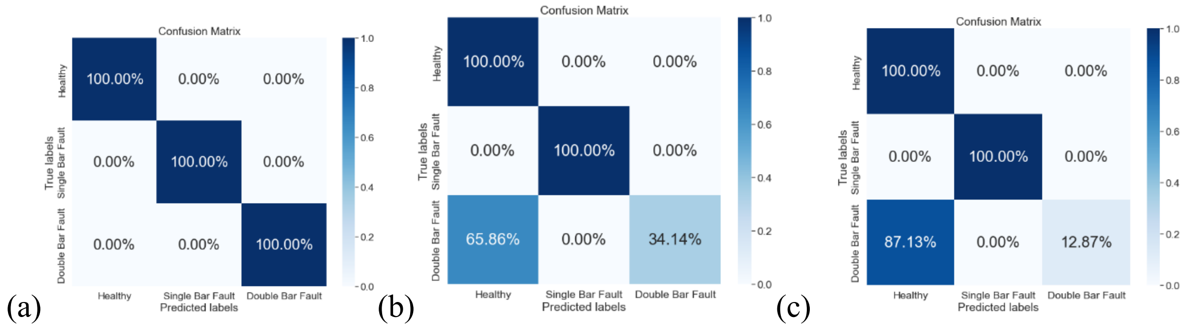


**Fig. 6** Confusion Matrixes of the DL models (a) LSTM, (b) MLP, (c) 1D-CCN

The above figures show that for the LSTM model, none of the predictions are inaccurate, and several predictions are erroneous for other models. To summarize, the LSTM model outperforms all other models in terms of accuracy.

# 5. Conclusion

In this paper, a broken rotor bar fault detection and classification method are implemented using DL-based models. The fault diagnosis is performed using raw three-phase motor current signature data. The designed system includes current sensors, myRIO board, and a GPU based workstation. The algorithms explored are MLP, LSTM, and ID-CNN. Among these models, LSTM has yielded best fault identification results and achieved 100% accuracy. The proposed approach provides effective BRB fault identification even with the raw input data.

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