LSTM based Supply Imbalance Detection and Identification in Loaded Three Phase Induction Motors

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Abstract:
Mostly in motor fault detection the instantaneous values 3 axis vibration and 3phase current in time domain are acquired and converted to frequency domain. Vibrations are more useful in diagnosing the mechanical faults and motor current has remained more useful in electrical fault diagnosis. With having some experience and knowledge on the behavior of acquired data the electrical and mechanical faults are diagnosed through signal processing techniques or combine machine learning and signal processing techniques. In this paper, a single-layer LSTM based condition monitoring system is proposed in which the instantaneous values of three phased motor current are firstly acquired in simulated motor in in health and supply imbalance conditions in each of three stator currents. The acquired three phase current in time domain is then used to train a LSTM network, which can identify the type of fault in electrical supply of motor and phase in which the fault has occurred. Experimental results shows that the proposed single layer LSTM algorithm can identify the electrical supply faults and phase of fault with an average accuracy of 88% based on the three phase stator current as raw data without any processing or feature extraction.

Keywords:
Condition Monitoring, Motor fault diagnosis, Electrical faults, LSTM

1. INTRODUCTION

The key machines used in industry are the motors which produce mechanical torque. Different environmental and operational conditions including process of aging make them vulnerable and expose to faults. Repair, downtime and even machine failure are the counter effects[1]. Industry and academia both have been involved in extensive research activity for detection and identification in the health condition of motors to ensure the safe and reliable operation[2]. Study carried out by Institute of Electrical and Electronics Engineers (IEEE), by Electric Power Research Institute (EPRI), and General Electric Corporation[3] reveals that bearing faults are the one of the common faults and make up 40%. However 28% are the stator faults, 8% are the rotor faults and more than 12% of unspecified. Number of techniques such as acoustic analysis, vibration, current signature [4], electromagnetic field and thermal analysis has been incorporated for detection and identification of motor health condition. Vibration and motor current are the major parameters to be measured and analyzed for mechanical and electrical fault detection[5, 6]. Supply imbalance is one of the electrical faults observed in induction motors. Induction motors observe high currents exceeding the rated currents due to voltage unbalance and therefore reduction in motor efficiency [7, 8]. Supply imbalances are observed in every electrical installation and it is one of the common disturbances. The unbalanced voltage defined by the Line Voltage Unbalance Rate (LVUR) by National Electrical Manufacturer Association (NEMA) [MUHAMMAD AMAN] which is given by (1)

$$\%LVUR = \frac{Maximum\ voltage\ deviation\ from\ average\ line\ voltage}{Average\ line\ voltage} \times 100 \quad (1)$$

Worst-case condition of unbalance supply is single phasing, in which any phase-out of three-phase supply voltage goes missing. In this condition motor continues to run on load until it is not turned OFF through an overload relay.

Motor current signature analysis (MCSA) is a widely used technique to diagnose the motor faults[9]. In MCSA the acquired motor current is analyzed in time domain and frequency domain**.** In [10] the authors have detected the broken rotor bar with supply imbalance in a simulated

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induction motor with the use of FFT and STFT. In recent past the neural networks and machine learning techniques have been widely used to determining the motor faults and predict the remaining useful life[9]**.** MCSA combined with deep learning techniques have been also incorporated for fault detection. In [11] the authors have implemented FFT, STFT and CWT for the detection of supply imbalance and stator winding faults in an Induction motor. Further they have used MLP, 1DCNN and LSTM to identify the motor faults and their phase or occurrences. In [12] the authors have implemented and analyzed multiple faults in a simulated motor with the use of FFT, STFT, and CWT. Further they have identified the multiple faults by 1D-CNN and LSTM.

1.1 LSTM in Fault Detection:

Problem of extracting the information from time varying signals is provided in Recurrent Neural Network (RNN). RNN performs better with sequential or time-series data, making them most suitable in condition monitoring of motors[9]. RNNs [13] are the deepest among all neural networks. RNNs map the entire history of past inputs to target vectors owing to their memory capacity. To remember the information and calculation in next time step there is loop in RNN. RNN lacks to process long sequences and become difficult in training due to vanishing gradient. For supervised tasks, RNNs can be trained by employing back-propagation over time[14, 15]. Long Short-term memory (LSTM) can be used to judge whether to remember or not the information in each loop[16]. LSTM can memorize and forget data[17]. In [18]stator current is used to diagnose bearing faults, inner and outer raceway, using the LSTM network. LSTM was used to detect bearing and BRB faults based on the raw vibration signals which outperformed the MLP and RNN[14].

In this study the current signature based on instantaneous values of raw data is used to train and test a LSTM model to identify the imbalance supply and its phase of imbalance including healthy conditions.

The remainder of this paper proceeds as follows. In Section 2 the Methodology and the MATLAB Simulink model of motor is discussed. Discussion on LSTM model is presented in Section 3. Finally, time domain based analysis on motor conditions and LSTM based classification are presented in results and discussion Section 4 followed by a conclusion in section 5.

2. METHODOLOGY

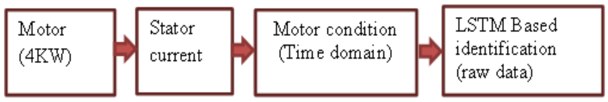


Fig 1: Block diagram of Methodology

A 4KW three-phase squirrel cage induction motor as shown in Fig: 1 is simulated in healthy condition first, and then electrical faults (Unbalance voltage and single phasing) are generated. Measurement of stator current is carried out and analyzed in healthy, supply imbalance and single phasing. Measured three phase current of simulated motor is saved in csv file in each condition having fault in it for 0.1second out of 2 second simulation time. 23215 samples of instantaneous values of three phase current are stored in each file. Finally, a deep learning algorithm is trained (LSTM) to classify the 7 different conditions of IM, including healthy, single phasing , and unbalance supply voltage in each phase respectively.

2.1 Fault Simulation

Motor model in MATLAB/ Simulink shown in Fig: 02 simulated for 2 seconds with full load of 27NM in healthy and fault conditions. In Healthy condition the motor is operated at 400V supply voltage. However, motor is operated with 10% reduced supply voltages and one phase missing out of three to simulate faulty conditions. Three phase programmable voltage source implements unbalance voltage in for time variation of the amplitude only. A three-phase circuit breaker is used to open any one out of three phase supply voltages, thus causing single phasing in any one phase of terminal voltages at motor.

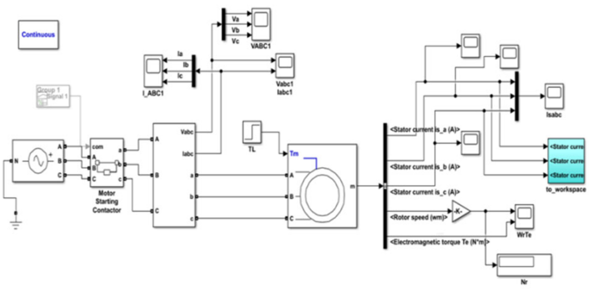


Fig 2: Squirrel cage induction motor with components in MATLAB/Simulink

3. FAULT CLASSIFICATION USING DEEP LEARNING TECHNIQUES

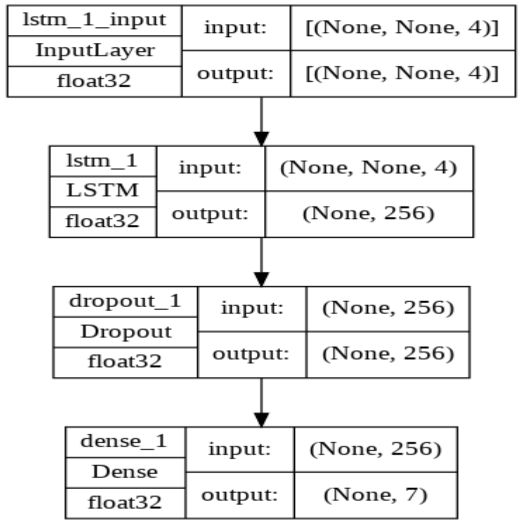
Different signal processing-based methods are reported in [12] to detect the healthy and unhealthy conditions of the 3 phase motor. To detect the faulty condition of the motor, it is essential to analyze the motor current in time domain and spectrums of all the three phases, then it can be distinguished that which phase has been exposed to the imbalance supply voltage or single phasing. LSTM's are widely used for time-series or sequential data analysis owing to their advantages, such as higher learning capabilities even with raw input data. In this work single layer LSTM has been trained and tested on instantaneous values of three phase current as raw data without any preprocessing or feature extraction. The classification of fault and its phase of fault can be performed with the properly trained machine learning algorithm on motor current data acquired during operation. DL model employed (LSTM) can effectively classify the motor health conditions (Healthy, Single phasing, Unbalance voltage) with the information about the phase of the fault. To perform the classification, a dataset is established through collecting data in time domain from the simulated motor, operating for 64 simulations under different load conditions in each class. The detail of the motor conditions for which the data set is prepared is given in Table 1. The obtained dataset is a balanced dataset in which each class comprises 64 files having different simulated condition for 2 seconds. Each simulated condition comprises 23215 samples as raw data (instantaneous values) of three phase motor current.

Table 1 Labels and motor conditions

Conditions	Labels
Healthy	Healthy
Single phasing phase A	SPPA
Single phasing phase B	SPPB
Single phasing phase C	SPPC
Unbalance supply voltage phase A(0.9Pu)	SWFPA
Unbalance supply voltage phase B(0.8Pu)	SWFPB
Unbalance supply voltage phase B(0.8Pu)	SWFPC

LSTM predicts multiclass labels accurately depending on layers employed in their structure. The model architecture employed is shown in Table 2.

Table 2: LSTM architecture



	Units
LSTM Layer 1	256
Dropout 1	256
Dense 1	7

During training the variation of LSTM parameters to achieve best performance are listed as table 3.

Table 3: Hyper parameters

Batch	4
Iterations	33
Learning rate	1 × 10-4
Training dataset	60%
Validation and testing respectively	20%

4. RESULTS AND DISCUSSION

The healthy and unhealthy motor conditions observed by measurements of three phase current in time domain for fault detection and DL technique for classification/identification in healthy and unhealthy conditions of simulated three phase motor are reported in subsections as under.

4.1 Motor in Healthy Condition

Time domain three-phase current of the simulated motor in for 2 seconds in healthy condition is given in Fig 3. This figure is showing measurement of three phase current. It is showing initial rise in current at starting time of motor at 0seconds, which then stabilizes at stays at steady state level at 11.33Amperes in each phase at full load.

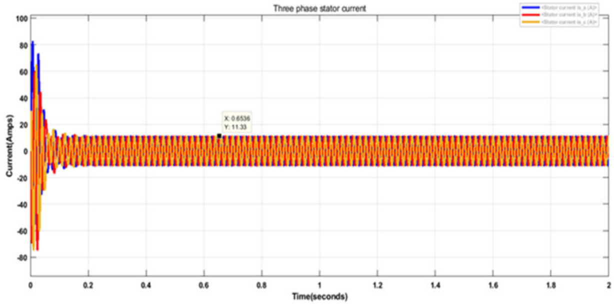


Fig. 3: Healthy motor current

4.2 Motor with Supply Imbalance

The supply imbalance of 0.9pu (10% reduction in supply voltage of yellow phase) induced through the programmable voltage source in motor, which generated the phase to phase voltages equal to 360Vac at supply. It is observable in Fig 4. The motor current initially increased and settled then, and remains at steady state level 11.33ampere which is normal and healthy condition. During the time duration of 1s to 2s the supply imbalance causes the reduction in amount of blue phase current up to 7.38 Ampere but an increased current in red and yellow phase nearly 18Ampere. However the motor continues to operate during supply imbalance.

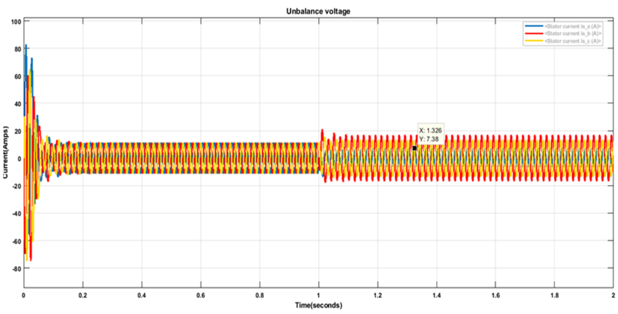


Fig. 4: Motor current in supply imbalance

4.3 Single Phasing

Simulated single phasing condition reduces the three phase supply voltages up 348Vrms by opening the one of the three phase supply voltages at circuit breaker. Impact of this condition on three-phase motor stator current waveform in time domain simulated for 2 second is shown in Fig. 5. Figure represents healthy condition between 0 to 1 second and with single phasing fault between 1 to 2 seconds. Fig. 6 is showing zoom view of the simulated motor current in which the current of two phases has risen up to 23 Ampere which is 12 A higher than normal and both phases are 180 degree out of phase with each other from 1 second to 2s. However the red phase in which with single phasing fault condition has occurred is showing 0 amps.

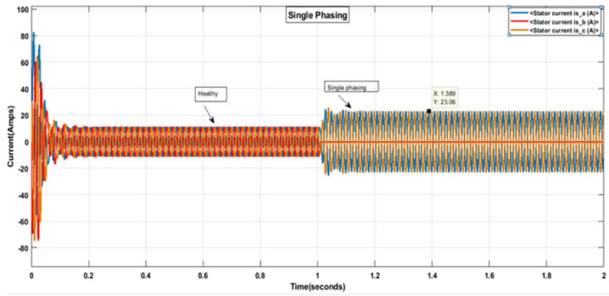


Fig 5: Motor current in fault

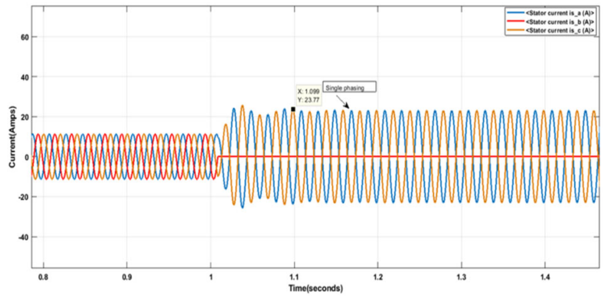


Fig. 6: Motor current in fault

4.4 Fault Classification using LSTM

The test results achieved for identification/classification of the motor health conditions are depicted as multiclass confusion matrix in Fig 7 and normalized in Fig 8 showing classification of 7 types of conditions in LSTM, and summarized in Table 4, showing individual accuracy observed for each class. The classification result shows that LSTM has demonstrated effective performance in individual faults and also classified multiple faults with phase information. Single phasing condition in terminal voltage in phase B and unbalance voltage at phase A is classified with highest accuracy. LSTM has shown 87.85% average accuracy in normalized multiclass confusion matrix.

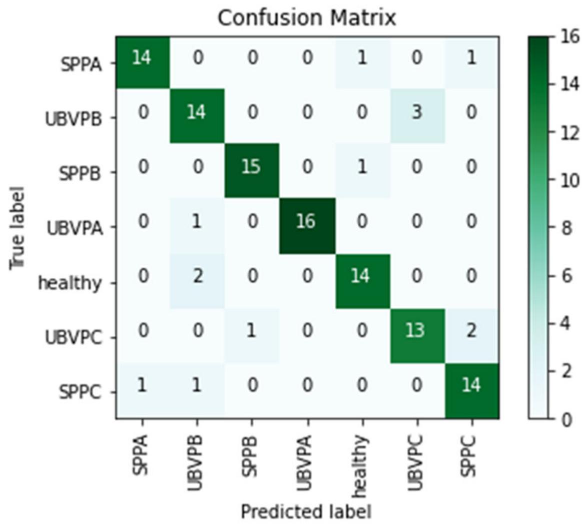


Fig.7: Multiclass confusion matrix on test data

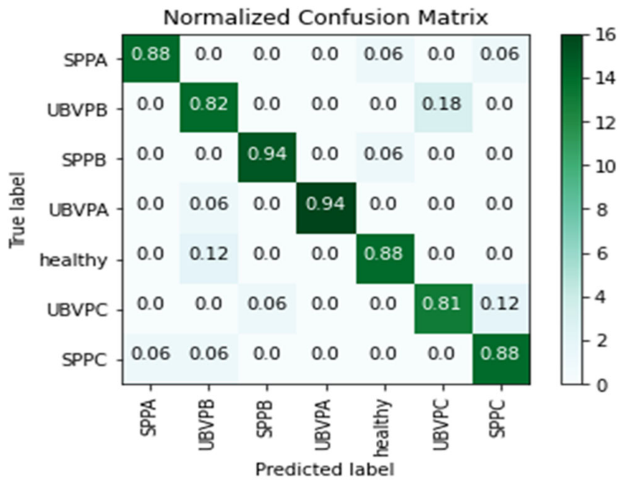


Fig.8: Normalized multi-class confusion matrix on test data

Table 4 Individual class accuracy

Class	Accuracy in %
Healthy	88
UBVPA	94
UBVPB	82
UBVPC	81
SPPA	88
SPPB	94
SPPC	88

The precision, recall and F1 score as performance parameters of identified motor conditions is given in Fig 9 in which highest value of precision and F1 score 1 and 0.97 respectively for identification of unbalance voltage condition in phase A at motor terminals.

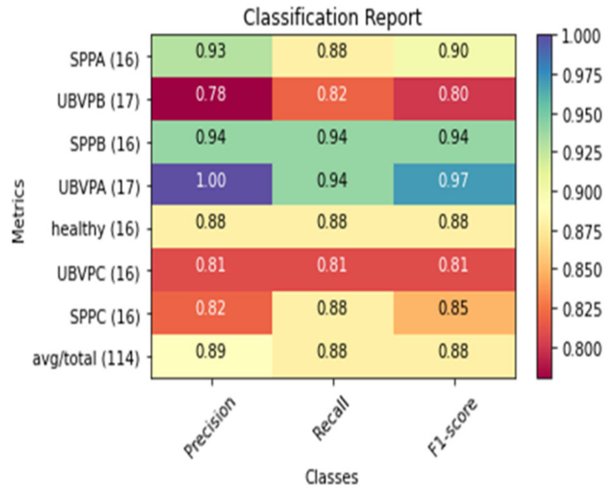


Fig.9: Classification report

5. CONCLUSION

MCSA technique time domain measurement and analysis of healthy and unhealthy conditions of three phase squirrel cage induction motor for detection of supply imbalances and single phasing can be applied for detection of healthy and faulty condition. The MCSA applied on motor current detects the healthy and unhealthy conditions of motor. It can provide the phase information in which fault has occurred by performing analysis on individual phase current with some expert knowledge. Using the instantaneous values of raw data of three phase motor current as sequential or time series input to LSTM also can be used to classify the healthy and unhealthy conditions of motor and the phase of fault. The applied LSTM algorithm, provided the fault type information and the phase in which the single phasing or unbalance supply voltage has occurred without need of any analysis through time domain or frequency domain MCSA technique. Classifications of different fault conditions as multiclass confusion matrix by LSTM have shown good accuracy. MCSA, in conjunction with LSTM, could be utilized for condition monitoring of motors to detect and classify the type and phase of the fault with accuracy.

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