High Accuracy LSTM Classifier for Induction Motor Fault Monitoring System

N. Sivaraj [1], B. Rajagopal [2]

[1] *Research Scholar, Department of Electrical Engineering, Annamalai University, Chidambaram, Tamilnadu, India*

[2] *Associate Professor, Department of Electrical Engineering, Annamalai University, Chidambaram, Tamilnadu, India*

Abstract—**Motors are one of the most critical components in industrial processes due to their reliability, low cost and robust performance. Motor failure will lead to the shutdown of a whole production line and cause great loss. Therefore, accurate, reliable and effective motor fault diagnosis must be performed. Currently, motors fault diagnosis has gained much attention to guarantee safe motor operations. In this paper a fault diagnosis method is proposed for three-phase asynchronous motor using Long Short-Term Memory (LSTM) neural network, which possesses the capacity to learn meaningful representations from raw signal without any feature engineering. Firstly, the acceleration signals of different fault motors were collected. Then, the raw data were directly fed into LSTM neural network to establish the relationship between the raw vibration signals and fault states. The whole proposition was experimentally demonstrated and discussed by carrying out the tests of six three-phase asynchronous motors under different fault conditions in the drivetrain diagnostics simulator system. Performances of other classification methods such as LR, SVM, MLP, and basic RNN, are tested and contrasted. Results show that the proposed approach achieves the highest fault diagnosis accuracy.**

***Index Terms*—LSTM, Motor, Fault**

I. INTRODUCTION

Motors have been widely used as key machine components for the production of torque. Motors are exposed to a wide variety of environments and conditions. These factors, coupled with the natural aging process of any machine, make the motor subject to various faults. Any motor failure will cause unwanted downtime, expensive repair procedures, and even human casualties [1]. The two major approaches in the feature engineering for motor fault diagnosis are the traditional feature learning and state-of-the-art deep learning techniques. Traditional feature learning which heavily depends on manual feature extraction, is often unable to discover the important underlying representations of faulty motors. State-of-the-art deep learning which have somewhat improved diagnostic performance, while the intrinsic characteristics of black box and the lack of domain expertise have limited the further improvement. To cover those shortcomings, in this paper, two manual feature learning approaches are embedded into a deep learning algorithm, and thus, a fault diagnosis framework is proposed for three-phase induction motors with a hybrid feature learning method, which combines empirical statistical parameters, recurrence quantification analysis (RQA) and long short-term memory (LSTM) neural network [2]. The stator current is used to diagnose two bearing faults, inner and outer raceway, using the well known deep learning algorithm, LSTM network. The bearing fault data considered takes into account different operating conditions such as speed, load variations and varying fault severity levels. Hence, the method developed is independent of the speed and the loading conditions [3]. Recurrent neural network (RNN) architectures such as long short-term memory (LSTM) neural network and its variants have exhibited state-of-the-art performance on a wide range of complicated sequential problems including signal processing, speech classification and video captioning. LSTM can adaptively learn the dynamic information of time sequences by non-linear gating units regulate the information into and out of the memory cells of LSTM [4].

LSTM neural network architecture is utilized in feature selection and fault detection. The LSTM networks are capable of handling streaming data of any length. However, the maximum length of the input sequence should be limited for the training of LSTM. Thus, the LSTM network is employed with a sliding window approach. A time window of features that includes the current and past measurements is fed into the LSTM model at each step to detect the fault [5]. Different types of external electrical fault conditions are generally experienced by a 3-phase induction motor. The faults include overload, locked rotor, over voltage, under voltage, unbalanced supply voltage, and single phasing. Protective relays monitor the motor to disconnect when these fault occur [6]. Deep LSTM based classification model has been proposed for fault diagnosis of CNC machines. Different structures can be combined to obtain higher accuracy rates. LSTM structures having two layers, three layers, four layers, and five layers have been proposed and then compared with each other with respect to the classification accuracy of fault diagnosis. The highest accuracy rate obtained in this study was 99.53% [7].

Long short-term memory network (LSTM) is used to learn the temporal dependencies among features. At last, fault identification is achieved. 1DCNN-LSTM does not require any manual feature extraction, and the errors caused by reliance on expert experience and incomplete information in traditional feature extraction methods are avoided. This shows that the proposed classifier with good generalization performance not only diagnoses the category of fault quickly and accurately under different load conditions but also achieves an average fault identification accuracy of 99.95% [8]. The LSTM is widely employed in the field of fault diagnostics. An electric motor defect detection approach based on the LSTM. LSTM perform well in fault diagnosis when the difference in the fault feature quantity is not significant. LSTM can effectively avoid parameter selection difficulties and has a superior accuracy rate [9]. In LSTM the previous values are remembered over an arbitrary period of time, which makes these layers suitable for time series where the lags between events are uncertain. Moreover, the input of an LSTM is a triplet consisting (samples, timesteps, and features) [10]. LSTM is a kind of RNNs, to achieve robust classification, a one dimension-aggregate approximation (1d-AX) is employed to extract effective signal representation for LSTM networks. Nowadays, there are a number of variants of LSTM, Gated Recurrent Unit (GRU) peephole connection thus LSTM developed from different perspectives. [11].

Condition monitoring is used for achieves performance of machinery, reducing consequential damage, increasing machine life, reducing spare parts inventories and reducing breakdown maintenance. An efficient condition-monitoring scheme is one that provides warning and predicts the faults at early stages. Monitoring system obtains information about the machine in the form of primary data and through the use of modern signal processing techniques [12]. Motor Current Signature Analysis (MCSA) is widely reported as a condition monitoring technique in the detection and identification of individual and multiple Induction Motor (IM) faults.

Continuous monitoring and interaction of motor operating parameters such as vibration, current, and temperature with sensors enable us to diagnose and identify the related issues within interconnected processes and even plan predictive maintenance. Faults in Induction motors (IM) could be electrical or mechanical. Single phasing and Stator winding faults (SWF) are significant electrical faults. Single phasing is the worst-case scenario of supply unbalances causing overheating of the motor. Stator inter-turn winding faults could lead to severe stator winding faults such as phase winding to the ground. Faults can be avoided and repaired if detected early [13]. Stator winding faults make up around one-third of the total faults observed in induction motors and these can very quickly damage the motor. Inter-turn short faults can quickly escalate to become inter coil, phase winding, and phase to ground faults, which in turn causes significant circulating currents, thereby generating enormous thermal stress at the point of the short and leading to machine failure [14]. Among deep learning models, Long Short Term Memory networks (LSTMs) are able to capture long-term dependencies and model sequential data. Therefore, LSTMs is able to work on the sensory data of machine condition. Here, the first study about an empirical evaluation of LSTMs-based machine health monitoring systems is presented. Basic and deep LSTMs are designed to predict the actual tool wear based on raw sensory data [15].

This paper presents an LSTM-based technique to detect faults in an induction motor. The LSTM is trained to identify faults using RMS currents and voltages obtained in real-time from an induction motor. The trained LSTM is tested with fault current and voltage data from the induction motor.

II. PROPOSED FRAMEWORK

In this work, LSTM neural network architecture is utilized in feature selection and fault detection. The input data should be preprocessed appropriately to feed into the neural networks. In this section, the LSTM network is briefly reviewed and discussed. Then, the feature selection approach is presented. Lastly, the section is ended with the fault detection model.

A. Long short-term memory network

Recurrent neural network (RNN) is a kind of deep neural network. In the past, the LSTM network was successfully used in the deep learning techniques to overcome the problems associated with vanishing and exploding gradients in basic Recurrent Neural Network (RNN).LSTM network is a special type of recurrent neural network to capture long short-term dependencies in time sequence data. LSTM should be superior compared to traditional RNN due to its capability to capture long-term dependencies. A basic LSTM structure has four different gates called input gate, output gate, forget gate, and a cell unit.

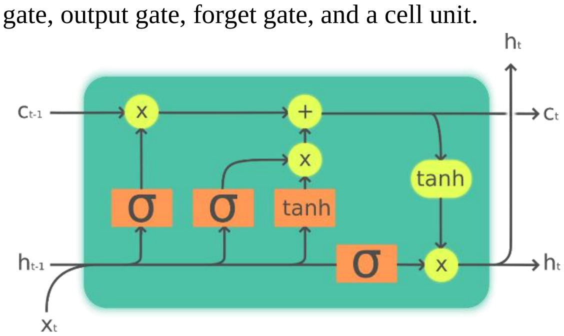

Figure 1: Long short-term memory network

The architecture of LSTM cell can be described as Fig. 1. At each time step t, hidden state h_t is updated by current data at the same time step x_t, hidden state at previous time step h_t-1, input gate i_t, forget gate f_t, output gate o_t and a memory cell c_t. The following updating equations are given as follows:

$$i_t = \sigma(w_i x_i + v_i h_{t-i} + b_t) \quad (1)$$

$$f_t = \sigma(w_f x_t + v_f h_{t-i} + b_f) \quad (2)$$

$$o_t = \sigma(w_o x_i + v_o h_{t-i} + b_o) \quad (3)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot tanh\,(w_c x_t + v_o h_{t-i} + b_c) \quad (4)$$

$$h_t = o_t\ i_t \odot tanh(c_t) \quad (5)$$

where model parameters including all $W \in R^{dXk}$,$V \in R^{dXd}$ and b$\in$ R^{dX} are shared by all time steps and learned during model training, σ is the sigmoid activation function, ⊙ denotes the element-wise product, *k* is a hyper-parameter that representing the dimensionality of hidden vectors.

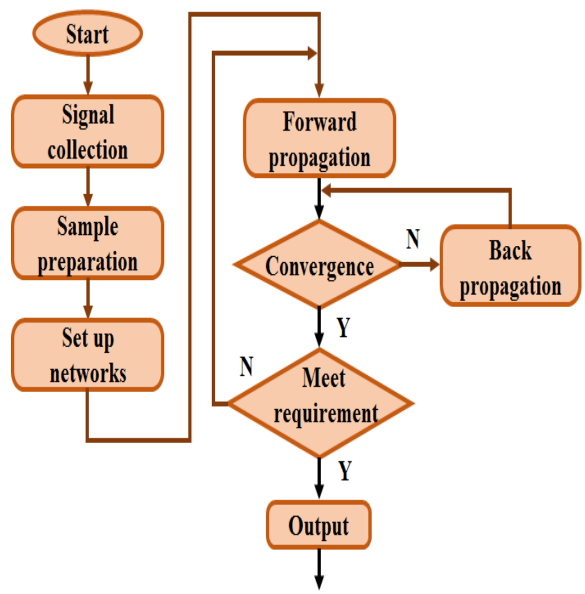

Figure 2: The flowchart of the proposed approach

B. Fault detection model

The fault detection model consists of 8 independent fault specific binary LSTM classifiers. Each classifier takes only fault-related features as input. For instance, a binary LSTM is designed to operate with the measurements only from the sensors, Smart Motor Position Error and Duration Robot from Feeder to Test Bench. A fully connected layer, with a single hidden neuron and sigmoid activation, follows the LSTM layer. The fault alarms are counted, and the fault decision is taken when the number of fault alarms reaches the window length of the classifier to increase the accuracy. It is assumed that the classifier's decision with the highest precision in the validation set is more reliable than the others. Thus, it is preferable to the others in case of multiple fault alarms. The important order of the fault-related features is also of interest to identify the root cause of the fault.

The proposed model of the LSTM method for induction motor faults identification is shown in Fig. 3. The RMS values of voltage and current inputs are given to LSTM layer as sequence input after proper data preparation.

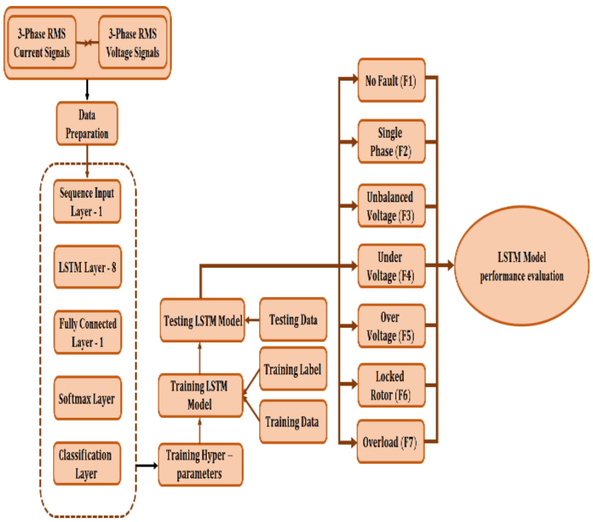

Figure 3: Proposed model for induction motor faults detection

3. EXPERIMENTAL SETUP

The experimental verification of the performance of LSTM in induction motors under different fault conditions is carried out in the fault monitoring system. In Fig.4. A is denoted as the supply and acquisition switchboard is responsible for supplying the motor, acquiring the signals and send information to the processing unit. This switchboard holds the necessary relays to supply, start and operate the induction motor. The induction machine and the electromagnetic brake are fixed together in a mounting based, denoted as B in Fig.4. The system was designed for an induction motors denoted as C in Fig.4. Two fixing plates denoted as D and G in Fig.4.are designed. Fixing plate D is a standard fixing plate used to keep the motor in a perfect aligned position. Fixing plate G is a special fixing plate used to impose misalignments between the motor and the load. The electromagnetic break denoted as E in Fig.4. is controlled by its respective controller denoted as F in Fig.4.the controller is also responsible for acquiring the speed and torque of the induction motor. The processing unit is denoted as H in Fig.4. is implemented on a personal computer. After handling the input signals the processing unit can execute two distinct tasks: perform an automatic fault diagnosis or prepare the data for the trained LSTM is tested with the dataset used for training (so that they can decide if there is a fault condition or not).

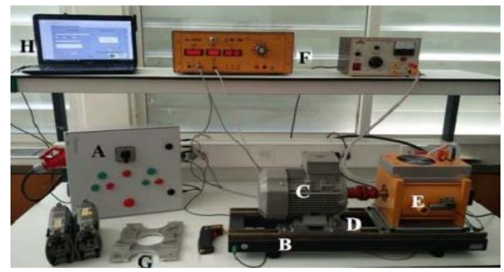

Figure 4: Experimental setup

The accuracy and loss for trained model are shown in Fig.5. The figure displays training progress, elapsed time, number of epochs, number of iterations, iterations per epoch, maximum iterations, type of learning rate schedule and learning rate. From this figure, it is clearly seen that accuracy of the trained model is reached at about 100% and loss function is also closed to zero after 40 epochs.

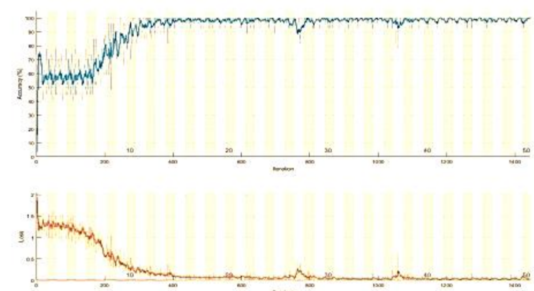

Figure 5: The accuracy and loss in LSTM fault detection method for 50 epochs of training progress

The input current and voltage waveforms for one of the cases used to test the LSTM method are shown in Fig. 6. and Fig. 7. Fig. 6. shows the waveforms for a no fault case and Fig. 7. shows an overload fault case. It can be observed from Fig. 6. and 7. RMS values of currents and voltages for all cases are calculated and reported in Table 1. The third row for each of the cases in the table corresponds to some of these seven currents and voltages waveform figures. The table also shows another two sets of data that are used as a part of the test data for the LSTM method. The confusion matrix for this test data is shown in Table 2. As it can be observed from the table, the LSTM method has correctly identified all the seven types of faults and no fault conditions for these three sets of test data giving an accuracy of 100%.

Table 1: Data used for testing the LSTM method

Faults	Inputs					
	V1	V2	V3	I1	I2	I3
No Fault (F1)	2.650	2.640	2.696	0.428	0.428	0.431
	2.694	2.652	2.690	0.517	0.521	0.502
	2.622	2.614	2.666	0.410	0.418	0.417
Single Phasing (F2)	2.688	2.609	2.721	0.625	0.629	0.013
	2.694	2.642	2.703	0.644	0.648	0.004
	2.616	2.600	2.642	0.628	0.632	0.004
Unbalanced Voltage (F3)	2.624	1.906	2.022	0.538	0.249	0.332
	1.682	2.475	2.702	0.186	0.634	0.628
	1.624	2.019	2.585	0.207	0.449	0.576
Under Voltage (F4)	1.088	1.087	1.084	0.231	0.239	0.225
	1.966	1.969	1.977	0.305	0.318	0.300
	1.976	1.967	1.995	0.306	0.312	0.307
Over Voltage (F5)	2.888	2.878	2.863	0.482	0.499	0.496
	2.856	2.839	2.871	0.478	0.477	0.467
	2.882	2.872	2.868	0.488	0.484	0.459
Locked Rotor (F6)	2.657	2.613	2.687	1.671	1.651	1.669
	2.649	2.614	2.647	3.090	3.096	3.043
	2.573	2.565	2.609	3.052	3.073	2.996
Overload (F7)	2.638	2.602	2.675	0.807	0.788	0.800
	2.681	2.639	2.679	0.831	0.833	0.820
	2.604	2.600	2.643	0.882	0.893	0.884

Table 2: Confusion matrix for testing data

n= 21	True Class								
	Faults	F 1	F 2	F 3	F 4	F 5	F 6	F 7	Accuracy
Predicted class	F1	3	0	0	0	0	0	0	100%
	F2	0	3	0	0	0	0	0	100%
	F3	0	0	3	0	0	0	0	100%
	F4	0	0	0	3	0	0	0	100%
	F5	0	0	0	0	3	0	0	100%
	F6	0	0	0	0	0	3	0	100%
	F7	0	0	0	0	0	0	3	100%

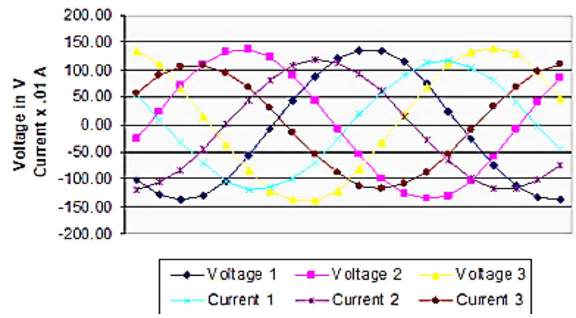

Figure 6: Voltages and currents for no fault condition

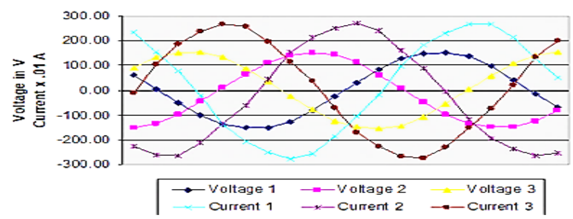

Figure 7: Voltages and currents for overload fault

A. Comparison with Other Methods

The performance of the proposed method is compared by the following methods:

SVM: Support Vector Machine classifier on extracted features

ANN: Artificial Neural Network classifier on extracted features

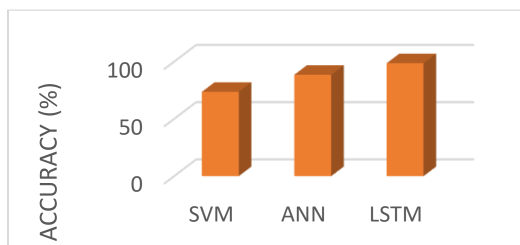

Figure 8: The performance of ANN, SVM and LSTM methods.

From Fig. 8, it is obvious that LSTM performs slightly better than ANN. The experiment verifies that the proposed method with the highest accuracy of health condition recognition performs better than other methods such as SVM, and ANN. The method plays an important role for fault monitoring for an induction motors and is helpful for predicting potential risks in factory manufacturing.

IV. CONCLUSION

The LSTM method is applied for identifying external faults in an induction motor in this paper. The paper gives details of various parameters used in the training of the LSTM method. It also gives testing results using fault data obtained from an induction motor. From the results, it can be noted that the testing accuracy of LSTM method is 98.6% in identifying all faults and no-fault condition. The performance of the LSTM method is observed to be better than ANN method in accuracy and SVM method in model formation. The paper uses RMS values of currents and voltages as inputs. Other signals that may be considered in future studies are directly using the instantaneous values of currents and voltages.

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