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Classification of Induction Motors by Fault Type with bidirectional Long-Short Term Memory Method

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Abstract – It is important to determine the initial level of failures of induction motors used in many industrial applications. The sudden stops of the system can be prevented with the pre-detection of the fault. The experiment mechanism was established to detect mechanical unbalance and short circuit faults in the induction motors. Current values were measured and saved at fault time. As a result, 9.000 data were obtained consisting of 3 phase currents. In this study, a Long-Short Term Memory (LSTM) deep neural network has been developed that classification of induction motors by fault type. In the training of the neural network, 3 input parameters and 3 classification types of 1 output parameter are used. It was reserved for training 60% of data and 40% for testing the model in the dataset. As a result of the fault type classification with the LSTM model, 98.5% accuracy and 1.12 average absolute error value were obtained. It has been shown that the proposed bi-LSTM network can be used for fault detection of asynchronous motors.

Keywords *– Classification, Deep Neural Network, Induction Motor, bi-LSTM, Type Fault.*

I. Introduction

Induction motors are one of the critical components of Industry 4.0. In case of failure of these motors, unwanted system stops occur in automation. Asynchronous motors are preferred because of their low cost and easy maintenance, but they cause great economic losses as a result of faults. Therefore, it is very important to determine the faults that may occur at the initial level of asynchronous motors. Faults in asynchronous motors are caused by bearing, rotor, stator winding short circuit, eccentricity, and unstable energy feeds [1].

In asynchronous motors, data such as vibration, current, voltage, moment and magnetic flux are used to determine the faults beforehand. After the data obtained from the sensors are pre-processed with signal processing (RMS, FFT, time-frequency, etc.) methods, it is attempted to detect failures with different techniques such as artificial neural networks [2], fuzzy logic, expert systems, and model-based approaches [3].

Deep learning is a machine learning technique that mimics the human brain with mathematical models and can perform operations such as classification, feature extraction, and conversion, either supervised or unsupervised. There are many classification problems in the literature using deep learning algorithms (especially RNN, LSTM, CNN) [4]. Some of the deep classifications respectively; images [5], sound [6], human activities [7], sentences [8], cyber-attacks [9].

In this study, a model was proposed to classify faults from current values obtained from squirrel cage type 3-phase asynchronous motor. The proposed model is developed with the LSTM algorithm which has a 3 inputs 3 outputs classification. The output layer is classified as engine robustness, mechanical imbalance, and short circuit. The classification with the LSTM model has obtained 98.5% classification accuracy.

II. Long-Short Term Memory (LSTM)

One of the methods of deep learning, LSTM is used in processing sequential incoming data by time, or to analyze events that have a specific relationship between them [10]. LSTM is an RNN (recurrent Neural Network) based technique that has an architecture of random recall and learning of long-term dependencies [11].

The LSTM consists of memory blocks containing memory cells and gates. Memory blocks have 3 special gates. These are respectively the input, forget and output gates (Figure 1). The input gate is responsible for controlling the flow of data to the memory cell. The output gate is responsible for the flow of data out of the memory cell and into other blocks. The Forget gate is responsible for determining the effectiveness of previous block that exists within the existing block [12].

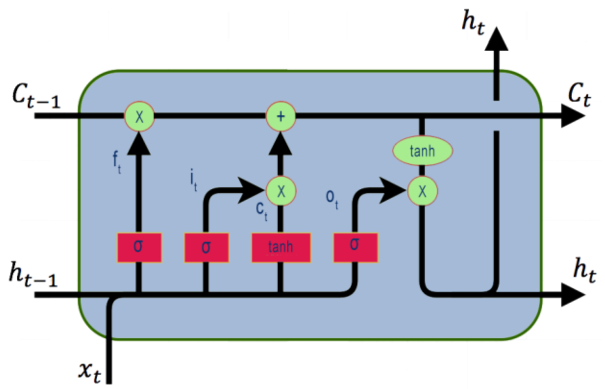


Fig.1 LSTM cells

Located in the first stage of the LSTM network the forget gate consists of a simple single-layer neural network where information from the previous cell is decided which to hold and which to discard. In this layer, operations are performed by the sigmoid layer. The value from the Sigmoid layer is obtained by Equation 1 [13].

$$f_t = \sigma\left(W_f . [h_{t-1}, x_t] + b_f\right) \quad (1)$$

The resulting value is a number produced between 0 and 1. If the result is close to zero or zero, the previous memory is forgotten.

The input gate consists of the tangent layer where the new vector (C_t) that needs to be stored is created and the sigmoid nerve layer where it is decided which values to update. The 2 different values (h_{t-1} and x_t) that come to this layer are passed from Sigmoid and Tangent layers through Equations 2,3 and 4, and a new value is obtained by combining them [14].

$$C_t = f_t * C_{t-1} + i_t * C_t \quad (2)$$

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \quad (3)$$

$$C_t = tanh(W_C . [h_{t-1}, x_t] + b_C) \quad (4)$$

The vector (C_t) to emerge from the entry gate is obtained by summing it with the value determined in the previous stage (f_t*C_{t-1}) (Equation 5).

$$C_t = f_t * C_{t-1} + i_t * C_t \quad (5)$$

The output gate provides the production of short-term memory and output using the input and forget gates. This gate consists of layers of tangent and sigmoid, such as the input gate. The value obtained in the Sigmoid layer is calculated by Equation 6.

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o) \quad (6)$$

The values generated are values between 0 and 1 in this layer. If the resulting value is close to zero, it is decided that the new information will not be used. After calculating the values from the input and forget gates in the tangent layer, it was obtained a value between -1 and 1 [15]. The output gate transmits to the next cell as the output value which the value obtained from the multiplication of the values from the sigmoid and tangent layers (Equation 7).

$$h_t = o_t * \; tanh\,(C_t) \quad (7)$$

III. EXPERIMENT

A. Dataset

The processes for developing and testing the model are shown in the flow chart in Figure 2. The process that started with engine selection was completed with the development of the proposed model.

The dataset used in the training and testing of the model consists of I1, I2 and I3 data taken from the squirrel cage asynchronous motor. The technical specifications of the engine used to obtain the data are shown in Table 1.

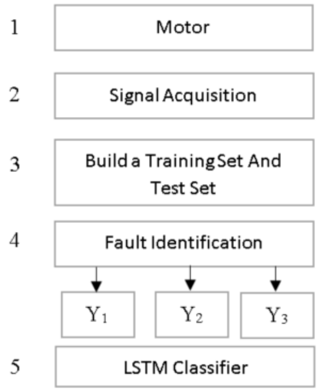


Fig. 2 Fault classification scheme.

Table1. Features of squirrel cage asynchronous motor

Features	Values
Power (kVA)	1.2
Voltage (V)	220
Frequency (Hz)	50
Speed (d/dk)	1475
Stator Resistance rs (ohm)	4.85
Xls (ohm)	0.274
Xlr (ohm)	0.274
rr (ohm)	3.805
J (kg.m2)	0.031

There are 3 different states in the data set to be used for classification. These are respectively; Normal, short circuit and mechanical imbalance. In Table 2, the numbers and output layer code of the data contained in the dataset are given by the type of classification. A total of 9,000 data were used for training and testing.

Table 2. Grouping of data set by classification type

Classification	Code	Samples
Normal	0	3.000
Short Circuit	1	3.000
Mechanical Imbalance	2	3.000

B. Model Training

LSTM has a higher learning than feedback neural networks. For this reason, the proposed model was used bi-LSTM neural network architecture that processes data in both directions. As mentioned earlier, It's have been obtained 3 features (X_{t-1}, X_t and X_{t+1}) in the input layer. There are 3 neurons in the output layer to represent motor fault conditions. It has been used to train the neural network 60% of each fault condition.

The Model consists of the input layer, the hidden layer, and the output layer (Figure 3). In the three layer bi-LSTM network, the dropout value *p*=0.5 was determined in the hidden network of 256, 128 and 64 dimensions. Each of the embedded inputs feeds a separate bi-LSTM network with 50 neuron units in the dual direction. Each output of the Bi-LSTM networks is then passed through a dense network of 128 neurons with ReLU activation function. The results are obtained by placing the outputs of the previous layer into a three-layer neural network with layers 64, 32 and 8. It was used in the training of the entire model Momentum=0.9, L2 regularization weight=0.001 and primary learning rate η=0.01

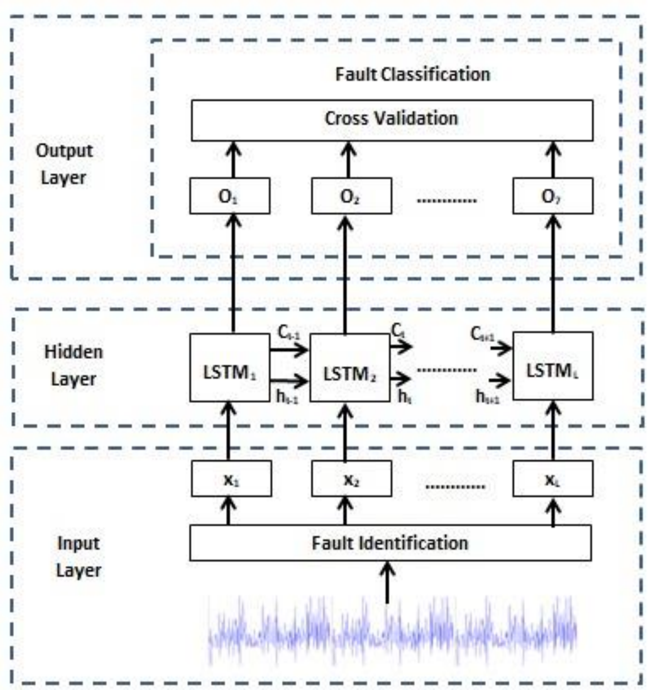


Fig. 3 Architecture of proposed model

IV. RESULT

The dataset contains 3,000 data for each type of fault. To ensure high classification performance, the dataset for each type of fault is divided into 60% training and 40% testing. Accuracy metric was used to measure the success performance of the model [16].

$$\text{Accuracy} = (TP+TN) / (TP+TN+FN+FP) \quad (8)$$

TP: True Positive
TN: True Negative
FP: False Positive
FN: False Negative

The confusion matrix for the classification accuracy of the model is given in Figure 4.

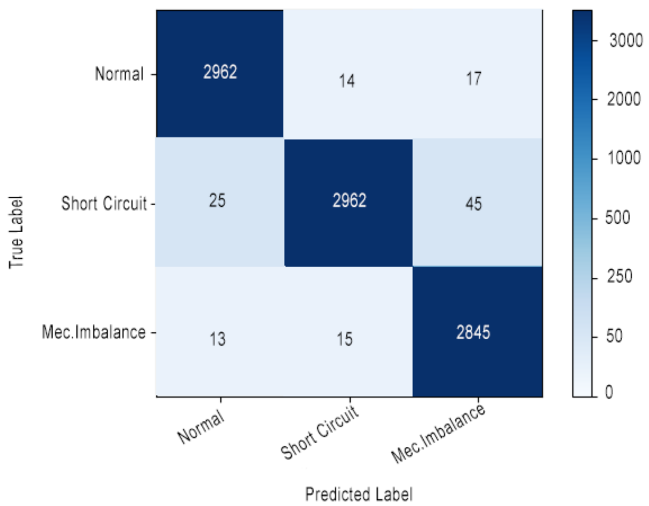
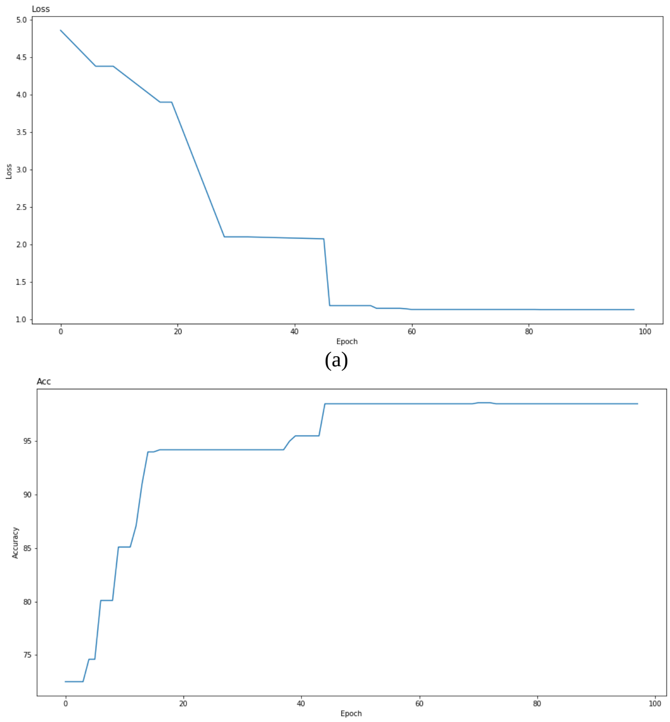


Fig 4. Confusion matrix

The loss and accuracy rate of the trained model is shown in Figure 5 for each epoch. Accordingly, as the number of training increases, the change in the loss rate is slower. The rate at which the loss rate falls is similar to that of increased accuracy. The accuracy and loss value in the final steps have hardly changed, suggesting that the neural network is fully trained. As the curve becomes smooth, the training of the neural network appears to be healthy.



(a)

(b)

Fig. 5 Accuracy and loss graph of the model

V. CONCLUSION

Prior detection of a fault in asynchronous motors minimizes the damage to the system. In this context, a bi-LSTM model has been proposed that allows the classification of fault States from the current values of asynchronous motors. The types of fault states, the input features of the model, and the dataset were created with the data measured in the engine. Hyper parameters have been set to accuracy the highest performance from the model. The dataset consists of 9,000 data determining 3 faults states. In the training of the Model 60% of the data having each fault type was selected. As a result, it was obtained 98.5% accuracy in fault classification with the bi-LSTM model. It is envisaged that the proposed practical bi-LSTM model could be used for the fault detection of asynchronous motors.

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