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Classification and Detection of Faults in Induction Motor using Dwt with Deep Learning Methods under the Time-Varying and Constant Load Conditions

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Abstract*: This article proposed a method to detect the faults in multi-winding induction motor using Discrete Wavelet transform combined with Deep Belief Neural Network (DBNN). This technique relies on the instantaneous reactive power signal decomposition, from which detail coefficients and wavelet approximations are extracted which are termed as features. In order to obtain a robust diagnosis, this article proposed to classify the feature vectors extracted from DWT analysis of power signals using DBNN (Deep Belief Neural Network) to distinguish the motors state. Subsequently, in order to validate the proposed approach, a three phase squirrel cage induction machine is simulated under MATLAB software. To check the effectiveness of the proposed method of fault diagnosis the motor is simulated in different simulation environments like time varying load and constant load condition. Promising results were obtained and the performance of DBNN i.e. 99.75% accuracy. The proposed algorithm is compared with various other state-of-art methods and the comparison proves its robustness in diagnosing the fault in motors.

***Index Terms*: Fault Diagnosis, DBNN, deep learning, DWT, broken rotor bar, Stator Fault, Combined fault**

I. INTRODUCTION

The fault diagnosis of the electric machine has aroused great interest. The monitoring of electrical machines for diagnostics and fault prediction has been much researched in recent years in various industrial sectors, including electric drives using asynchronous motors in excess [3]. An effective diagnosis is the detection of errors in early stage that reduces machine maintenance and downtime. Because of its cost effectiveness and ruggedness, the asynchronous machine is certainly the one most widely used machine in the industry.

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However, different types of failures can affect its optimal function. The electrical or magnetic defects and mechanical defects can be highly unpredictable, making the machines maintenance and diagnostics an economic problem. A broken rotor bar is a common fault of the asynchronous machine [4]. Much research has been devoted to the development of various real time fault monitoring and diagnostic techniques. Most of them use steady-state stator current spectral analysis [5]; others use more sophisticated techniques as wavelets transform the analysis of the stator current into a transient state. Under steady state conditions like constant torque, voltages and speed the method FFT of signal processing works very well and it perform well with high-power motors as well. On the other side, when it comes to non-stationary signals, the spectrum deteriorates due to its spectral components averaging in time principle, and the information of the fault diagnosis may be lost. The Fast Fourier spectral analysis was generally is applied to identify the harmonic which in turn can distinguish the faults in the Induction motor like broken rotor bar under steady state. However, this approach is heavily dependent on the sampling frequency, number of samples taken and quality of measurement. In order to improvise on the performances of diagnostics and monitoring of induction motor in real time various machine learning methods like Artificial Intelligence, Random Forest, decision trees, support vector machine, K-nearest neighbor have been used [6]. Through DWT analysis, these additional components can change at modulation frequencies (characteristic frequency components of error) depending upon the frequency energy content and its sampling frequency. This complete amalgamation provides the important diagnostic information in case of fault presents in the Induction machine. In this article, the focus is on rotor, stator and combined faults and proposes the use of the discrete wavelet transform to the stator current signal to diagnose the occurrence of rotor fault, stator fault & combined fault. For the simulation, a three phase squirrel cage induction motor is used and the influence of faults on measurable quantities (torque, current and speed) of the induction machine in its various operating conditions (healthy and faulty). Fast Fourier Spectral analysis is quite sensitive to the sampling frequency, the number of samples and quality of the measurement.

We have proposed a method to overcome these disadvantages wherein we extract the feature vectors using DWT and perform a classification with Deep learning DBNN (Deep Belief Neural Network) method with Support vector machine method to identify broken rotor bars faults and a comprehensive comparative analysis of DBNN classification with state of art algorithm is done.

II. DEEP BELIEF NEURAL NETWORK FRAMEWORK

The DBNN network is a deep learning architecture with multiple hidden layers that is able to learn hierarchical representations automatically and without supervision while performing a classification. To structure the model accurately, it includes both an unattended preparation procedure and a supervised fine-tuning strategy. Due to the vanishing gradient problem, it is often difficult to learn a large number of parameters in a deep learning model with multiple hidden layers. To solve this problem, an improved training algorithm is used, which processes and learns one shift at a time and considers each shift pair as an RBM model. RBM is the basic unit of the DBNN network. Therefore, RBM is introduced first.

A.Restricted Boltzmann Machine (RBM)

The RBM *(Restricted Boltzmann Machine)* is a mathematical model commonly used in the theory of probability statistics and follows the linear logarithmic linear-logarithm (MRF) theory [7-10], which has several special forms including RBM. An RBM template has two levels: one is the input level (also referred as the visible level) and the other level is the output level (also referred the hidden level). All visible RBM units are completely connected to hidden units, whereas single-layer units are not connected to each other. The A.Restricted Boltzmann Machine (RBM) architecture is shown in Figure 1.

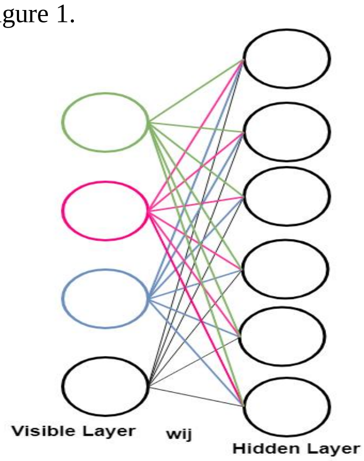


Figure1. Restricted Boltzmann Machine Architecture.

B.Training of RBM

To define the attributes of model, the RBM must be formed with a learning data set. In the educational process of an RBM model, stochastic gradient decay learning rule is adopted. The probability of the logarithmic probability of the training data is calculated, and the weight is considered to be the gradient indicated in the equation. (1).

$$\frac{\partial \log p(v)}{\partial w_{ij}} = < v_i h_j >_{data} - < v_i h_j >_{model} \quad (1)$$

The rules for updating parameters are originally derived from Hinton and Sejnowski shown in eq. (2):

$$\Delta_{w_{ij}} = \varepsilon\left(< v_i h_j >_{data} - < v_i h_j >_{model}\right) \quad (2)$$

Where, ε is the learning rate, the symbol$<.>_{data}$ represents an expectation from the data distribution while the symbol $>$*model* is an expectation from the distribution defined by the model.

$$\Delta_{w_{ij}} = \varepsilon\left(< v_i h_j >_{data} - < v_i h_j >_{recon}\right) \quad (3)$$

Reconstruction model with Gaussian-Bernoulli RBM to deal with the real valued data in practical problems is shown in eq. (3) where in updating of visible unites are done in parallel to get a reconstruction and the model updated using eq. (3).

C.Architecture of DBNN

The DBNN model is a familiar neural network architecture with a combination of multiple hidden layers containing multiple non-linear representations. It is a probabilistic generative model that may consist of RBM (see Figure 2). It demonstrates how to stack multiple RBMs together. The DBNN architecture can be built in succession by piling up multiple RBMs to develop the architecture of deep network.

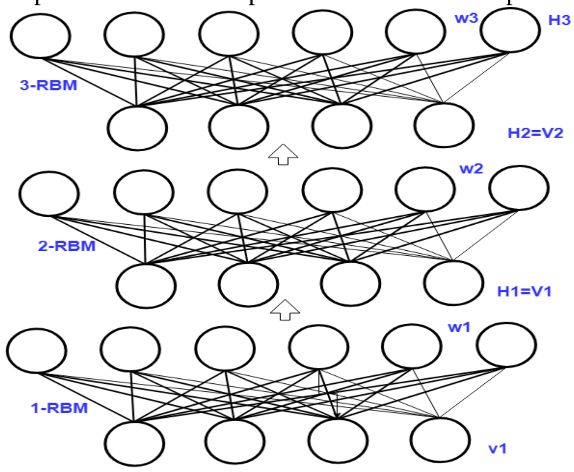


Figure2. DBNN Architecture

Because the DBNN has several number of hidden layers, the input data can be trained and extract a categorized representation with respect to each and every hidden layer. The joint distribution between the l hidden layers h_m and visible layer v can be mathematically calculated from conditional distribution $P(h^{m-1}|h^m)$ for the (m–1)th layer conditioned on the m'th layer and joint distribution of visible hidden $P(h^{n-1}, h^n)$:

$$P(v, h^1, \dots, h^n) = \left(\prod_{m=1}^{n-1} P(h^{m-1}|h^m)\right) P(h^{n-1}, h^n). \quad (4)$$

For deep neural networks architectures, learning such a large number of parameters using a traditional supervised training strategy is impractical because the errors that are transmitted to the lower-level levels are muted across multiple levels, and the ability to adjust the settings, is low for the traditional method of back propagation. It is difficult for the network to generate globally optimal parameters. Here for the formation of DBN the greedy method of unsupervised layer-by-layer pre-training is used. This procedure of training can be elaborated as follows:

Step1- Input units (v) and the hidden layer (h1) are trained using RBM rule (referred as RBM1).

Step2- The output of first hidden layer (h1) is treated as input to the second hidden layer (h2) which is again trained using RBM rule (referred as RBM2) . In a similar way, all the hidden layers are trained naming them as RBM3, RBM4 and soon till the last set of hidden layer is met. The step wise training process of DBNN is illustrated in Fig. 3.

DBNN is a process of supervised learning using classes to reduce the error of training and improve the classification accuracy.

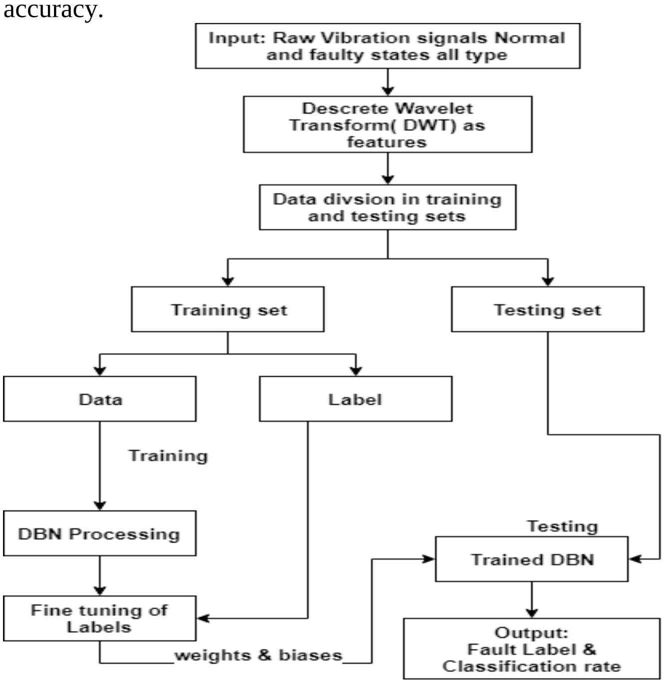


Figure3. Supervised Fine tuning process of DBN

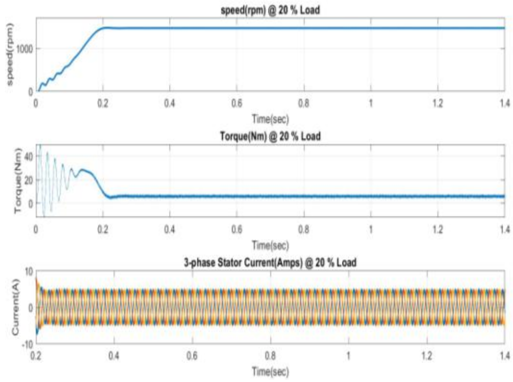
D.Fault Diagnosis based on DBNN

The waveform signals of the stator currents are selected as the system-wide input for fault diagnosis because they generally holds some important pattern that can imitate the operating condition of the induction machines. However, there is a correlation within the collected sampled data points. Handling of correlation is difficult for the architecture of DBNN network because the correlation within the input attributes cannot be performed, which might affect the next identification task. Consequently, in this work, the current signals of stator are processed with a discrete wavelet transform to convert the stator current signals from the time to the frequency domain with two DWT levels, and then a wavelet of each signal is used as a signal to enter the DBNN architecture. This is advantageous for the classification task during training. In particular, the DBNN network trains a model that produces input data, which allows inherent input properties to be achieved, thereby improving the accuracy of the classification. In this proposed methodology, the numbers of RBM units are stacked one on other forming the DBNN architecture. The model is then trained to from the database created to obtain the trained model parameters. Initially, the number of neurons, hidden layers and output layers with input attributes like number of training epochs and tolerance level is initialized. Each layer is trained one after other in a layer-by -layer learning process to settle the weights and the biases which signifies the training process completes. After the training the prediction of the induction motor fault category is executed.

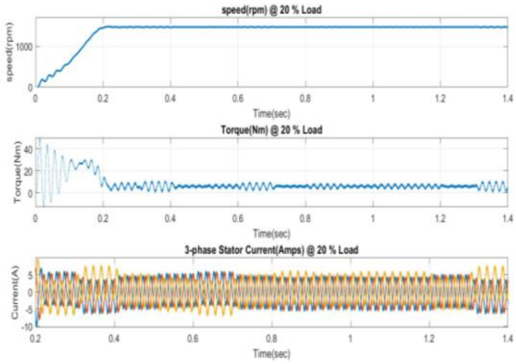
III. Results and Experimentation

A. Motor Simulation with effect of change in load

For the simulation and experimentation squirrel cage induction motor (5Hp, 460Volts and 50Hz) is considered. Motor behavior on various faults are analyzed using the wavelet transform by converting the stator current variations into the frequency component transform and treated as the features for the deep learning classifier to detect the fault and classify the fault with its type. For this article experimentation, Broken Rotor Bar, Stator fault and Combined Broken Rotor Bar & Stator are taken into consideration. Figure 4, 5 and 6 represents the performance of induction motor under healthy as well as different fault condition



(a)



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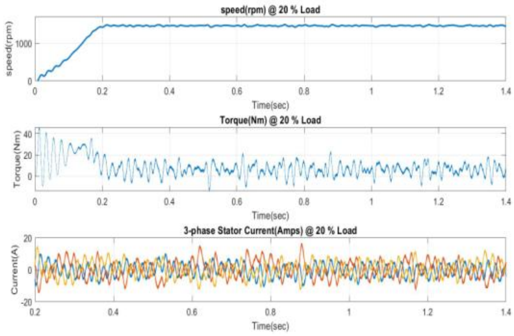

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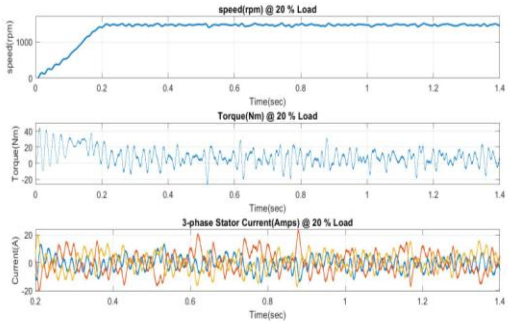
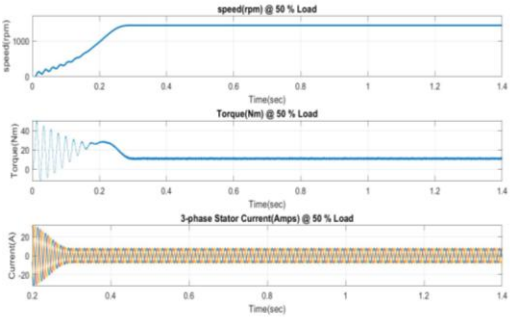


(d)

Figure 4 (a), (b),(c) &(d) speed, torque and 3-ϕ stator current output of healthy state, broken rotor bar fault, stator fault and combined fault at 20% loading of 3-phase induction motor respectively



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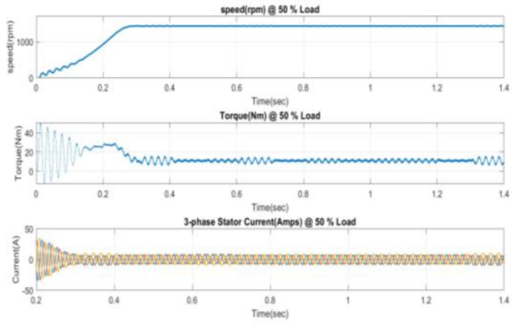

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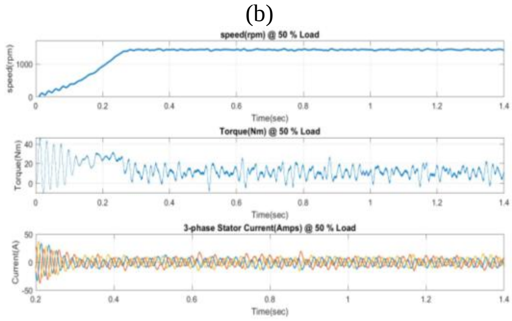

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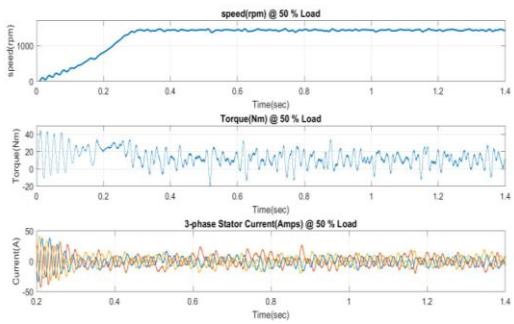
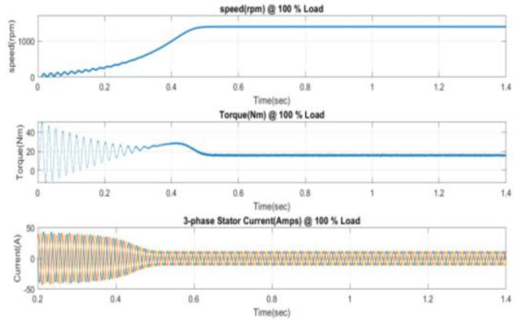
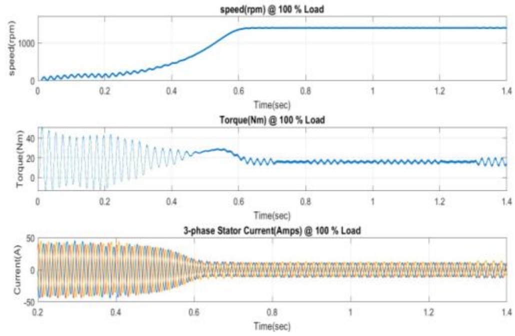


(d)

Figure 5 (a),(b),(c) &(d) speed, torque and 3-ϕ stator current output of healthy state, broken rotor bar fault, stator fault and combined fault at 50% loading of 3-phase induction motor respectively



(a)



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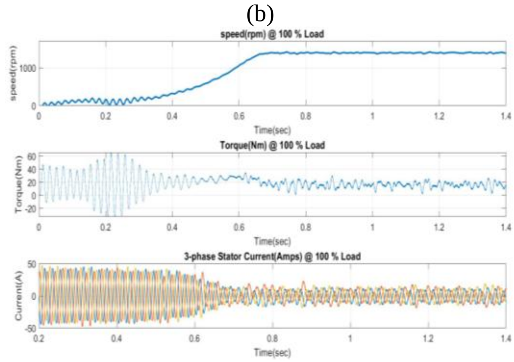

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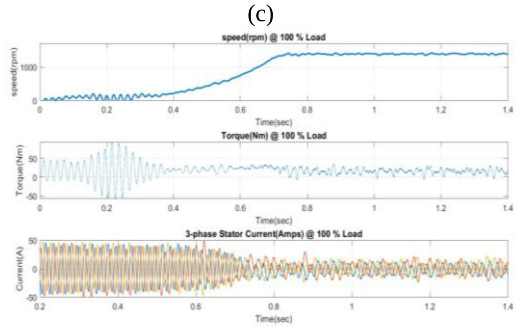

(d)

Figure 6. (a),(b),(c) &(d) speed, torque and 3-ϕ stator current output of healthy state, broken rotor bar fault, stator fault and combined fault at 100% loading of 3-phase induction motor respectively

B. DWT feature extraction of Stator current

The discrete wavelet transform are utilized for the feature extraction of the induction motor current variations. The motor stator current is taken as input and 2 level DWT is performed with 'db4' as the wavelet. The low frequency components of the wavelet is selected from the Ist level and computed 2nd level DWT which finally taken as features. Figure 7 depicts the samples of DWT features on different faulty conditions.

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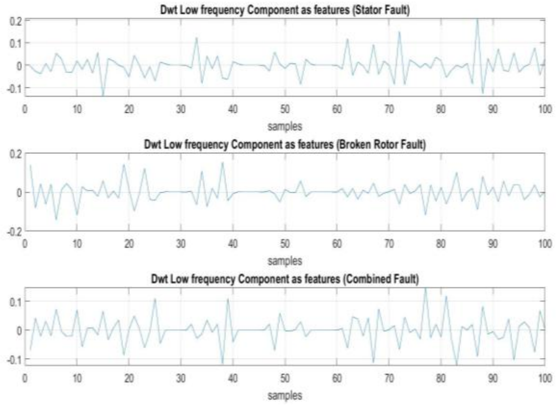

Figure 7. DWT features samples for stator, rotor and combined fault

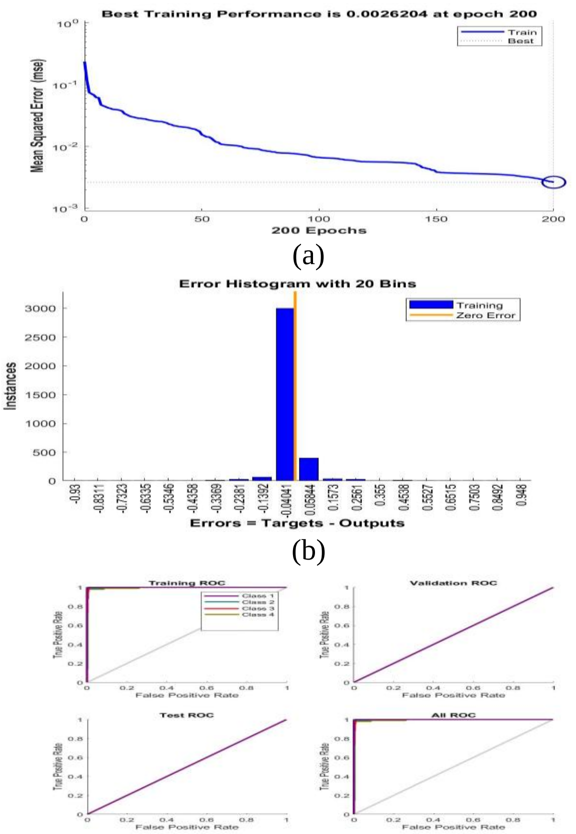

Figure 8. DBNN training (a) performance parameters, (b) error histogram & (c) roc curve

C. DBNN training

The DWT feature dataset is divided into three categories, called training data, fine-tuning data and test data. 2400 set data as training data fine-tuning data and test data. 800-set data as training data without fault types is used to make the forward stack-learning of each RBM from input layer to high layers. Moreover, another 800-set data with fault types divided into 1000-set optimal data and 800-set test data based on 4-Fold Cross-Validation method. 800-set optimal data is used to make the backward fine-tuning learning from the classification layer to low layers and 800-set test data is used to investigate the recognition rate of DBN classifier. Additionally, it is found in this study that the main factors affecting the recognition rate are three aspects: different units in second layer of DBN classifier, the number of layers and training data

The deep belief neural network training is performed using scale conjugate gradient method for training with MSE as a performance measurement calculation. Total numbers of epochs considered are 200 and performance achieved is 0.00262.The error graph, error histogram and ROC curve of training is shown in figure 8. All the lines of each fault in ROC are towards 1 show the high accuracy of the system with minimal false positive rate.

Table I. Confusion Matrix

		class1	class2	class3	class4
Actual Label	class1	200	0	0	0
	class2	0	200	0	0
	class3	0	0	199	1
	class4	0	0	1	199
		Predicted Labels			

Table I illustrates the confusion matrix of all the faults where all the classes are recognized with 100percent accuracy only class 3 and class 4 1 sample each is incorrectly classified. The overall accuracy of the system is **798/800 = 99.75%**

D. Application: effect of time invariance on the motor under faulty condition

The induction motor is put under various load variations in continuous operation for the simulation of 5 hours for each hour, the load torque is varied and the effect of that variation is analyzed and depicted in figure 9. The variation of speed and torque can be seen significantly and the stator current also got affected with dynamic variation of the load.

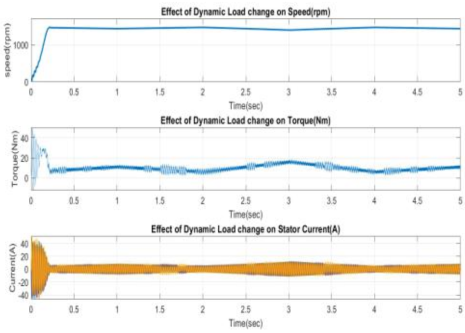

Figure9. Effect of Dynamic Load change on speed, torque and current respectively

E. State of Art comparison

The proposed method to detect the fault in induction motor is compared with the others state of art results and noted in table II. From the table it can be seen that the accuracy of the proposed work DWT with DBNN i.e. 99.75% have outperformed the other algorithms (SVM, LSSVM, KNN MLP NN) works stated in [1-2].

Table II: state of art comparison with previous work

S. No.	Comparison	Year	Accuracy (%)
1	KNN[2]	2018	94.31
2	MLP NN [2]	2018	98.40
3	SVM[1]	2014	97.5
4	LSSVM[1]	2014	99.5
5	Proposed Method	-	99.75

IV. CONCLUSION

In proposed methodology stator current is analyzed using wavelet transform which identify the patterns caused during the different operating condition of the motor (healthy or faulty) and furthermore, the classification of the faults is done using deep learning method DBNN. The training dataset used is built from stator current envelope i.e. spectral analysis and its feature extraction at each level under different motor operating conditions. Several Matlab simulation have been performed of the induction motor (squirrel-cage) setting the motor under different healthy and faulty operating condition (with load, No-load and a broken rotor bar), stator fault and combined fault). The simulation showed that the condition of any fault causes vibrations in the stator current, torque and speed. It can be seen that these oscillations are proportional to the type of fault. The overall accuracy obtained is 99.75 % in identifying the faults type.

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