INDUCTION MOTOR FAULT MONITORING AND FAULT CLASSIFICATION USING DEEP LEARNING PROBABLISTIC NEURAL NETWORK

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INDUCTION MOTOR FAULT MONITORING AND FAULT CLASSIFICATION USING DEEP LEARNING PROBABLISTIC NEURAL NETWORK

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Abstract-

Asynchronous motor plays a major part in all kind of industries. Even though, Induction motors are robust and reliable, they are liable to various faults. Faults in induction motor may leads to terrible events such as, operating personal injuries, disturbance in production and loss of raw material. Therefore identification of fault became more important in Induction motor maintenance. Among the various defects occurring in the motor, bearing failure is a major fault, which leads to disastrous harm to machine if it is left unobserved at early stage of fault. So the condition of bearing in induction machines has to be monitored continuously. In this work, a novel approach is proposed employing Discrete Cosine transform (DCT) for analyzing speed and Probabilistic Neural Network (PNN) is utilized to identify the bearing failures. The induction motor stator currents are analyzed and classified when the motor is operated at various loading conditions with healthy and faulty bearings. The proposed PNN classifier has the ability to classify the types of fault in bearing and the experimental result supports the worth of the developed method. The PNN based motor bearing fault detection and diagnosis provides better performance compared with conventional SVM and ANN classifiers.

Keywords: Induction Motor, Bearing Defects, Probabilistic Neural Network, Discrete cosine Transform, Fault Identification.

I. INTRODUCTION

Industrial applications require prime mover to drive the machineries related to their process cycle. Several motors are available to act as prime mover for industries. Among the various motors available, induction motors are extensively used as they are easily controllable, robust design, uncomplicated installation procedure and flexible for numerous industrial applications. In addition, induction motor does not require separate excitation and capable to produce high twisting force. This makes induction motor more suitable for industrial purposes. Even though induction motors are highly reliable, they are liable to mechanical and electrical failures. Bearing defects and rotor eccentricities are the mechanical disturbances leads to increased vibration, decrease in efficiency, torque and excess heating [1]. Therefore induction motor bearing has to be guided in order to prevent from major faults.

Bearing condition can be observed by detecting the speed and vibration using accelerometer and Piezo-electric sensors respectively, identifying faults in the bearing using this technique is not appropriate for noisy surroundings, very costly and requires human intervention to analyze the data from the field [3, 4]. Fault can also be found out by monitoring the flow of current through the stator using current signatures [5]. Current signature analysis of motor fault detection does not require any special equipment. Data from current signal helps to diagnose various faults of induction motor. Fren.L et.al used wavelet packet decomposition to find the bearing faults by studying stator currents in defect frequency bands [6, 7]. Stator currents are decomposed using discrete wavelet transform to find the fault in the bearing [8]. Gabor filter [9] and Weiner filter [10] are utilized to analyze current signals to detect fault in the bearing. In order to identify the bearing fault stator current frequency is analyzed with root-music algorithm [11]. Comparative study of Concordia and Park Transform was reported to classify the bearing faults [12]. Stockwell Transform is applied for detecting bearing fault in induction motor. Convolutional Neural Network has the ability to classify the bearing faults occurring in induction motor [16]. There is a necessity to find the competences of numerous transforms in bearing fault identification and classification at the starting stage of fault. Hence, classification and detection of bearing fault at incipient state is essential using innovative techniques. Probabilistic neural network (PNN) is formed by using exponential activation function instead of sigmoidal function used in conventional neural networks. PNN can able to calculate nonlinear decision boundaries leads to Bayes optimal [17]. Voltage stability of power system is improved during contingencies using probabilistic neural network. [18]. Principal component analysis along with Probabilistic neural network provides better results in fault classification of transformers [19]. A PNN classifier is utilized for identification of rock types and found PNN based classifier provides better performance compared with other classifiers [20]. PNN based crop disease recognizer trained based on feature extracted from crop leaves and meteorological data has an accuracy of above 90% [21]. Recently, PNN classifier has been applied for several engineering problems and it generates valuable results. This paper elaborates the application of Probabilistic Neural Network (PNN) for bearing fault detection and classification of induction motor [22-25]. This article is elaborately discussed as follows, Chapter II describes the proposed system considered for study. Chapter III explains the architecture of Probabilistic neural network. Chapter IV elaborates the results obtained in this study and Chapter v is the conclusion of this proposed work.

II. RELATED WORKS

Deekshit K.C et al (2017) proposed wavelet decomposition technique to find out the fault in the 3 phase induction motor. In this paper, to overcome the failures caused by the induction motors due to the hectic process without maintenance, a technique with different fault indexing parameters has been proposed. Due to the use of the various parameters, the early fault can be detected with the use of total power parameter. However, there arises various failures like corrosion and deformation occurs even after using different wavelet technique.

Ashok Kumar et al (2014) proposed probabilistic neural network in computer vision-based limestone rock-type classification. In this paper, by using the PNN (Probabilistic Neural Network) an effective method for identifying and analysing the limestone with ease, with the help of machine and without any human inclusion was proposed. As the proposed method is capable of learning through the process, the input and the output patterns for the training process can be learned during the regression and classification stage. The main issue is that there are too many rocks to be examined and the classification requires examining of the whole rock.

Hong-Hee Lee et al (2014) proposed discrete wavelet transform for the better analysis of fault detection in induction motor. In this paper, as the existing works clearly exhibits a static nature for the fault behaviour, the fault frequencies becomes constant, thus a method for bearing faults has been proposed. A major reduction in the harmonics and additional high-energy components are found, which are effective against the damage-causing faults in the motor. However the method sometime ignores the Gaussian form and prevents from detecting the faults.

Santi Behera et al (2016) proposed a novel approach for voltage secure operation using PNN classifier. In this paper, during the time of contingencies to detect the reasonable controls of the system, a technique that uses the PNN has been proposed. As to improve the load margin, the training sets of VSENN are tested for its robustness along with the contingencies, a performance enhancement can be noticed. However, sometimes the Bayesian classifier's convergence change may remain constant.

III. PROPOSED SYSTEM DESCRIPTION

Figure 1 clearly describe the structure of PV fed induction motor drive. Three phase induction motor speed control is done by adjusting the variable frequency technique. Variable frequency input is obtained from fixed input AC supply with the help of 3φ voltage source inverter. The control pulses for inverter is obtained by Sinusoidal Pulse width modulation. Sine PWM signals are obtained by comparing three sinusoidal signal with 120 degree phase shift to a 10 kHz carrier signal. Modulation index of the inverter is adjusted to control the velocity of the motor.

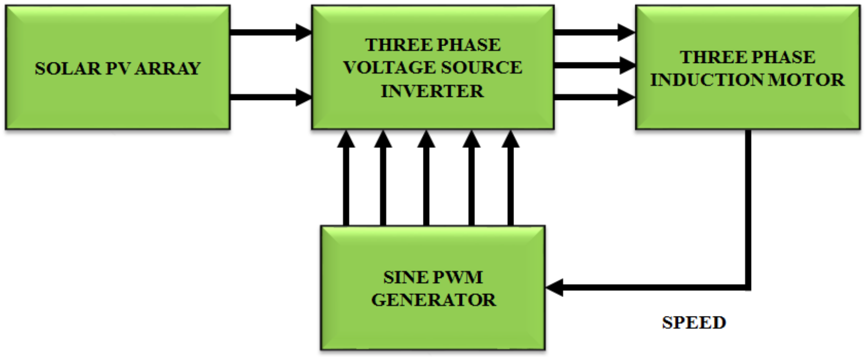

Figure 1. Block Diagram of Voltage Source Inverter Fed Induction Motor Drive

Fig 2 represents the probabilistic neural network based fault classifier for induction motor drive. The significant objective of this proposed system is to detect the main cause of fault in the motor as well as to analogize the speed of the motor between trained and test set data using PNN classifier. The workflow of this proposed system elaborately explained as follows, initially the retrieved input is fed to the process of preprocessing. It filters out the noisy distortion present in the input signal. After the filtering process over, the preprocessed input gets segmented into samples by pixel wise. In order to process the entire input, by performing the process of segmentation it enables us to process the operation in the significant segments of the input. After gaining the segmented image, GLCM method is performed to extract the features to detect the default region of motor and its causes astutely. The features which were retrieved was optimized and finally it undergoes a process of PNN classifier. The PNN classifier made a comparative analysis between the normal speed of trained data and the speed which was obtained through test set data. It detect the type of fault occurred in the motor as well as enunciate the causes which speed up the motor in an astute manner.

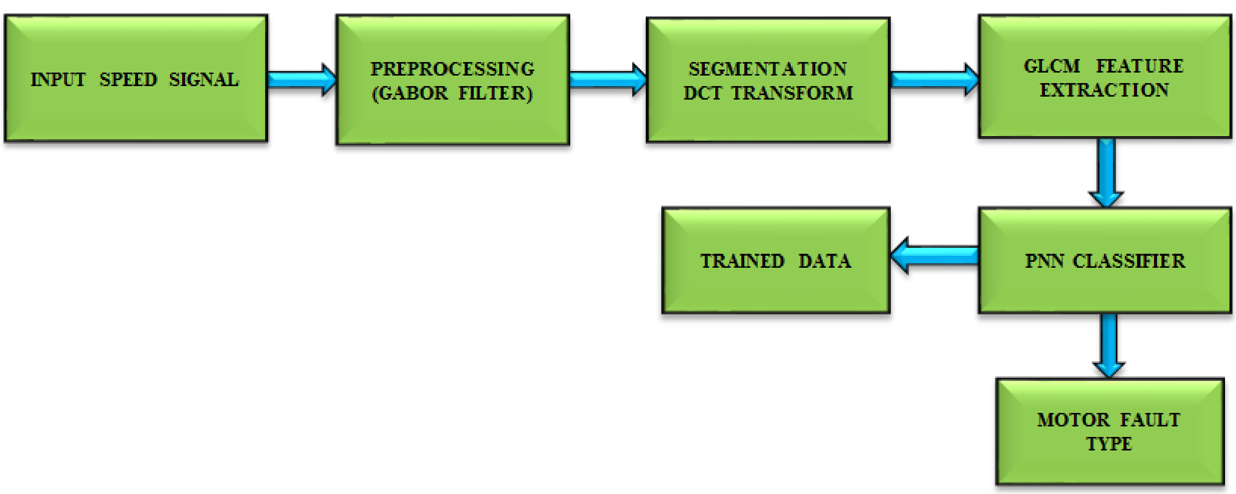

Figure 2. Proposed Probabilistic neural network based Fault classifier for Induction Motor

3. 1 Gabor Filter

Gabor filters are generally band pass filters normally used in extraction of features and texture analysis in image processing applications. In this proposed system, Gabor filter retrieves the input signal and filter out the noise and it smoothens to have a fine details for better processing. The Gabor filter impulse response is given in equation 1, multiplying Gaussian envelope with complex oscillation gives the impulse response of the filter. In order to make the filter orientation discriminatory, the functions are outspreaded in two dimension.

$$g_{mn}(x) = \frac{1}{2\pi a_n b_n} e^{-\frac{1}{2}x^T A_{mn} x} e^{jK_o^T{}_{mn} x} \tag{1}$$

Bandwidth and filter orientation selectivity is adjusted by varying the matrix and K_o is the modulation frequency vector**.**

$$A_{mn} = \begin{bmatrix} cos\varphi_m & -sin\varphi_m \\ sin\varphi_m & cos\varphi_m \end{bmatrix} \begin{bmatrix} a_n^{-2} & 0 \\ 0 & b_n^{-2} \end{bmatrix} \begin{bmatrix} cos\varphi_m & sin\varphi_m \\ -sin\varphi_m & cos\varphi_m \end{bmatrix} \tag{2}$$

$$k_{0nm} = k_{0n} \begin{bmatrix} cos\varphi_m \\ sin\varphi_m \end{bmatrix} \tag{3}$$

The transfer function of Gabor filter is given in equation 4.

$$G_{mn}(k) = e^{-\frac{1}{2}(k-k_{omn})^T (A_{mn}^{-1})(k-k_{omn})} \tag{4}$$

Where k is the spatial frequency $\boldsymbol{k} = [k_1\ k_2]^T$ is the spatial frequency.

$$k_{on} = \frac{\pi}{2^{n+1}}, \qquad n\epsilon[0 \dots \dots N-1] \tag{5}$$

3.2 Discrete Cosine Transform

After filtering out the noise, the input retrieved from Gabor filter is fed to the process of segmentation, it segments into samples by pixel wise. By performing this operation, time consumption is minimized because processing the overall segment is too complicated. By splitting out into samples, we can process the significant segment to analyze the fault detection. Discrete cosine transform (DCT) transforms time domain signals into frequency components. Discrete Fourier Transform and DCT have close relation with one other. DCT finds major application in image processing.

3.2.1 One-Dimensional Discrete Cosine Transform

One dimensional DCT is used to process signals with one dimension such as speed waveforms. The DCT y(x) is computed as follows, where X ranges from 0 to n-1.

$$y(u) = \left(\frac{2}{n}\right)^{\left(\frac{-1}{2}\right)} * C(u) \sum_{x=0}^{n-1} y(x) \cos\left(\frac{(2x+1)u\pi}{2n}\right) \qquad for\ u = 0 \ldots\ldots..n-1 \qquad (6)$$

$$\text{Where } C(u) = \begin{cases} 2^{\frac{-1}{2}} & for\ u = 0 \\ 1 & otherwise \end{cases}$$

Elements of y(u) is obtained by inner multiplication of a basis vector and the input time domain element y(x). The constant are selected such that the basis vectors are normalized and orthogonal.

By applying inverse discrete cosine transform y(x). The expression for inverse discrete cosine transform is given in equation 7.

$$y(x) = \left(\frac{2}{n}\right)^{\left(\frac{-1}{2}\right)} \sum_{u=0}^{n-1} c(u) y(u) \cos\left(\frac{(2x+1)u\pi}{2n}\right) \qquad for\ x = 0 \ldots\ldots..n-1 \qquad (7)$$

$$\text{Where } C(u) = \begin{cases} 2^{\frac{-1}{2}} & for\ u = 0 \\ 1 & otherwise \end{cases}$$

3.2.1 Two-Dimensional Discrete Cosine Transform

Two-dimensional (2-D) signals like images require two dimensional form of DCT for processing the signal. The two dimensional DCT can be separable as two one dimensional DCTs. For an n×m matrix s, the two dimensional DCT can be computed as,

$$y(u,v) = \left(\frac{2}{n}\right)^{\left(\frac{-1}{2}\right)} * C(u)C(v) \sum_{x=0}^{n-1} \sum_{z=0}^{m-1} y(x,z) \cos\left(\frac{(2x+1)u\pi}{2n}\right) \cos\left(\frac{(2x+1)v\pi}{2n}\right) \qquad for\ u = 0..n-1 \quad v = 0 \ldots \ldots m-1 \qquad (8)$$

$$\text{Where } C(u), C(v) = \begin{cases} 2^{\frac{-1}{2}} & for\ u, v = 0 \\ 1 & otherwise \end{cases}$$

The inverse DCT for the two-dimensional DCT is determined using the expression 9.

$$y(x,z) = \left(\frac{2}{n}\right)^{\left(\frac{-1}{2}\right)} \sum_{u=0}^{n-1} \sum_{v=0}^{m-1} C(u)C(v) y(u,v) \cos\left(\frac{(2x+1)u\pi}{2n}\right) \cos\left(\frac{(2x+1)v\pi}{2n}\right) \qquad for\ x = 0 \ldots\ldots..n-1$$

for z=0………… m-1 (9)

$$\text{Where } C(u), C(v) = \begin{cases} 2^{\frac{-1}{2}} & for\ u, v = 0 \\ 1 & otherwise \end{cases}$$

A DCT based Discrete Orthogonal Stockwell Transform (DCT-DOST) in which the DFT kernel is replaced with DCT kernel [22]. . DCT is widely used in various applications such as compression and filtering and it is a real-valued function. DFT can be easily replaced with DFT as they are related to each other and it results in smooth adaptation of DOST algorithm. The block diagram of DCT based DOST approach in displayed in figure 3.

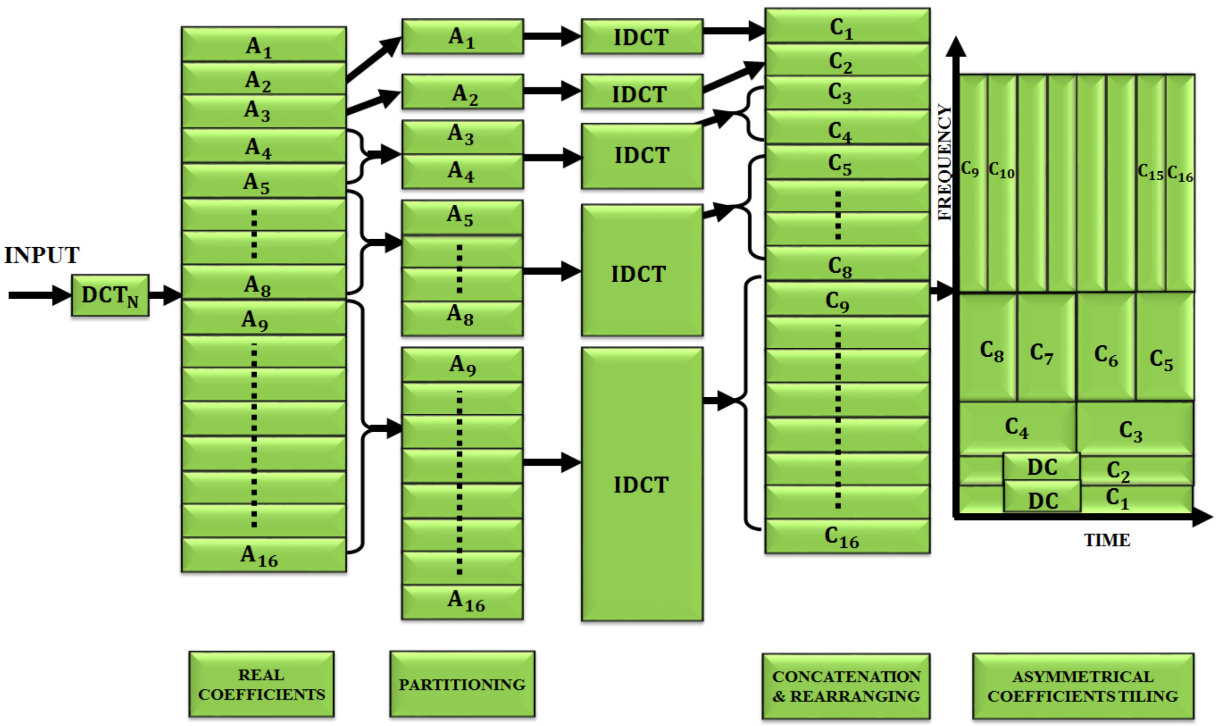

Figure 3. DST-DOST approach block diagram

4 Probabilistic Neural Network (PNN)

PNN classifier helps to perform comparison between normal speed of trained data and the speed obtained through test set data. While performing comparative analysis, if it found to be the speed exaggerates the normal speed it results in a problematic state. PNN classifier analyzes the state of fault in the motor and it generates the rectified result. Artificial intelligence plays a significant role in solving classification and optimization problem. The key feature of neural network is flexibility, any linear or non-linear relationship can be represented between input and output by proper training. Probabilistic neural networks classifier follows Bayesian classifier concept of statistics. It gives answers for problems based on pattern classification. PNN classifier is able to solve difficult multi-class classification problem and decomposes it in the form of dichotomies [23]. PNN architecture structured as shown in fig 4. The input layer transfer the retrieved input to the pattern layer and it does not perform any calculations. The next two layers are similar to RBN and competitive network respectively. The number of neurons in pattern layer is equal to input samples, whereas the number of neuron is same as target class in summation layer.

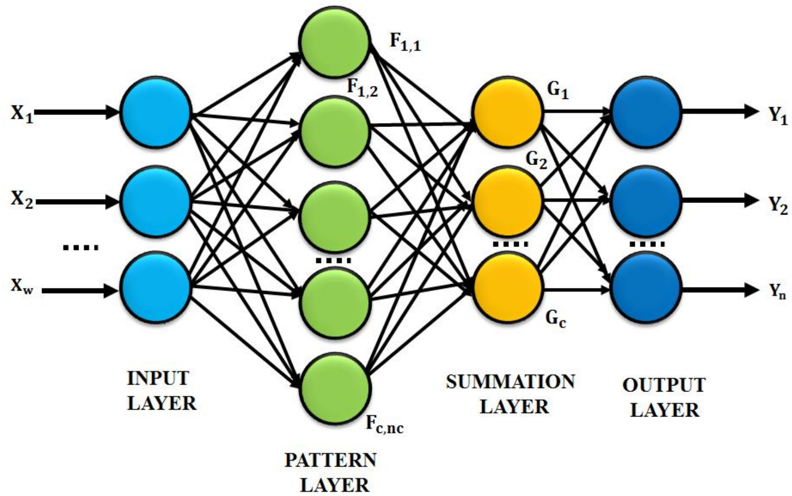

Figure 4. Probabilistic Neural Network Architecture

The neurons present in the input layer receives the input and pass it to the pattern layer in which the neurons are grouped to various classes. The output of the neuron of kth pattern and cth class can be computed using equation 1. Where $X_{c,k} \in R^n$ is the kernel center, α is the smoothing parameter, finds the kernel receptive field size.

$$F_{c,k}(X) = \frac{1}{(2\pi\alpha^2)^{\frac{n}{2}}} exp\left(-\frac{\|X-X_{c,k}\|^2}{2\alpha^2}\right)$$

(10)

Approximate conditional class probability function is calculated by the summation layer using the combination of densities already computed.

$$G_C(X) = \sum_{k=1}^{N_c} F_{c,k}(x) \qquad C \in \{1,2, \dots \dots \dots . C\}$$

(11)

Where Nc is total number of class c pattern neurons, Pattern vector is classified in a particular class based upon the maximum output of the summation unit.

$$Y(X) = argmax_{1\le c\le C}(G_c)$$

(12)

IV. RESULTS AND DISCUSSION

The condition of the motor bearing has to be analyzed, when the motor operates at full load condition. The data’s are collected for fault conditions with artificially induced faults. The possible conditions in the bearings during operation are, at normal condition, defects in the outer race, defects in the inner race, rotor bar broken condition. Data collection systems are provided to collect speed information of the motor. The data pre-processing and extraction of features are the steps followed by the data collection.

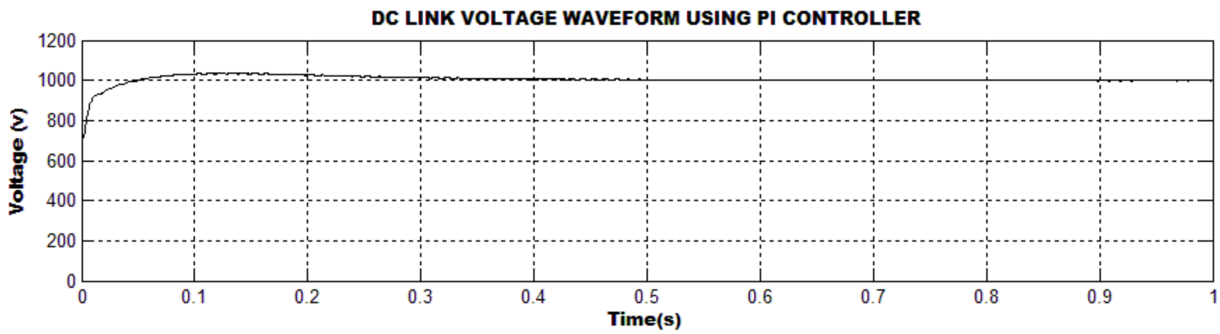

Figure 5. Three Phase Inverter DC input voltage waveform

The output voltage obtained from PV array is given as input to three phase inverter. The DC input waveform is represented in figure 5. Sinusoidal PWM method is applied to generate firing pulses for three phase inverter.

The three phase inverter output waveform is represented in figure 6. The output voltage of the inverter is controllable so as to maintain the speed of the motor in a steady state. Figure 7 shows the current waveform of the induction motor in all three phases, the initial peak represents the starting current consumed by the motor.

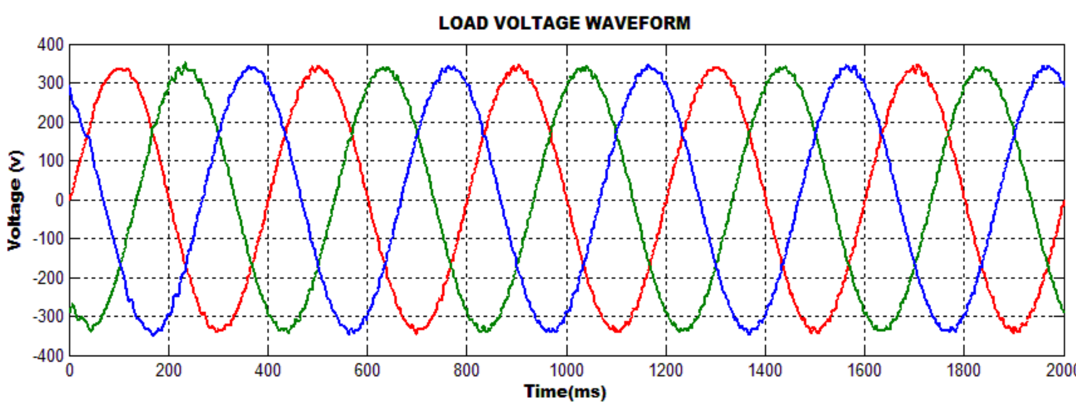

Figure 6. Three phase inverter output voltage waveform

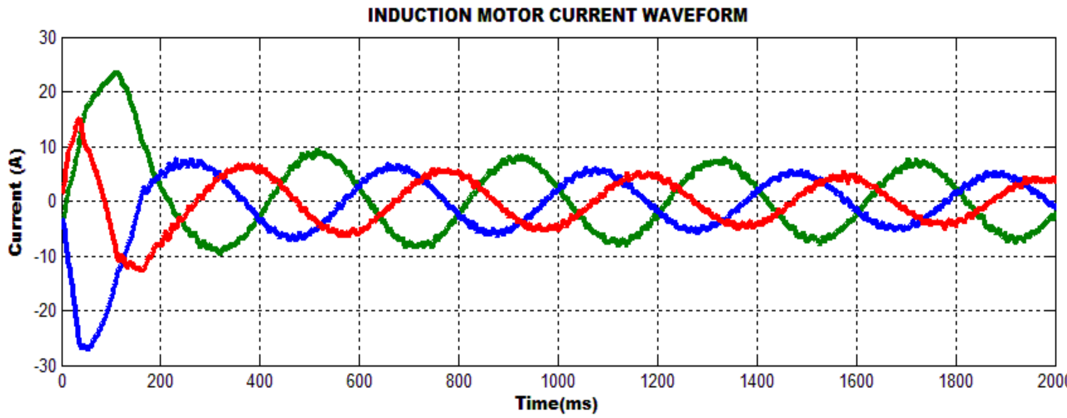

Figure 7. Three phase current waveform of induction motor

Figure 8 shows the very much oscillated speed waveform of the unhealthy induction motor, which is utilized for the added investigation of fault in the motor bearing. By analyzing the speed signal fault type is determined effectually by the PNN classifier.

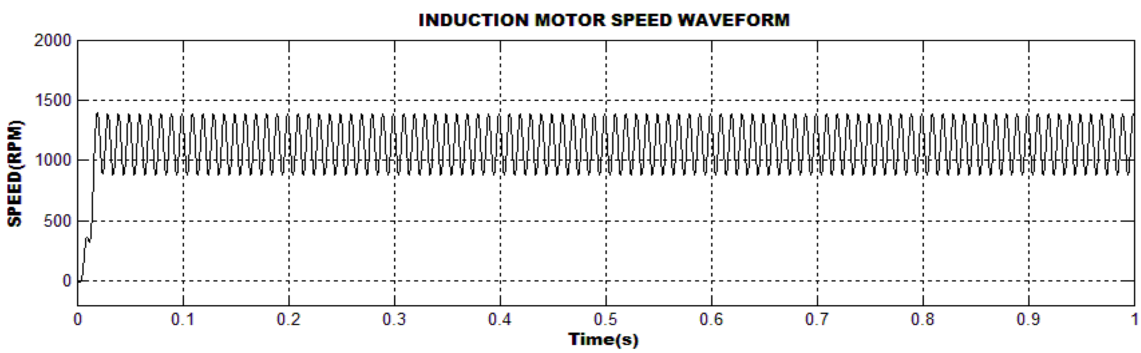

Figure 8. Speed waveform of induction motor with defects

The motor speed waveform given in figure 8 is sampled at frequent intervals and applied to the preprocessing stage, in this stage the unwanted noise signals present in the speed samples are removed with the help of Gabor filter. The speed samples obtained is shown in figure 9.

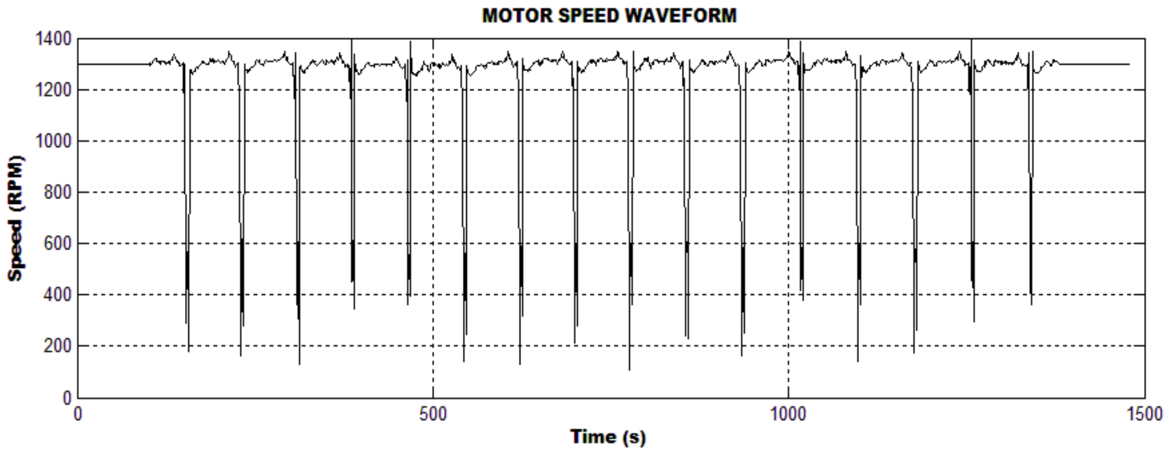

Figure 9. Speed Signal sampled waveform

The noise free signal output from the Gabor filter is displayed in figure 10. The noise free information of the motor output is then given to the segmentation stage for further processing. And to classify the fault type of bearing.

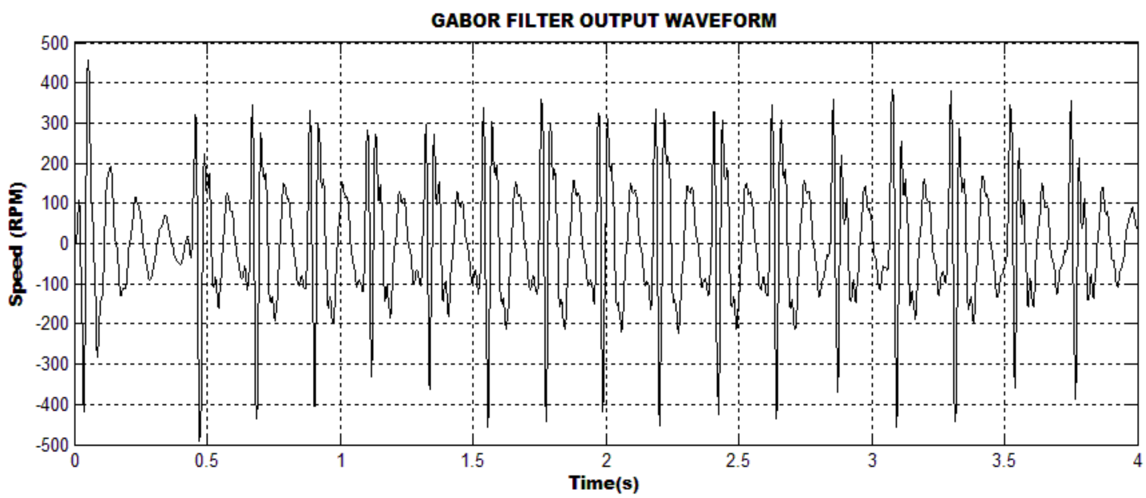

Figure 10. Gabor Filter output waveform

Discrete cosine transform is used to compute magnitude of the preprocessed signal and it is exposed in figure 11. Signals in the negative direction is eradicated with twice the amplitude in positive direction.

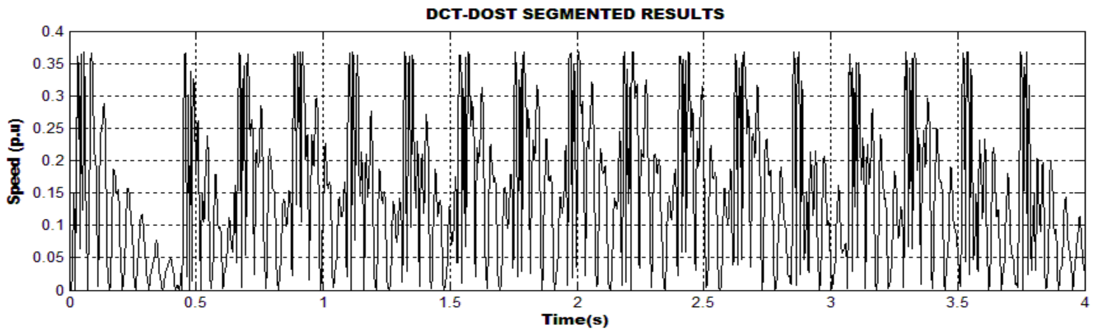

Figure 11. DCT-DOST output waveform

The DCT output signal is rebuild to recuperate the key information of the speed signal. The first level and second level reconstructed signal is shown in figure 12 and 13 respectively.

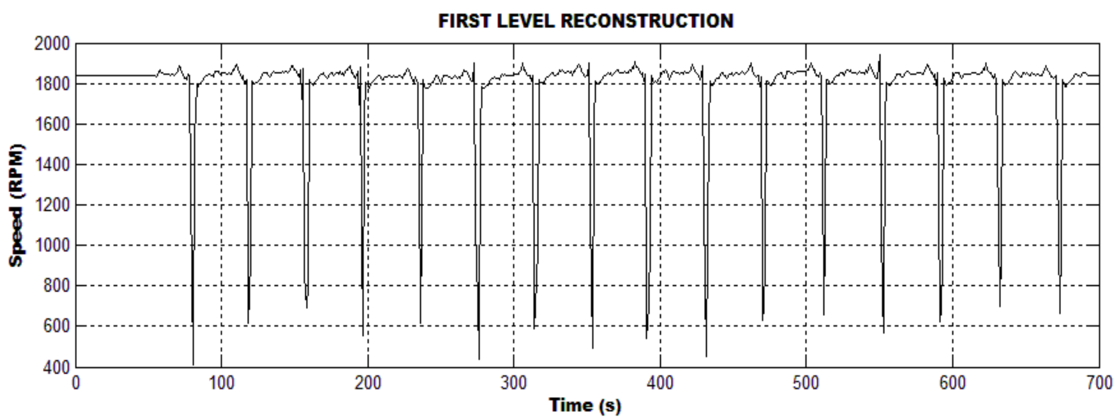

Figure 12. First level reconstructed Speed Signal

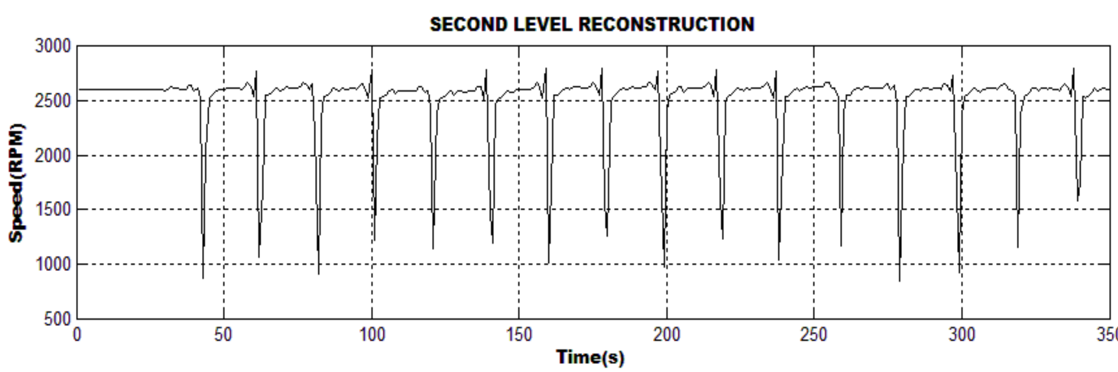

Figure 13. Second level reconstructed Speed Signal

Reconstructed speed signal peak amplitude is found by using zero crossing detector. Peak signal to noise ratio is used to determine the performance of the system. By identifying speed signal peak amplitude properly, classification of fault type performance will get increases.

The PNN classifier is trained with the typical fault data of asynchronous motor which are available. The results obtained using PNN classifier is depicted in figure 14.

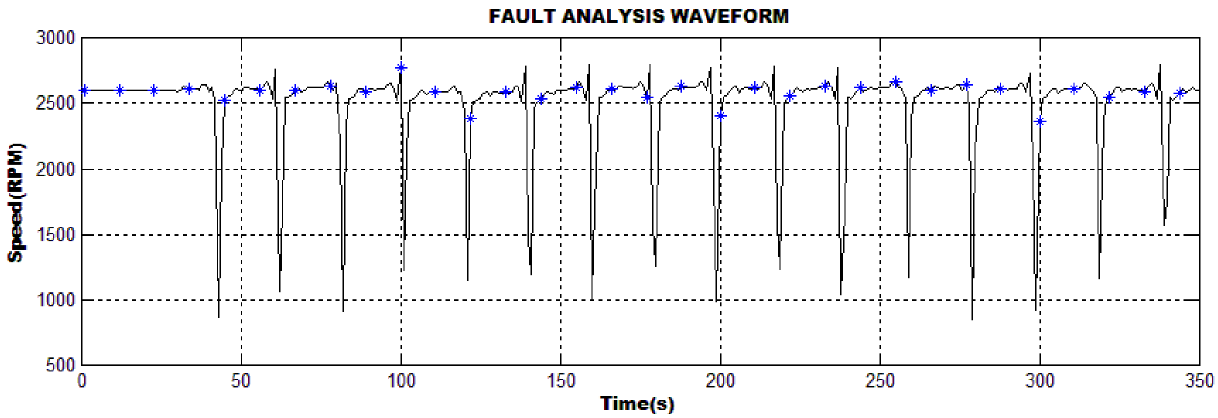

Figure 14. PNN classifier fault classification

The proposed classifier performance is analyzed by measuring performance index such as accuracy, specificity and sensitivity. The performance indices obtained using PNN classifier is compared with ANN and SVM types of classifier. Figure 15, 16 and 17 shows accuracy, sensitivity and specificity versus number of images obtained for various classifiers respectively. From the shown figure, it is clear that the sensitivity, accuracy and specificity of PNN classifier is about 95% and it is higher than the other classifiers considered for comparison.

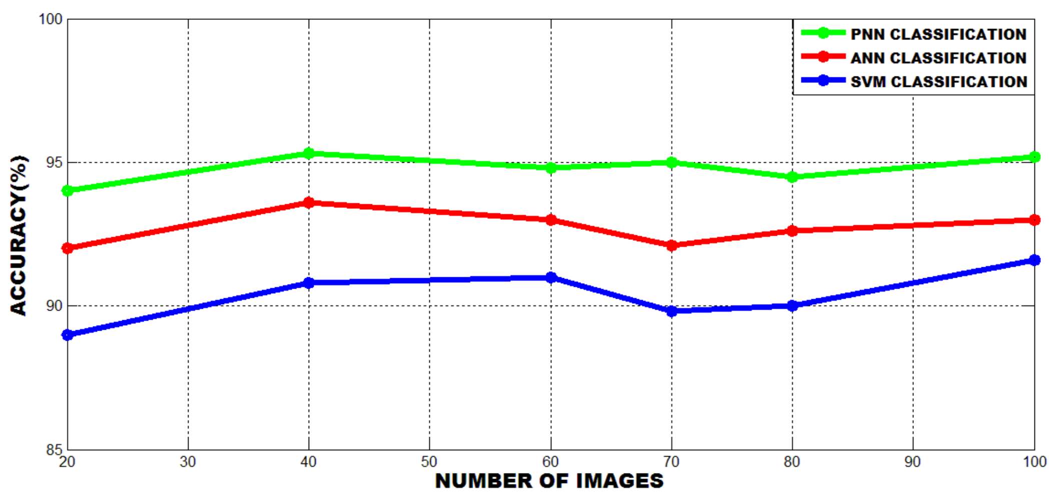

Figure 15. Accuracy of PNN, ANN and SVM Classifier

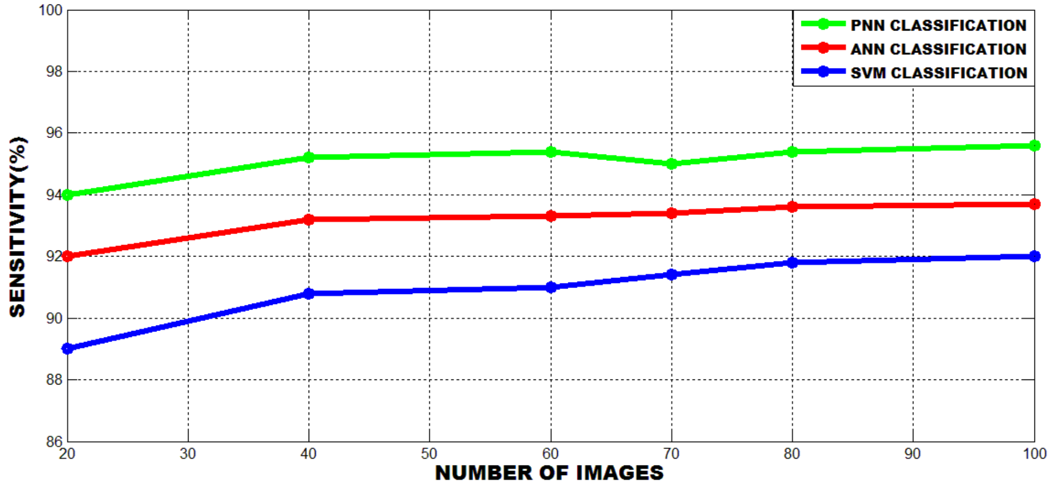

Figure 16. Sensitivity of PNN, ANN and SVM Classifier

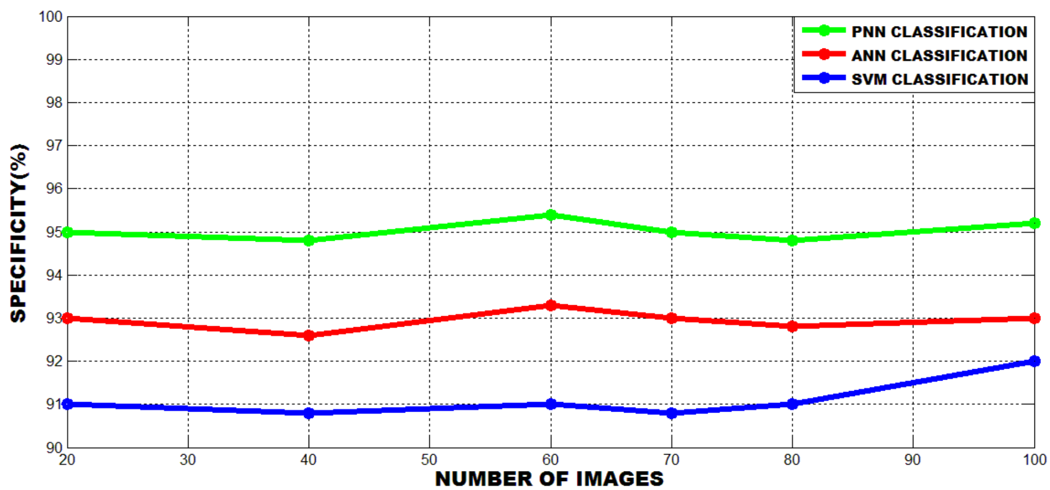

Figure 17. Specificity of PNN, ANN and SVM Classifier

V. CONCLUSION

In this work, induction motor bearing fault classification is performed using Probabilistic neural network. The efficiency of the PNN classifier is compared with SVM and ANN based classifier. PNN not only helpful to analyze the state of fault occurred but also computation is performed faster and it generates an astute result for the cause of exaggeration of speed. Accuracy, Specificity and Sensitivity are the performance indices considered for analyzing the performance of the proposed PNN classifier. The obtained result confirms PNN classifier outperforms with higher accuracy, sensitivity and specificity irrespective of the number of images compared with ANN and SVM based classifier. As PNN is trained by Q-learning approach. It is considered as one of the significant model in classification problem. Hence PNN classifier can be used in future bearing fault detection problems. This proposed method is very effective and it the maintains the speed in a steady state and it is also very important in power system.

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