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FAULT DIAGNOSIS OF DFIG USING WAVELET TRANSFORM

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Abstract: Fault diagnosis of DFIG is a prominent challenge in wind turbine condition monitoring. Many machine learning algorithms have been applied to DFIG fault diagnosis. However, these current machine learning algorithms failed to give satisfactory fault diagnosis results due to some of their drawbacks. This paper presents a wavelet transform and support vector machine (SVM) technique based algorithm for fault diagnosis of DFIG. The SVM is used to extract the information from a signal over a wide range of frequencies. This analysis is performed in both time and frequency domains. Experimental results are validated by using MATLAB.

Index Terms:—Doubly-fed induction generator (DFIG), fault diagnosis, rotor current, support vector machine (SVM), Wind turbine, Continuous Wavelet Transform, MATLAB.

Introduction: —

Wind turbines equipped with a doubly-fed induction generator (DFIG) have dominated the wind turbine market, especially the market of medium- and large-scale wind turbines. Since the cost for maintenance and repair constitutes a significant portion of the total cost of electricity produced by wind turbines, it is highly desirable to perform condition monitoring and fault diagnosis for DFIG-based wind turbines to improve their availability, safety, and reliabilityand reduce the downtime and maintenance costs. In the vibration monitoring, signals are measured by vibration sensors (e.g., accelerometers) attached to the casings of the gearboxes, which are situated on high towers and are difficult to access during wind turbine operation. Moreover, wind turbines usually operate in varying speed conditions. In order to process the vibration signals acquired under such non stationary conditions, the instantaneous shaft rotating speed of the wind turbine is required and usually provided by a rotor speed sensor. The use of vibration and rotor speed sensors increases the cost, size, and wiring complexity and causes additional issues to the reliability of the wind turbine systems whenever their sensors fail. Compared to vibration-based techniques, current-based techniques have the following benefits. First, since current signals have been used in wind turbine control systems, there is no need of installing additional sensors or data acquisition devices, which makes the current-based monitoring techniques easier and lower cost to implement. Moreover, current signals can be collected at convenient locations, such as the bottom of the tower, which is easily accessible and nonintrusive to the wind turbine being monitored. However, due to the varying shaft rotating speed of a wind turbine, the signals collected from the condition monitoring system of a gearbox are usually non stationary with low signal to noise ratios (SNRs). Thus, the fault-related information (i.e., fault features) contained in the collected signals often changes with time and is difficult to extract. To facilitate the extraction of fault features from the non stationary signals, a variety of methods such as continuous wavelet transform (CWT), adaptive optimal kernel (AOK), and order tracking have been proposed for the purpose of signal conditioning [1]. Among them this paper deals with continuous wavelet transform.

Wavelet Analysis: There are various mathematical tools which have been introduced for EEG signal feature extraction such as Fourier Transform (FT), Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT) and Wavelet Transform (WT). However in Fast Fourier Transform, there was information loss about time domain and gave only spectral information in the frequency domain. To overcome the problems related to FFT, STFT was introduced that represented the signal in both time as well as in frequency domain using moving window function. The main problem associated with STFT is that it does not give multi-resolution information of the signals as it always has constant size. In order to overcome the problems related to Fourier transform, Fat Fourier Transform and Short Time Fourier transform, a powerful method was proposed known as Wavelet transform. Wavelet Transform is not only working on a single scale that is time or frequency rather it works on multi-scale basis and also addresses the problems related to non-stationary signals. Wavelet transform theory has found many interesting applications in the field of Digital Signal Processing.

In recent years, Wavelet analysis plays an important role for analyzing time – domain signals. Wavelet is also known as time-frequency analysis, which provides information about both frequency and time within signals. Wavelet represents a special type of linear transform of signals and also physical data represented by the signals and their physical properties of mediums and objects.Compared to other transform methods such as Fourier transform, Short Time Fourier Transform the wavelet Transform has been more efficient for signal analysis. The main advantage of wavelet transform is that it can holds the multi resolution properties in all frequency ranges which means by varying window size which is broad at low frequencies and narrow at high frequencies leading to an optimal time frequency resolution in all ranges. In mathematics, a wavelet series is a representation of real or complex valued function of square integrable. A wavelet is represented by a wave like oscillation with amplitude that begins at zero, increases and then decreases back to zero. For signal processing the wavelets are generally crafted to have specific properties. Wavelets can be combined using a reverse, shift, multiply and integrate technique known as convolution [2]. Wavelets transforms are broadly divided into three classes: continuous, discrete, and multi resolution-based Wavelets transforms are broadly divided into three classes: continuous, discrete, and multi resolution-based.

The objective of this paper is to develop and test a detection method for condition monitoring, suitably adapted for implementation in wind generator systems based on the CWT [5].

Continuous Wavelet Transform (CWT):

In definition, the continuous wavelet transform is convolution of the input data sequence with a set of functions generated by the mother wavelet. The convolution can be done by using a Fast Fourier Transform (FFT) algorithm Normally ,the output is a real valued function except when the mother wavelet is complex. We can convert the continuous wavelet transform to a complex valued function by the complex mother wavelet. The

power spectrum of the continuous wavelet transform is given by

$|X_w(a,b)|^2$

$$X_w(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t)\overline{\psi}\left(\frac{t-b}{a}\right) dt$$

Whereψ(t) is a continuous function in both the time domain and the frequency domain called the mother wavelet and the over line indicates the operation of complex conjugate.The mother wavelet has to provide a source function to generate the daughter wavelets which are simply the translated and scaled versions of the mother wavelet. The first inverse continuous wavelet transform can be exploited to recover the original signal.

$$x(t) = C_\psi^{-1} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} X_w(a,b) \frac{1}{|a|^{1/2}} \tilde{\psi}\left(\frac{t-b}{a}\right) db\, \frac{da}{a^2}$$

In determining the damping ratio of oscillating signals (e.g. identification of damping in dynamic systems) the continuous Wavelet Transform (CWT) is very efficient and also very resistant to the noise in the signal[6].

Theoretical Background and Wavelet Analysis:

Reduction of operational and maintenance costs of wind turbine is one of the most important factor, helping to avoid undesirable operating conditions and detecting component failures, is to provide wind generators with advanced condition monitoring and diagnosis system during operation [7],[8-9]. To prevent major component failures the autonomous on-line condition monitoring systems with integrated fault detection algorithms enable early warnings of mechanical and electrical faults to it. Side effect on other components can be reduced significantly. Many faults can be detected while the defective component is still operational. Therefore and because of the importance of condition monitoring and fault diagnosis in wind turbines (blades, drive trains, and generators); this section is intended to be as a tutorial overview describing different type of faults, their generated signatures, and their diagnostic schemes. It should be noted that the presented study is focused on DFIGs as they are the most used in wind turbines.

In addition to fault detection, fault classification is also a crucial part of wind turbine condition monitoring and fault diagnosis. Many studies have been done for gearbox fault classification using a support vector machine (SVM) or an artificial neural network (ANN).

Support Vector Machine (SVM)

SVM is a new type of classifier that is motivated by or based on two concepts. First concept includes transforming of data into a high dimensional space. This concept can transform complex problems into simpler problems that use linear discriminant functions. And the second concept of SVMs are motivated by training and using only those inputs that are near to the decision surface as they provide the most important information about the classification[3]. The SVM algorithm is depends on the statistical learning theory and it is used for data classification, pattern recognition, bioinformatics applications and also for regression analysis because of their ability and accuracy to deal with large number of predictors. The support vector classifier itself has many advantages. In SVM, Nonlinear boundaries can be used without much extra computational effort. Moreover, the performance of SVM is very competitive with other methods. The disadvantage of SVM that it has is the problem complexity which is not of the order of thedimension of the samples, but of the order of the number of samples [4].

Artificial Neural Network (ANN):

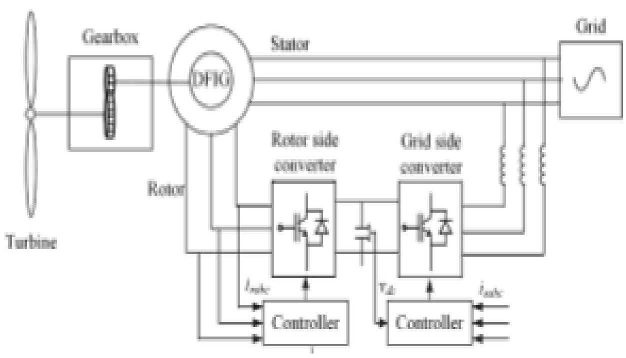
In generally an artificial neural network is an interconnected group of nodes. In machine learning, ANNs are family of statistical learning algorithms and it is an electronic model based on the neural structure of the brain. Basically, ANNs consists of the systems made up of more number of firmly interconnected adaptive processing elements (neurons) and for the data processing and knowledge representation these elements perform massively parallel computations. ANNs learning is accomplished through special training algorithm and it can be trained to recognize the non-linear models and patterns developed during training. ANNs have evolved as a powerful tool for classification, pattern recognition, prediction as well as pattern completion[3] .The classification boundaries are hard to understand intuitively and ANNs are computationally expensive. For the dataset with small number of input features it might be better to use some other model in order to reduce computation complexity as it is possible to classify the non-linear data with other different classifiers, such as polynomial logistic regression or SVMs as well.

This paper proposes a new multiclass SVM deep classifier for fault diagnosis of DFIG-based wind turbines under varying speed conditions using rotor current signals [1].

SVM can discover high-level features from the input data, the classification accuracy can be improved compared to the traditional classifiers.

Proposed Fault Diagnosis Method:

This paper explores a novel fault diagnosis method of DFIG wind turbines using rotor current signal analysis and multiclass SVM classifier The three-phase rotor current signals used in the control system of the DFIG are used for fault diagnosis. The instantaneous shaft rotating frequency of the DFIG is estimated from a rotor current signal using a time-frequency distribution (TFD)-based method after the DFIG operating mode is identified. Meanwhile, the envelope of a rotor current is extracted by a Hilbert transform-based amplitude demodulation algorithm. Then, the nonstationary rotor current envelope signal in the time domain is converted to a stationary signal in the angle domain by using an angular resampling method according to the estimated shaft rotating frequency. By selecting a constant reference frequency, the PSD analysis is performed on the resampled envelope signal for fault detection. In the meantime, both time- and frequency-domain fault features are extracted from the rotor current signals and the PSDs of the resampled rotor current envelope signals, respectively. Finally, fault classification is carried out by the proposed multiclass SVM classifier according to the fault features extracted[1].



A .Instantaneous Shaft Rotating Frequency Estimation:

In the proposed method, the instantaneous shaft rotating frequency is required to provide the phase information for angularre sampling. In this paper, the instantaneous shaft rotating frequency of the DFIG, fshaft(t), is estimated based on signals and the operating mode of the DFIG as follows.

$$P\ .f_{shaft}(t) = f_s \pm f_r(t)$$

where p is the number of pole pairs of the DFIG; fs is the frequency of the power grid, which is fixed at 60 Hz in the United States; and + or − is used in when the DFIG operatesin the super-synchronous or sub-synchronous speed mode respectively.

Firstly, the operating mode of the DFIG is identified by the phase sequence of the three-phase rotor current signals. If the phase sequence of rotor currents is positive, the DFIG operates in the sub-synchronous speed mode; otherwise, if the phase sequence is negative, the DFIG operates in the super-synchronous speed mode.Fig. shows the three-phase rotor current signals and shaft angular speed measured by an encoder during the process that the DFIG changes from the sub-synchronous speed mode to the super-synchronous speed mode. From 19.5 s to 20.7 s, the shaft angular speed is smaller than the synchronous speed and the sequence of the three-phase rotor current signals is positive. Thus, the DFIG operates in the sub-synchronous speed mode. After 20.7 s, the shaft a speed exceeds the synchronous speed and the sequence of rotor currents changes to negative, meaning that the DFIG operates in the super-synchronous speed mode.

After the operating mode of the DFIG is identified, it is necessary to estimate the fundamental frequency of rotor current signals. Phase-based and TFD-based methods are two popular approaches for instantaneous frequency estimation (IFE). The phase-based method is sensitive to small interference, which results in a noisy estimation; while the TFD-based method produces more reliable and more robust-to-noise results [20]. The TFD of a signal gives a two–dimensional representation of both the time and frequency information of the signal and, therefore, is effective for the analysis of a nonstationary signal. The variations of the frequency components contained in the signal can be readily visualized on the time-frequency plane. The short-time Fourier transform (STFT) is a simple and easy tool to construct the TFD. Mathematically, the STFT of one phase rotor current signal (e.g., ira(t)) is defined as

$$STFT(t,f) = \int_{-\infty}^{\infty} Ira(\tau)h(\tau - t)e^{-j2\Pi ft}\, d\tau$$

where h(t) is a short-time analysis window function centered around zero and $\|h\|^2 = 1$. The length of $h(t)$ should be large enough to obtain a high frequency resolution of the TFD so that the target frequency component varies continuously. The STFT of ira(t) presents a series of “local spectra” of the signal ira(τ) around the analysis time point τ = t. The magnitude of the STFT yields the TFD of the signal:

$$TFD(t, f) = |STFT(t, f)|$$

Since the fundamental frequency component is dominant in the rotor current signal, it can be treated as mono-component signal. Therefore, the IFE can be easily implemented by the following direct maximum method, which searches for the global maximum value over the whole frequency range of the signal’s TFD along the time axis[1].

$$F_r(t) = \mathrm{argmax}\{ (TFD(t,f)) \}$$

B .Fault Classification Using Multiclass SVM:

SVM is a widely used machine learning algorithm to solve classification problems. It aims at solving a binary classification problem by constructing a hyper-plane as the decision plane, which separates two classes with the largest margin . Since there are many different faults in drivetrain gearboxes, fault classification is a multiclass classification problem. Therefore, a multiclass SVM classifier is needed. Some effort has been made to extend the binary SVM to solve multiclass classification problem. It is hard to distinguish different fault types based on characteristic frequencies only. To overcome this challenge, it is necessary to use more fault features for fault classification[1].

Experimental Validation:

Experimental tests are performed on a DFIG-based wind turbine drivetrain simulator to validate the proposed fault diagnosis method by using MATLAB Simulink. The DFIG based wind turbine simulation diagram is as shown in the figure(1) . Grid and wind turbine is directly connected to the DFIG .

In between DFIG and grid two types of converters are connected.one is rotor side converter which is known as front end converter and another one is grid side converter which is known as back end converter. There are two three-phase windings, one is stationary and other is rotating, both are separately connected to the equipment outside the generator..Hence this connections indicates the term doubly fed.

One of the winding is directly connected to the output, to produce 3-phase AC power at the desired grid frequency. The other winding (traditionally called the field winding) is connected to 3-phase AC power at variable frequency. The input power is adjusted in frequency and phase to compensate for the changes in the speed of turbine.

Adjusting the both frequency and phase requires an AC to DC and DC to AC converter. This is usually constructed from the large IGBTsemiconductors. This converter is bidirectional, and it can pass the power in either directions i.e. it can flow from input winding as well as from the output winding.

By using the converter we can control the rotor currents, and it is possible to adjust the active and reactive powers fed to the grid from the stator independently of the generator's turning speed.

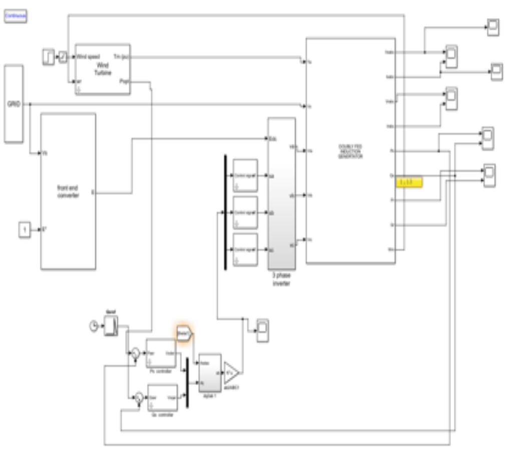


Fig.1.simulation diagram for DFIG based Wind Turbine

The voltage and current output waveforms are obtained from the scope of the MATLAB Simulink are as shown in the figure (2) .Rotor current output wavwe form is as shown in figure(3)

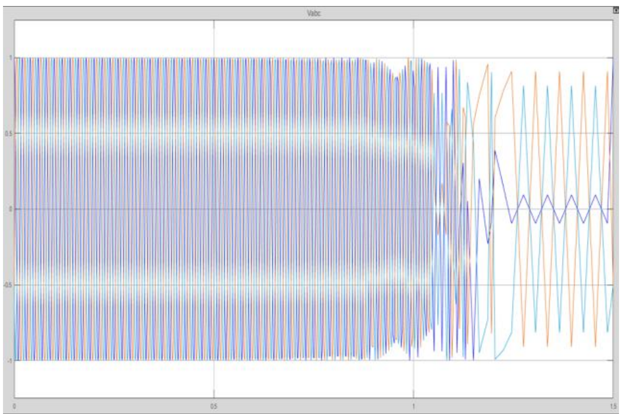


Fig.2.voltage output for DFIG generator

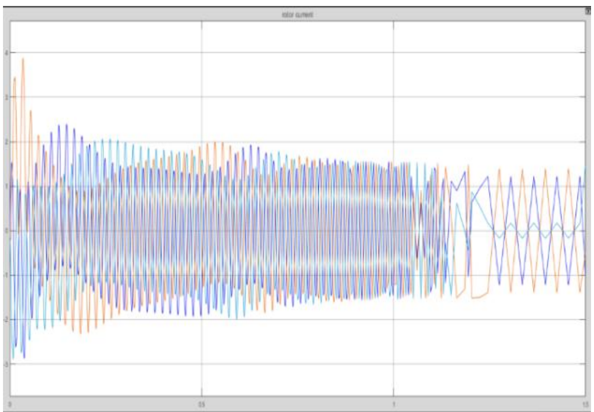


Fig.3.Rotor current output for DFIG generator

The trigger signal to the three phase inverter used at the grid side which is back end converter is as shown in the figure(4).

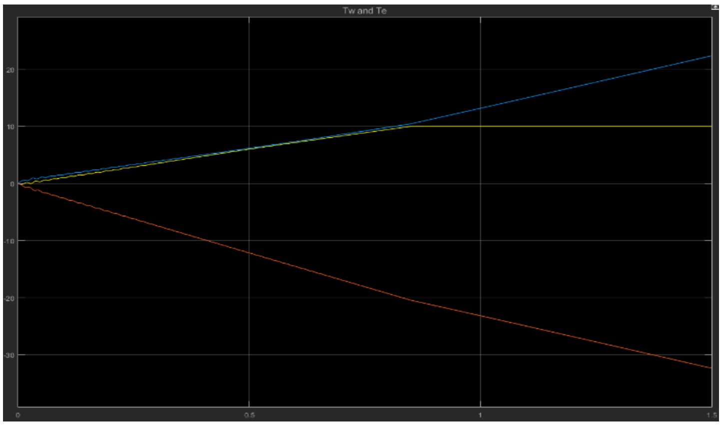


Fig.4 .Trigger Signals to 3 Phase Invertor

Finally Analysing the signals by using continuous wavelet transformthe results are as shown in the figure(4).

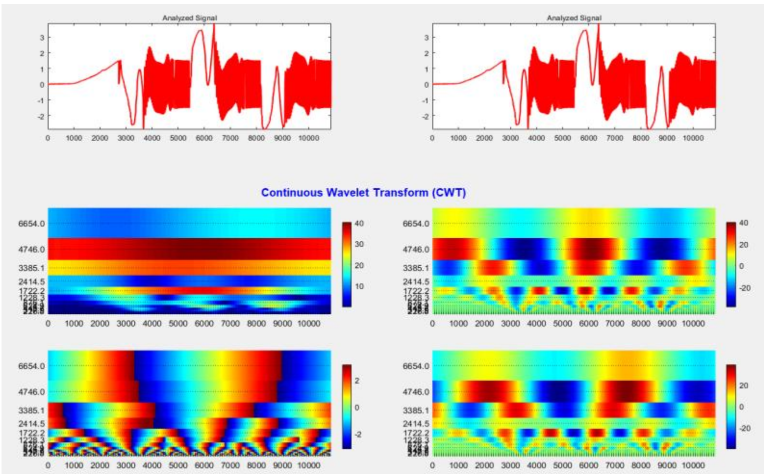


Fig.5.Cwt For Current

Conclusion:

This paper has proposed a new rotor current-based fault diagnosis method of DFIG wind turbines under varying rotating speed conditions. First, a signal conditioning method containing a TFD-based instantaneous shaft rotating frequency estimation algorithm, a Hilbert transform-based signal envelope extraction algorithm, and an angular resampling algorithm was developed to extract a stationary resampled envelope signal of the measured nonstationary rotor current signal to solve the spectrum smearing problem caused by shaft speed variations. After selecting a reference frequency, the PSD of the resampled envelope signal was then calculated from which the amplitudes of the constant fault characteristic frequencies were used as features for gear fault detection. Finally, a multiclass SVM classifier was designed to learn higher-level representation of the input fault features for fault classification. The proposed method has no or very low hardware cost and is nonintrusive to the wind turbines being monitored because it does not require any additional sensors, such as vibration and rotor speed sensors used in the traditional condition monitoring and fault diagnosis systems, and can be integrated into the existing DFIG control system. Experiments were performed on a DFIG-based wind turbine drivetrain test rig in the healthy and four different gear fault conditions. The results have validated that the proposed method is effective to detect and better than the traditional multiclass SVM method to identify different gear faults in the test rig under various operating conditions.

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