Sindh Univ. Res. Jour. (Sci. Ser.) Vol.47 (2) 291-294 (2015)

SINDH UNIVERSITY RESEARCH JOURNAL (SCIENCE SERIES)

Fault Detection and Identification in Horizontal Axis Wind Turbine Using Current Signal Analysis

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Received 18th December 2014 and Revised 23rd January 2015

Abstract: The occurrences of sudden faults in wind turbines cause the inconsistency in energy production. Most of the faults can be prevented by continuously monitoring the condition of the machine parts. However continuous monitoring of the mechanical parts requires extensive use of sensors which is not only expensive but reliability of such methods is also an issue because sensors themselves are also prone to faults and disturbances. This Paper focuses on the issue of occurrences of faults in horizontal axis wind turbines without use of extra sensors. The faults are detected and identified using current signals which are readily available and are more reliable than the other sensors used for condition monitoring. Advanced signal processing techniques are used to analyze different frequency modes of current signals and faults are diagnosed on the basis of frequency spectrum.

1. INTRODUCTION

Fault Detection and Identification (FDI) is becoming very important in modern systems due to increasing demands on reliability and safety during the operation. The basic idea is to analyze measured data to detect or predict occurring a fault, e.g. a system competent deterioration (Gong, 2012).

Currently in several wind turbine farms around the world preventive maintenance methods are applied, together with the breakdown maintenance better known as “fix it when it breaks”. Scheduled maintenance is based on the average component lifetime and is not effective as components mat deteriorate before or after average time (Gong, 2012).

Recent development in fault detection and identification methodologies has motivated researchers to use similar techniques to monitor the condition of wind turbines. Problem with these techniques is that different faults require different set of sensors and different analysis techniques to detect and correctly identify the faults. For instance, the blade or shaft imbalance generates vibrations of the nacelle in the horizontal direction.

Wear in the tooth of the gearbox can produce vibration of low frequencies. The fault in bearing may produce a radial rotor movement and consequently vibration of the wind turbine housing (Amirat, 2010). Therefore, vibration-based fault detection and identification systems require large number of sensors, which makes them very costly (Gong, 2012). Other

methods include oil/debris monitoring, temperature monitoring and acoustic emission monitoring also use large pool of sensors and data processing units. Therefore these methods are also not very effective. According to statistics more than 40% faults in wind turbines are related to sensor failures (Kumar, 2013; Qiao, 2011).

Therefore in this paper a sensorless method is proposed to detect and identify faults in wind turbines. The proposed method uses current signals and advanced signal processing techniques to identify faults from the frequency spectrum.

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2. DRIVE TRAIN MODEL

Fig.1 shows the simplified model of wind turbine drive train. The system dynamics are modeled in equation (1) to equation (4) (Xiang 2011; Xiang 2012; Bertling, 2007; Xiang 2012).

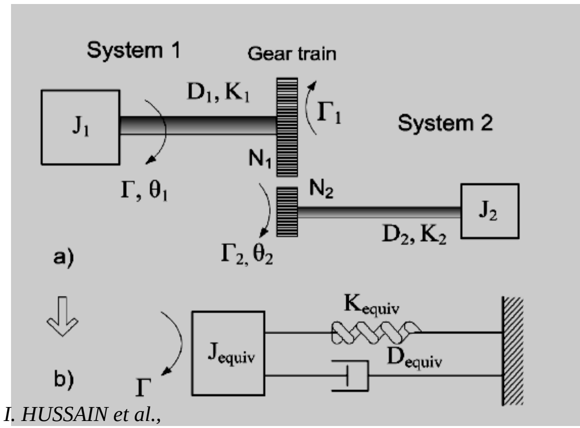


Fig. 1: Drive Train Model of wind Turbine

$$\tau_1 = \frac{J_1 d^2\theta}{dt^t} + \frac{D_1 d\theta^2}{dt^2} + K_1\theta_1 \quad (1)$$

$$\tau_2 = \frac{J_2 d^2\theta}{dt^2} + \frac{D_2 d\theta^2}{dt^2} + K_2\theta_2 \quad (2)$$

$$\tau_t = \frac{J_t d^2\theta_t}{dt} + D\left(W_t - W_g\right) + K(\theta_t - \theta_g) \quad (3)$$

$$-\tau_g = \frac{J_g d^2\theta_t}{dt} + D\left(W_g - W_t\right) + K(\theta_g - \theta_t) \quad (4)$$

Where

D_t = damping of the wind turbine rotor

D_g = damping of the generator

N_1 = gear-1

N_2 = gear-2

J_t = moment of inertia of wind turbine

J_g = moment of inertial of generator

τ_t = wind turbine torque

τ_g = generator torque

3. IMF Algorithm

The flow diagram of intrinsic mode function (IMF) algorithm is shown in (**Fig. 2)**. Following are the steps involved to extract intrinsic modes of current signal.

Step 1: Identify all extrema of current signal x(t)

Step 2: Interpolate the local maxima to form an upper envelop u(x)

Step 3: Interpolate the local maxima to form on lower envelop l(x)

Step 4: Calculate the main envelop

$$m(t) = \frac{U(x) + l(x)}{2}$$

Step 5: Extract the mean form the signal

H(t) = x(t) – m(t)

Step 6: Check whether h(t) satisfies the IMF condition.

Yes: h(t) is IMF. Stop shifting

: let h(t) = x(t), keep shifting.

Integrate until mean envelop = 0

and

{extrema = zero – crossing} ≤ 1

Once the intrinsic mode functions are extracted they are further processed to calculate the power spectral density.

4. SIMULATION RESULTS

A mathematical model of drive train system was presented in section 2. A simulation model using these equations is developed in Simulink for further analysis.

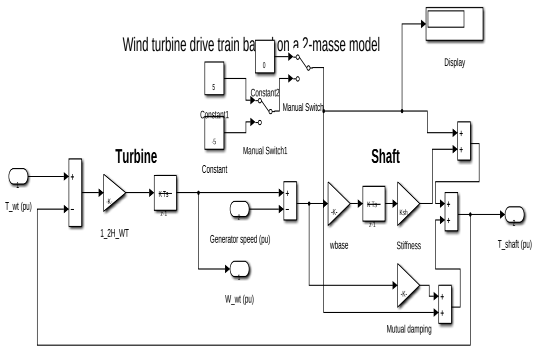


Fig.2: IMF Algorithm Flow Chart

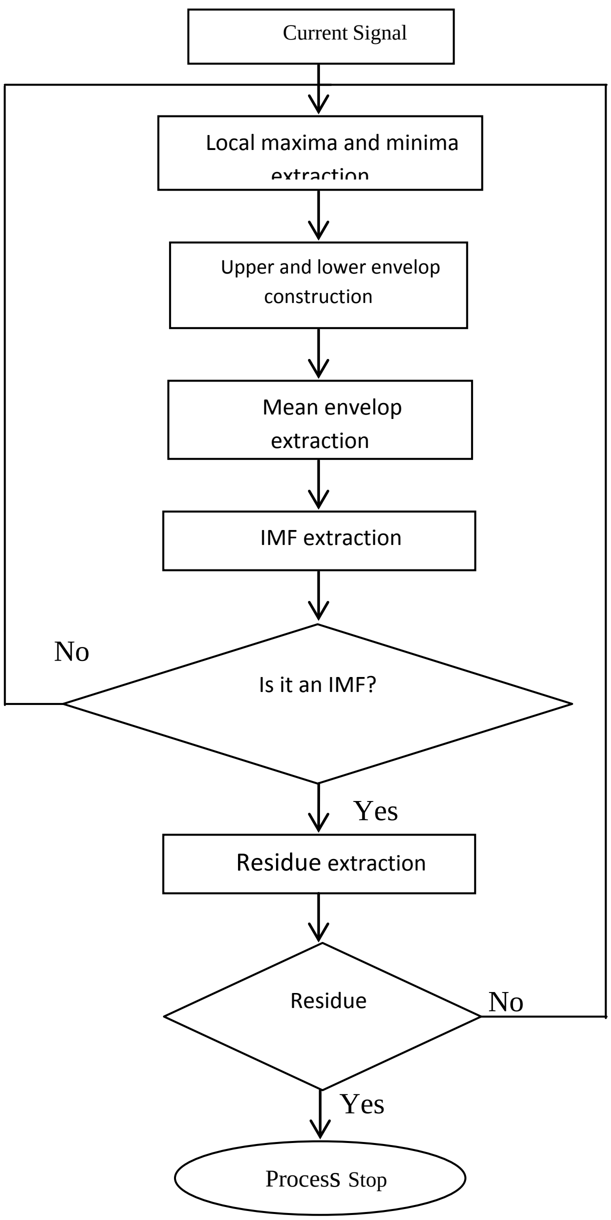


Fig.3: Drive Train Model in Simulink

The model shown in (**Fig.3)** is sued to simulate the behaviour of wind turbine drive train with and without fault. The developed model is simulated in three different scenarios and the respective simulation results are presented below.

4.1 Simulation without any fault

(Fig.4) shows the first intrinsic mode function of current signal when the wind turbine is running under normal circumstances. Spikes shown in following figure are the result of sudden change in wind direction during the simulation.

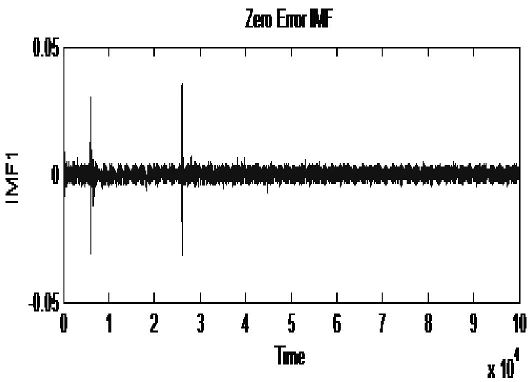


Fig. 4: First Intrinsic mode function without any fault. The power spectral density of the first intrinsic mode function is shown in **Fig.5.**

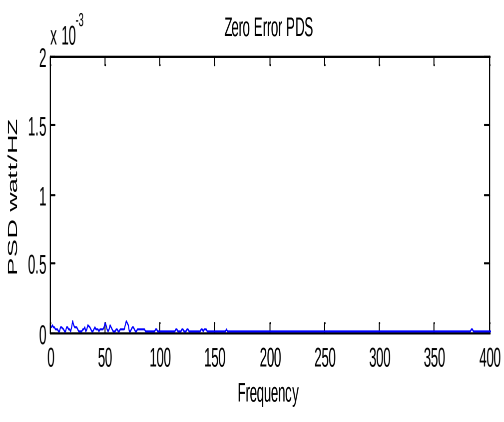
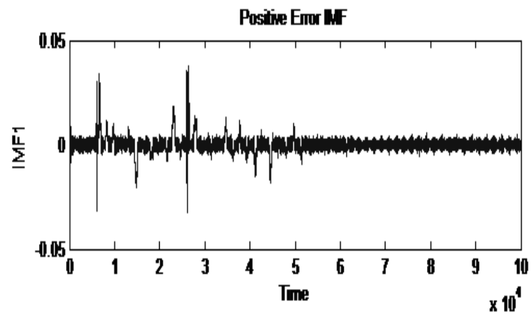


Fig.5: PSD of 1st IMF (No fault introduced)

4.2 Internal Bearing Fault

When the bearing balls deviate from pure rolling friction is increased. That increase of friction adds extras damping in the shaft. This is modeled by adding damping to the shaft using a manual switch as shown in fig. 3. When the damping in increased vibrations are produces in the intrinsic mode function as shown in **Fig.6.**



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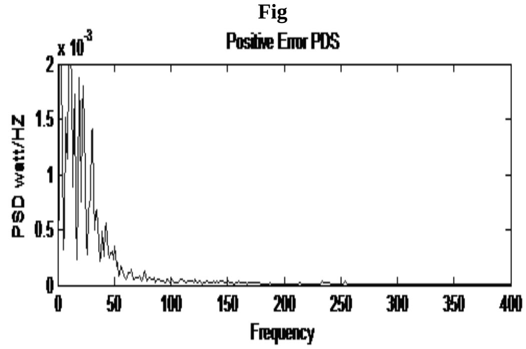

.6: IMF (Positive Damping)

Fig.7: PSD of IMF with positive damping

Fig.7 shows the power spectral density of 1st intrinsic mode function. Vibrations if frequency less than 50Hz can be clearly observed.

4.3 External Bearing Fault

External bearing fault loosens the shaft which in turn reduces the overall damping. This modeled by adding negative damping in the system.

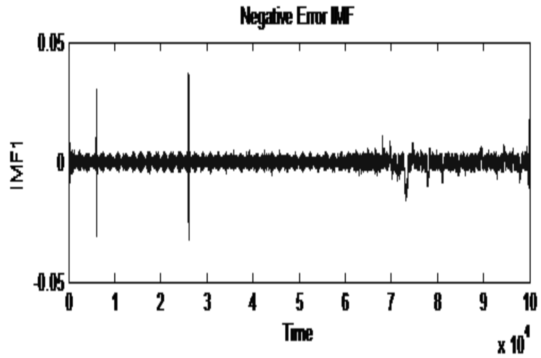

Fig.8: IMF (Negative Damping)

Fig.8 shows the first intrinsic mode function when the negative damping is added in the system. Vibration of relatively low amplitude can be observed from the power spectral density shown in Fig.9. However the frequency of vibration is almost same as the positive damping fault.

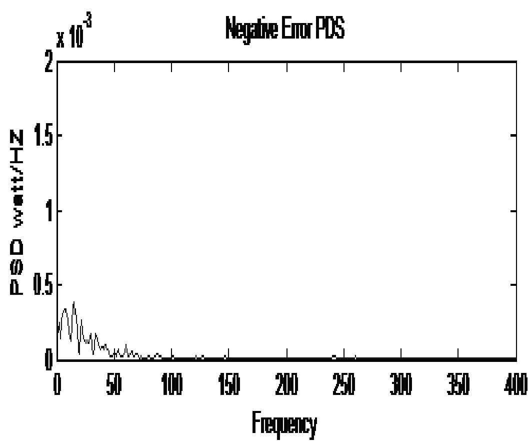

Fig.9: PSD of IMF with positive damping

5. CONCLUSION

The major aim of this research is to monitor the condition of the wind turbine during operation. This is done by monitoring the very small fluctuations in the current of the WTG. The major advantage of this method is that does not require extensive use of sensors to monitor the temperature, vibrations and acoustic data produced by WTGs. The potential of the research is quite evident from the simulation results presented. Further work can be carried out to identify more faults (e.g. blade imbalance fault, pitch angle fault e.t.c).

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