Application of Probabilistic Neural Network in Fault Diagnosis of Wind Turbine Using FAST, TurbSim and Simulink

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Abstract

This paper presents an intelligent diagnosis technique for wind turbine imbalance fault identification based on generator current signals. For this aim, Probabilistic Neural Network (PNN), which is a powerful algorithm for classification problems that needs small training time in solving nonlinear problems and applicable to high dimension applications, is employed. The complete dynamics of a permanent magnet synchronous generator (PMSG) based wind-turbine (WTG) model are imitated in an amalgamated domain of Simulink, FAST and TurbSim under six distinct conditions, i.e., aerodynamic asymmetry, rotor furl imbalance, tail furl imbalance, blade imbalance, nacelle-yaw imbalance and normal operating scenarios. The simulation results in time domain of the PMSG stator current are decomposed into the Intrinsic Mode Frequency (IMF) using EMD method, which are utilized as input variable in PNN. The analyzed results proclaim the effectiveness of the proposed approach to identify the healthy condition from imbalance faults in WTG. The presented work renders initial results that are helpful for online condition monitoring and health assessment of WTG.

1. Introduction

The wind generating power utilization has proliferated widely in the previous decade in the world and across the India. The installed power industry of in India is 22465MW upto December 2014, which is a now rank 5th in the
world after China, USA, Germany and Spain [1]. As a result, wind turbine industry is being grown up continuously, and becomes more challenging for power engineers to do condition monitoring and health assessment of wind turbines (WTs).

In general, every WT is under shut-down condition for 0.595% to 2.705% time period of a year [2]. This shutdown condition is due to the installation errors, manufacturing defects or effects of aging, nasty environmental condition and perturb loading scenario experienced by WT apparatus. There are different types of failures occurs in the WTGs, i.e., failure of components, control system, grid failure due weak connections, failure due to high wind, lightening, loosening of part and icing, generator, turbine blades, brake system, axle bearing, hydraulic system, pitch mechanism, gear box and yaw system etc. [2]. The faults due to imbalance form a major part of all faults in WTGs [2]. The imbalance faults in blade, shaft and furl and aerodynamic asymmetry are common imbalance faults in WTGs. The main causes of a blade imbalance are errors in construction or manufacturing, icing condition, degradation due to aging, or wear and fatigue in WTG the operation. Due to imbalance on blades and rotating shaft, equipments gravitate to shift and wear in varying degree over time. For example, effect of icing condition can develop a blade imbalance due to increasing extra burden by loads on WT supporting tower, which may create fractures and possible to collapses [3] the tower. The aerodynamic asymmetry is due to assorted reasons, containing errors in the control mechanism and high wind shear. For example, due to the error in control system, the pitch angle of any one blade is slightly changed from remaining two. This causes the aerodynamic asymmetry in the WTGs. Furl imbalance faults can be caused by changing in initial or fixed rotor/tail-furl angle in degree [4-5] which create the imbalance in tail and rotor part of the WT. Hence, a fault due to small imbalance can source of consequences on the WT, towers and finally on WTGs. So, effective condition monitoring and fault diagnosis of WTGs is become more advantageous to reduce repairing cost and enhance operating life with safety of catastrophic failure condition [6].

Generally available techniques for imbalance faults identification require additional vibration sensors (i.e., accelerometers) and data acquisition system [5]. These vibration sensors are placed on the WT equipment’s surface, which are very difficult to access due to high height of tower during WTGs operation. Furthermore, the components and sensors are naturally subject to failure, and lead extra problems related to stability and reliability of system and extra costs for maintenance. So, current signature based (without mechanical sensors) fault identification approaches become more reliable, which utilize generator current measurement approach only, and no data acquisition device or sensors is required. Measured current signatures have been utilized by the WTGs control system. Current signals are more reliable for condition monitoring of WTGs and easy accessible without including the WT. As a result, Current signature based imbalance fault identification approaches have enormous economic profit.

In this paper, the application of simulations is investigated to analyze the WT's faults due to imbalance conditions using PNN technique. The complete WTG model are design in an integrated domain of Simulink [8], FAST [4], and TurbSim [9], where TurbSim is used to produces the wind data, complete wind turbine dynamics is simulated by FAST (Fatigue, Aerodynamics, Structures and Turbulence), and MATLAB based Simulink software imitates the dynamics of the electrical generator and related equipments of the WTGs. Simulation observations are then carried out in six distinct conditions, i.e., aerodynamic asymmetry, rotor furl imbalance, tail furl imbalance, blade imbalance, nacelle-yaw imbalance and normal operating scenarios. The simulation results in time-domain of the WTG output stator current are decomposed into n-number of IMF using EMD technique and analyzed using PNN technique. Results represent that a variation appears at the energy entropy amplitude of the WT in the IMF of generator current signature in the imbalance fault condition. This study presents initial results that are helpful for online condition monitoring and imbalance faults identification of wind turbine.

This article is organized as follows: The introduction and literature review is given in Section 1. The dynamical model development along with the database generation is presented in section 2. The proposed methodologies used are represented in Section 3. The results are presented and discussed in Section 4, and a conclusion is given in Section 5.

| Nomenclature | Description |
|--------------|-------------|
| $b$          | biases      |
| $E_e$        | energy entropy |
| $P_e$        | power       |
| $t$          | target function |
| $w$          | output weight |
| $w^*$        | output weight |
| $y(t)$       | signals     |
| $\phi_i$     | output nodes |
| $\chi_i$     | input nodes |
2. Dynamical model development of WTG system

2.1. Brief detail of WTG mode

The vigorous model of a 10KW wind turbine generating system is developed in an amalgamated domain of thee software (i.e., TurbSim and FAST of NREL and Simulink of MATLAB), as represented in Fig. 1. The FAST is a comprehensive aeroelastic simulator. It is competent of forecasting both the fatigue and extreme loads of 2 & 3 bladed horizontal axis WTs. The TurbSim (version 1.06.00) is used to generate wind data which is utilized in FAST. The FAST (version 7.0) is utilized to design the dynamics of the non linear WT, whereas Simulink of MATLAB (version R2014a) is utilized to simulate the electrical generator and other equipments of the WTGs. In the WTGs model, FAST performs as a subroutine in Simulink. Three signals of rotating speed (\( w \) in rad/s), electric power (\( P_e \) in Watt) and electric torque (\( T_e \) in Nm) are utilized to link the Simulink and FAST models of WTGs.

![Fig. 1. WTG model in combined simulation platform of FAST and Simulink](image1)

Fig. 1. WTG model in combined simulation platform of FAST and Simulink

Fig. 2. Complete arrangement of WTG model in combined simulation platform of TurbSim/FAST/Simulink.

The WT model in FAST commonly incorporates support platform, shaft, blades, tower and furl. The parameters of the WT includes: hub height of tower above ground is 34 m, 3 numbers of blades of upwind configuration with rotor diameter of 2.9m, nacelle and hub mass is 260.5Kg and 113kg respectively. The means of upwind arrangement is that the blades are upwind of the tower. A PMSG of 48-poles is imitated in Simulink domain to convert the mechanical energy from WT into electrical energy (\( P_e \)). Three phase output signals of current and voltage in time domain are recorded for the further analysis of WTGs condition whether it is in normal operating condition or faulty condition. The Fig. 2 represents the complete arrangement of the WTGs model along with wind velocity data.

2.2. WTG system imbalance fault imitation

The FAST is utilized to simulate the whole dynamics of WT model in five imbalance fault conditions and normal operating scenario. These five imbalance fault states are aerodynamic asymmetry, blade/shaft imbalance, nacelle-yaw angle imbalance, tail furl imbalance and rotor furl imbalance. The Blade/shaft imbalance happen due to the mass of the WT components are not uniformly allocated w.r.t. the rotor. The main reason for blade imbalance are error in construction, manufacturing, wear and fatigue during the operation of WT or unbalance icing condition on the surface of blades.

Furl imbalance fault is other one imbalance fault in WT, which are rotor-furl imbalance and tail-furl imbalance. This type of imbalance fault is due to change in furl angle position from the required position due to this WT get spinning too quickly, and turning the blades away from the direction of the wind, either vertically or horizontally to save the system from collapse during high winds. This type of imbalance attempt to twist the generator shaft and in extreme cases can lead to air-gap closure in the generator, the ultimate consequence of which is a magnet collision with the stator.

The nacelle-yaw system of WTs is the component responsible for the orientation of the WT rotor towards the wind. Nacelle-yaw angle imbalance is due to change in the initial or fixed yaw angle position from the required position due to this orientation of WT rotor is changed.

The aerodynamic asymmetry imbalance fault in WT is due to the several reasons including variation in pitch angle of the blades, error in control system and high wind shear, which creates uneven distribution of the torque among 3 blades. For example, when angle of one blade pitch is changed slightly than other 2 blades, then electromagnetic torque (\( T_e \)) on rotating shaft is unbalanced, which creates an aerodynamic asymmetry in WTGs. Files and its parameters of FAST software used for simulating furl imbalance, blade imbalance, control error in yaw system, aerodynamic asymmetry are listed in Table 1.
Table 1: Files and Its Related Parameters Utilized for WTG Fault Simulation

| WTG fault type             | File name   | Parameters utilized |
|---------------------------|-------------|---------------------|
| Control errors of yaw system | Test17.fst | NacYaw              |
| Blade imbalance           | SWRT_BlkBlade.dat | AdjBlMs            |
| Aerodynamic asymmetry     | Test17.fst  | BlPitch             |
| Rotor furl imbalance      | Test17.fst  | RotFurl             |
| Tail furl imbalance       | Test17.fst  | TailFurl            |

In this paper, five imbalance faults conditions are simulated and analyzed with the normal operating condition of WTGs. The time-series output dataset of power, current and voltage of the WTGs are recorded for apiece simulation. Then the recorded data sets are decomposed into IMF by using EMD method, which has been explained in following section.

2.3. Data set generation for study

For preparing the data set, simulations are executed for WTGs in five imbalance fault conditions as well as healthy scenario. The imbalance in blade is created by changing the mass density of any one blade, which produces a non-uniform distribution of mass w.r.t. rotor. Three conditions are simulated with mass density of one blade modified by increasing 2%, 5% and by decreasing 3%, while mass density of other two blades are remain same. The furl imbalance is simulated by adjusting the rotor/tail furl angle, which creates uneven direction of the WT from the wind direction. In order to imitate furl imbalance fault of WT, the rotor/tail furl angle is adjusted by 10°,-5° and 5° degree apart from required position. The nacelle-yaw imbalance condition is simulated by changing yaw angle position (by increasing 10° and 20°, and by decreasing by -10°), which creates uneven orientation of WT rotor towards the wind. The asymmetry in aerodynamic is created by changing the pitch angle of one blade, which generates a non-uniform torque along the rotor. Three conditions are imitated with pitch angle of any one blade modified by increasing 5° and 10°, and by decreasing by -8°, while pitch angle of other two blades are remain same at 11.44°.

Each simulation runs for 40 seconds with sampling frequency of 2000Hz. The output information of wind speed, electric power, stator current of PMSG, and turbine shaft toque are recorded for each case, and are plotted in Fig. 3a-3d for healthy condition.

Fig. 3. The output information of (a) wind speed, (b) stator current of PMSG, and (c) electric power, and (d) shaft rotating speed

3. Methodology

3.1. Empirical Mode Decomposition

The EMD approach is a data dependent, adaptive approach. This approach does not entail any situation related to linearity and stationarity of the signal. Main application of EMD approach is to decompose the nonstationary and nonlinear signal $y(t)$ into a number of IMFs. Each IMF must satisfy following 2-conditions [17-18].

1) For a given dataset, both the number of zero crossings and the number of extrema must either be equal or differ at most by one.
2) At any point, the mean value of the envelope defined by the local minima and defined by local maxima is zero.

The brief explanation of the EMD approach is presented step-wise for the comprehension of the researcher as given bellow.

1) Load the signal $y(t)$.
2) Determine the extrema (minima & maxima) of the data set $y(t)$.
3) Connect the minima and maxima individually with cubic spline interpolation
4) Generate the upper envelopes $e_u(t)$ and lower envelopes $e_l(t)$.
5) Determine the local mean value of the envelope: $a(t)=[e_u(t)+e_l(t)]/2$.
6) Determine the difference between original signal data and mean value of the envelope: $H_1(t)=y(t)-a(t)$.
7) If $H_1(t)$ satisfy the two IMF condition, then $H_1(t)$ is the 1st IMF.
   Else $H_1(t)$ is not an IMF, then $H_1(t)$ treated as an original signal and repeat the procedure from 1 to 6.
After repeated shifting up to k-time, $H_i(k)$ become an IMF as $H_i(k) = H_i(k-1) - a(t)$.

8) Define smallest temporal scale in $y(t): \Omega_i(t) = H_{i+1}(t)$. Where $\Omega_i(t)$ is the $i^{th}$ IMF component from the original signal.

9) Determine the residue: $\psi_i(t) = y(t) - \Omega_i(t)$. Now consider the $\psi_i(t)$ as the original signal data set and repeating the above procedure for finding the $2^{nd}$ IMF.

10) The above procedure is repeated in n-times to get n IMFs of the signal $y(t)$. The procedure can be stopped when $\psi_i(t)$ become a monotonic function from which no more IMF can be extracted.

Finally, after complete decomposition of the signal, the original signal $y(t)$ is expressed as:

$$y(t) = \sum_{i=1}^{L} \Omega_i(t) + \psi_L(t)$$  \hspace{1cm} (1)

Where $L=$number of IMFs; $\Omega_i(t) = i^{th}$ IMF and $\psi_L(t)=$ final residue.

All IMFs of equation (1) is supposed to yield a meaningful local frequency, and unlike IMFs do not exhibit same frequency at the same time, Then equation (1) can be represented as:

$$y(t) \approx \sum_{i=1}^{L} A_i(t) \cos[\phi_i(t)]$$ \hspace{1cm} (2)

The MATLAB codes for EMD decomposition are available at http://perso.ens-lyon.fr/patrick.flandrin/emd.html [10]. The generated IMFs by EMD approach on the healthy and faulty signal are shown in Figs 4 and its energy distribution in Fig. 5. From the energy distributions of IMFs, we can differentiate the difference between the normal and imbalance fault condition of WTGs. Additionally, the energy entropies have been calculated using Eq. (3) are represented in Table 2. It is seen that the entropy of the imbalance fault condition is differ from that of the normal one for IMFs. Used energy entropy in this paper is defined as

$$E_e = - \sum_{n=1}^{N} p_n \log p_n$$ \hspace{1cm} (3)

where, $p_n = E_n / E$ is the percentage value of energy of the $n^{th}$ IMF of EMD in the whole signal energy $E$, where

$$E = \sum_{n=1}^{N} E_n$$

| Method | Normal operation condition | Imbalance condition |
|--------|-----------------------------|--------------------|
| EMD    | 0.575                       | 0.6094             |

Table 2. Energy entropies of recorded normal and imbalance fault signals of WTGs

Fig. 4. EMD decomposition results: (a) normal operation condition and (b) imbalance fault condition
3.2. Input Variable Selection

The relevant input variable selection is an important part for PNN model formation in imbalance fault diagnosis for WTGs. RapidMiner (version 5.2) based PCA algorithm [11-13] is used for feature selection as explained in detail in reference [16]. It is found that IMF1 to IMF10 are having higher rank out of generated 17 IMFs by EMD method, showing these are most influencing variables.

3.3. Probabilistic Neural Network (PNN)

The design of the PNN model has been described in Fig. 6, which contains 3 layers: the input layer, hidden layer and output layer. The hidden layer consists of an activation function applied to the distance between the unknown input & the training sample. As an example, the input vector \( \alpha = [\alpha_1, \alpha_2] \) is applied to input nodes \( \chi_1 \) to \( \chi_2 \). In the hidden layer, the network contains 5 nodes, \( \gamma_1 \) to \( \gamma_5 \), corresponding to five examples with weights attached to input nodes. Output weights are given 1 of 2 values, 1 represents a faulty condition whereas 2 signifies the opposite. Weights between hidden nodes & output node \( \phi_1 \) are designed to allow \( \phi_1 \) to compute the sum of all probabilities correspondent to the 1st category only from \( \beta_1 = (\gamma_1 + \gamma_2)/(\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 + \gamma_5) \), i.e. emulating the Bayesian confidence in decision making.

Now we extend the PNN design to \( n \) input nodes (\( \chi_1 \) to \( \chi_n \)), \( k \) hidden nodes & \( p \) output nodes (\( \phi_1 \) to \( \phi_p \)). The design process consists of 2 main steps: the learning stage & the recalling stage, which is explain below:

**Step 1:** Generate input weight \( \omega^I \) between input node \( (\chi_i) \) & hidden node \( (\gamma_k) \) for every training sample \( (\alpha_k) \):

\[
\omega^I_{ki} = \alpha_i(k) \quad (4)
\]

Where \( i = 1, 2, 3, 4, 5, \ldots , n \) and \( k = 1, 2, 3, 4, 5, \ldots , k \)

the & input weight \( \omega^I \) is the \( k \times n \) matrix = \( [\omega^I_{ki}]_{kn} \)

training samples are : \( \alpha(k)=[\alpha_1(k), \alpha_2(k), \alpha_3(k), \ldots , \alpha_i(k), \ldots , \alpha_n(k)] \).

**Step 2:** Generate output weight \( \omega^O \) between hidden node \( (\gamma_k) \) and output node \( (\phi_j) \) :

\[
\omega^O_{kj} = \begin{cases} 
1, & \text{if } k \in \text{Category 1} \\
0, & \text{if } k \in \text{Category 2} 
\end{cases} \quad (5)
\]

Where the numbers 1 & 2 represent the category of the sample.

where \( j = 1, 2, 3, \ldots , p \) output weight \( \omega^O \) is given by the \( k \times p \) matrix = \( [\omega^O_{kj}]_{kp} \) and the number of training samples by \( k \), dimensions of \( \chi \) by \( n \) & dimensions of \( \beta \) by \( m \).

**Step 3:** Applying the test vector \( (\alpha_{test}) \) to the network: \( \alpha_{test}=[\alpha_1, \alpha_2, \ldots , \alpha_n] \)

**Step 4:** Calculate the probability of test vector \( (\alpha_{test}) \) by means of the Gaussian activation function:

\[
\gamma_k = \exp\left(-\frac{\text{net}_k^2}{2\nu^2}\right) \quad (7)
\]

where \( \nu \) is smoothing factors, \( \nu_1 = \nu_2 = \nu_3 = \ldots = \nu_k = \nu \)

The distance between the test vector and all the training samples is used for the Gaussian function.

**Step 5:** Calculate the probability of \( \phi_j \) as the sum of

\[
\phi_j = \sum_{k=1}^{k} \omega^O_{kj}\gamma_k \quad \text{for } k \in \text{category 1} \quad (8)
\]

**Step 6:** Normalize the output probability by dividing the sum by \( \gamma_k \). The output probability \( P_j \) is:

\[
\Pr \text{ob} P_j = \frac{\phi_j}{\sum_{k=1}^{k} \gamma_k} \quad (9)
\]
Stages 1 & 2 are categorized as the learning stage. Stages 3 to 6 are termed as the recalling stage. In the learning stage, the network creates the input weight \((ω^I)\) and output weight \((ω^O)\). The recalling stage is where it tests the data & computes the probability for the test vector.

### 3.4. PNN based imbalance fault identification model formation

The classifier model used for imbalance fault diagnosis in WTGs is designed using ten inputs (first ten IMFs selected by PCA method). The diagnosis model is designed using the aforementioned 48000 training cases which includes 3000 healthy and 4500 faulty dataset. These data samples, along with their matching target vectors, are stored in the PNN Data Base. The PNN is an architecture of three layers along with 10 inputs \(α_1\) to \(α_{10}\), 2 outputs \(β_1\) to \(β_2\) (healthy and imbalance fault condition) and 48000 hidden nodes \(γ_1\) to \(γ_{48000}\) (i.e. being equal to number of training data samples). A graphical representation for the result is obtained using MATLAB is shown in Fig. 7 of section 4.

The performance of proposed model for imbalance fault identification is examined by evaluating measures after implementing required modifications.

**Imbalance fault identification accuracy (IFIA),**

\[
IA = \frac{\text{Correctly Classified Samples}}{\text{Total Number of Samples} \times \text{Dataset}}
\]

**Mean Squared Error (MSE),**

\[
MSE = \frac{1}{n} \sum_{q=1}^{n} (E_q)^2; \quad \text{Where } E_q = |T_q - OA_q|
\]

Where \(n\) = number of samples in data set, \(T_q\) = target value and \(OA_q\) = actual model output obtained from the trained ANN based MLP-classifier.

**Mean Absolute Percentage Error (MAPE),**

\[
MAPE = \frac{1}{n} \sum_{k=1}^{n} \frac{\text{Actual Fault Type} - \text{Predicted Fault type by model}}{\text{Actual Fault Type}} \times 100
\]

The IA, MSE and MAPE are evaluated with Eq. (10), (11) and (12) as represented in Table 3 of section 4.

### 4. Results and Discussion

Four PNN models are designed using different input variables. Three-phase stator current (48000x3) and voltage (48000x3) is used as input variable in model 1 and model 2 respectively. In model 3, a combination of 3-phase voltage and current signature (48000x6) is used as input variable. Thereafter, model 4 is designed using proposed input variables and then performance analysis of each model is analyzed as shown in table 3.

The prediction accuracy of ANN in term of MAPE is represented by A. K. Yadav *et al.* [15]. The maximum MAPE for proposed models at proposed input variables are found to be 2.008%, showing that after removing less influencing parameters, the classification accuracy is increased upto 98.04% as shown in Table 3. Therefore RapidMiner based PCA algorithm can be utilized for identifying the relevant input parameters for imbalance fault identification of WTGs.

**Table 3. PNN based accuracy analysis of fault diagnosis model**

| PNN model and it data set | MAPE  | MSE    | RMSE   | Successful identification (%) |
|---------------------------|-------|--------|--------|-------------------------------|
| 3-phase current signature based PNN model [48000x3] | 5.3583 | 0.0536 | 0.2315 | 94.64 |
| 3-phase voltage signature based PNN model [48000x3] | 2.1583 | 0.0216 | 0.1469 | 97.84 |
| 3-phase voltage & current signature based PNN model [48000x6] | 3.008 | 0.30858 | 0.5555 | 93.73 |
| Proposed PNN model [48000x10] | 2.008 | 0.02158 | 0.1469 | 98.04 |

As examples of the kind of graphical results of proposed method for WTGs imbalance situation that are identified by PNN using matlab (Matlab R2014a) [8] are shown in Figs. 7. The training samples for WTGs are shown using blue colored dots and the new sample after testing is represented by using red colored dots.
The detection of the wind turbine imbalance fault condition and healthy condition correctly and fast has great importance in the trend of improvement of the wind turbine operation and its maintenance level as well as increasing reliability of sustainable continuation of power supply. In this paper, PNN is employed for fault diagnosis based on generator current signals. The actual data sets, which are obtained from simulated WTGs model in combine environment of three software (FAST, TurbSim and Simulink) after run for 40 second with sampling frequency of 2000 Hz, are used to investigate performance of the proposed method. PNN models are obtained, validated and tested in order to find the healthy condition of WTGs. The simulated results indicate that the PNN can achieve both higher diagnosis accuracy and less training/testing time than other ANN methods and also it has better diagnosis accuracy than the conventional methods.

The future work is focused on categorizing the different type of imbalance faults and predicting the WTGs operation condition using most relevant input variables.

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