PERFORMANCE OPTIMIZATION OF WIND TURBINE USING CONDITION MONITORING AND FAULT DIAGNOSIS

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Abstract: In this paper, two learning algorithms called anomaly detection and Support Vector Machine (SVM) are employed to bearing fault diagnosis and CM. Basically the anomaly detection algorithm is used to recognize the presence of unusual and potentially faulty data in a dataset, which contains two phases: a training phase and a testing phase. In the former, the algorithm is trained with a training dataset and in the latter; the learned algorithm is applied to a set of new data. At their early stages is one of the most important aspects of machine CM. The second dataset was a test to failure data of bearings from the NSF I/UCR Centre for Intelligent Maintenance Systems (IMS) which was used to compare anomaly detection with a previously applied method (SVM) for finding the time incipient faults. Further in the proposed model we integrate the binning method was utilized to examine the failure data set of real bearings. In this paper, all the data from the time the bearing was working normally, until failure, were captured via vibration sensors.
Keywords: SVM, CM, NSF, UCR, Intelligent Maintenance System.

I. INTRODUCTION

The cost of wind power production can be predicted with a high degree of accuracy, whereas oil, gas and coal prices are subjected to market environment and are expected to increase. For instance the oil price has increased over the past few years from $20 to over $100 and has added $45 billion to the EU’s annual gas import bill. According to the new American Wind Energy Association (AWEA) industry report, the U.S. wind industry’s 45,125 operational utility-scale turbines represent an installed rated capacity of 60,007 Megawatts. As an electricity generator, there are different factors which can influence the wind turbines output, such as turbine size and wind speed. An average onshore wind turbine with a capacity of 2.5–3 MW can produce more than 6000 MWh in a year. An average offshore wind turbine of 3.6 MW can power more than 3,312 average households. Wind turbines operate under different wind speed, ranging from 4 to 5 m/s to a maximum of around 15 m/s.

A modern wind turbine has variable outputs depending on the location and wind speed, but generally it generates electricity at 70-85% of the time. It will typically produce about 24% of its rated power (41% offshore) over a year. Since wind turbines generally work in harsh environments with highly variable wind speed, they normally experience several downtimes in a year for maintenance or breakdowns. The downtimes account for the capacity factor of power plants to be in the range of 50%-80%. Wind turbines consist of various components and the four main parts are: the base, tower and foundation, nacelle, and rotor and rotor blades. The base is made of concrete reinforced with steel bars and there are two types of design for them, shallow flat disk and deeper cylinder. Based on the consistency of the underlying ground, a pile or flat foundation is applied for stability and rigidity of a wind turbine. Typically, towers are designed as a white steel cylinder, about 150 to 200 feet tall and 10 feet in diameter.

The tower construction not only carries the weight of the nacelle, rotor and blades; it also absorbs static loads created by wind power variation. The blades capture the wind's energy, spinning a generator in the nacelle. Their principle is the same as lift, that is, the passing air causes more pressure on the lower side of the wings and the upper side creates a pull. With the help of the rotor, the energy in the wind is converted to rotary mechanical movement. The nacelle holds all the turbine machinery and contains different components such as the main axle, gearbox, generator, transformer and control system.

II. BACKGROUND

The majority of literatures regarding fault and fatigues in wind turbine have focused on gearboxes for the most costly repairs are allocated to their damages [2]. The failures are normally gear tooth damage, backlash and bearing faults and they mainly occur for that of high pressure, structure and work environment. Failures are reported as the consequents of frequent stoppage, high loaded and particle contaminations [4]. The main objective of the generators in wind turbine is converting rotational energy into electrical energy. There are different kinds of generators used by wind turbines but induction or double fed induction machines are more common [8]. Bearing faults, rotor and stator breakdown are allocated the biggest proportion of failures in this component. There are many techniques and tools available for fault diagnostic in wind turbine sub-systems. The steady-state spectral components are applied in induction machine of the stator quantities which include voltage, current, and power. They can detect faults in rotor bars, bearings, air gap eccentricities [2].

Tsai et al. in [4] applied a wavelet transform-based approach to the damage detection of wind turbine blades. Watson et al. in [5] presents wavelet techniques to detect bearing failure of doubly fed induction generator (DFIG) based on power output data. Yuan and Cai in [1]. utilized a modified Fourier transform method, to study gearbox diagnosis based on vibration signals. Kusiak and Verma [9] provided a data-driven approach for monitoring wind turbine blade faults. L. Wenxiu and C. Fulei [2] discussed about noise analysis by the method of sound intensity. D. Brown, G. Georgoulas, H. Bae, G. Vachtsevanos, R. Chen, Y. Ho, et al. [7] employed a particle filter (PF) for fault diagnostic and prognostics in gearbox and bearings. This paper has verified fault diagnosis in wind turbines through a systematic review approach. There is a very negligible researches has been done in Africa, 2%, which belongs to Tunisia. Vibration analysis is one of the most known and popular approach in condition monitoring of wind turbines which is surveyed comprehensively.

There are two major groups of vibration analysis:
1) Broadband analysis and
2) Analysis based on the selected spectral lines.
Basic broadband analysis parameters are: root mean square, peak values, crest factor and kurtosis.

III. ALGORITHMS USED

In machine learning, unsupervised learning refers to the types of algorithms that try to find correlations without any external inputs other than the raw data, trying to find hidden structure in unlabeled data. Supervised learning is when the algorithm input data is "labeled" to help the logic in the code to make suitable decisions. Based on the wind turbine bearing characteristic discussed earlier, in this research work, the supervised learning technique was found best fit to detect faults and defects of rotating components of a wind turbine such as bearings, according to the following steps.

Step 1: Conduct a comprehensive literature review of wind turbine components and their failures. Investigate various fault detection techniques and acquire the knowledge of how the techniques work to bearing condition monitoring of wind turbine. Also investigate sensors and their characteristics in using them for this application. Learn data collection and signal analysis, in preparation to use these for vibration analysis.

Step 2: Employing two sets of data; the first is a bearing data set with seeded fault in different size and load from Case test rig and the second is a test from Suzlon Energy, Pune India

Step 3: Analyzing the vibrational signals to extract the relevant features associated with the defects and prepare the features for use in learning techniques.

Step 4: Applying supervised machine learning methods, Support Vector Machine (SVM) and Anomaly Detection (AD) algorithms to compare the methods and find the pros and cons of the different techniques.

IV. PROPOSED WORK

We here introduce the Machine learning process as SVM to calculate the efficiency of small wind turbine in term of power. The existed experiment on wind turbine is very dependent on the vibration due to rotational work and the optimum position of wind turbine so called the placement of wind turbine. We introduce the vibration to simulation by automatic modeling with tool of Support vector machine that is already existed with matlab. Further this research show that the measurement of the power curve of a small-scale wind turbine system following the IEC 61400-12-1 standard might lack consistency. This is due to characteristics specific to small-scale wind turbines. We give recommendations to ensure consistency, accuracy and reproducibility of the measurements. It can be concluded from the outcome statistics that accuracy of the anomaly detection technique is higher than the SVM technique in regard with bearing condition monitoring. Particularly with a ball defect, the F1 measures were close to 100%, which means that almost all of the anomalous and defected data can be captured through this technique. This quality is of high importance for the rotating component CM in the wind turbine.

V. PARAMETERS AND DATA

```
bin = [0:0.5:14.5]; % 0.5m/s wind bins
load blueDiamond3-TSR6.mat
% year,day,hour,spd,cur,volt Data rejection and selection 24 V range
ind = find(spd>0 & cur>=0 & volt>=23.94 & volt<=26.46); % 25.2+-5%
spd = spd(ind); cur = cur(ind); volt = volt(ind);
Correction factors
spd = spd*(24.4/20)^0.31; % speed corrected with Eq.(1)
pwr = volt.*cur/0.95; % power correct with Eq.(2)

Binning method
for i = 1:length(bin)
ind = find(spd>=(bin(i)-0.25) & spd<(bin(i)+0.25)); % 0.5m/s bins
pts_bin(i) = length(ind); % bin nb of points
if isempty(ind)
pwr_bin(i) = NaN; vel_bin(i) = NaN; err_bin(i) = NaN;
else
pwr_bin(i) = mean(pwr(ind)); % bin average power
vel_bin(i) = bin(i); % bin average speed
err_bin(i) = std(pwr(ind)); % bin standard deviation
end
end

Plot Figure
ind10 = find(pts_bin>=10); % >10 min
figure(); hold on , box on
plot(spd,pwr,'.r'); % measured
errorbar(vel_bin(ind10),pwr_bin(ind10),err_bin(ind10)); % >10 min
errorbar(vel_bin,pwr_bin,err_bin,'--'); % <10 min
legend('Measured','25.2V \pm 5%',2), legend('boxoff')
xlabel('Wind speed [m/s]'),
ylabel('Power output [W]'),
axis([0 14 0 1000])
```


VI. RESULT OF PROPOSED MODEL UNDER ALL CONSIDERATION

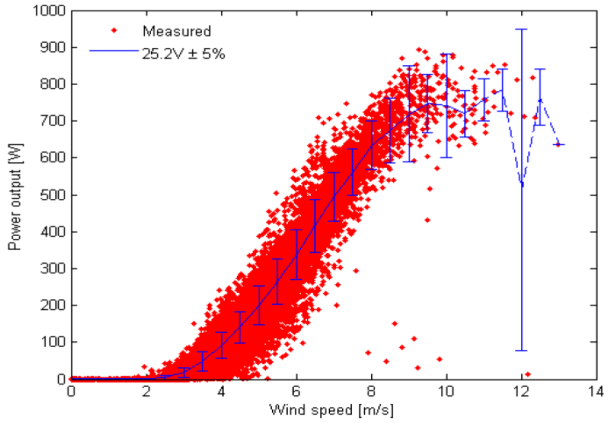

Fig 6.1 : it Shows the power vs wind speed for performance optimization

VII. CONCLUSION

Wind turbine CM, maintenance, and fault diagnosis have recently become an important matter for wind farm holders and researchers all over the world. There have been several techniques and methods for fault detection that have been applied by researchers and engineers to provide the ability to achieve fast and effective defect detection. Machine learning techniques have improved significantly in the last decade and have thus been employed for automatic classification, especially in fault diagnosis and their ability of learning and training, provide a range of possible applications. Two machine learning methods, anomaly detection and SVM, were employed in this research using real data from a fault seeded bearing test. Two features, kurtosis and NGS, were extracted, as part of the developed anomaly detection algorithm. The data which is used in this paper is 0.007 inch fault in Inner race, outer race and ball under 0 and 1 HP in a bearing test. The results indicate that learning techniques equipped with a high rate of accuracy, in this case anomaly detection, can achieve a higher percentage of accuracy for bearing fault diagnosis compared to previously applied methods such as the SVM classifier approach. In addition, it was shown that anomaly detection can carry out this accurate fault detection process using fewer data samples compared to the SVM classifier. This indicates that through the proposed anomaly detection scheme the fault detection process can be achieved more accurately and more efficiently.

VIII. FUTURE SCOPE

Although several techniques have been reported in the literature for bearing fault detection and diagnosis, it is still challenging to implement a reliable condition monitoring system for real-world industrial applications because of complex bearing structures and noisy operating conditions. The theme of this thesis is to develop a novel intelligent system to tackle these related challenges. The strategy is to develop more robust techniques at each processing stage to improve the condition monitoring reliability. This research investigated fault diagnostics and incipient failure and defect detection in rolling element bearings. The proposed method utilized machine learning techniques to detect abnormalities in system operation. Two real bearings vibration data sets from the Case Western Reserve University and NSF I/UCR Center for Intelligent Maintenance Systems were utilized to test the performance of the anomaly detection algorithm. The former was applied to validate the accuracy and the later was used to measure how fast this method can detect incipient faults. The same data were applied to state-of-theart SVM algorithm for comparison.

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