Data-driven fault identification of ageing wind turbine*

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***Abstract*— This paper proposes an ageing evaluation method for wind turbine system by using a data driven method. This method directly uses the input and output data of the wind turbine system, and the autoregressive with exogenous (ARX) model to identify the wind turbine system. The input and output data include wind speed, generated power, and pitch angle, and they are generated by a wind turbine simulation model with four ageing cases: mechanical power, magnetizing inductance, pitch angle controller gain and pitch angle change rate. By using the generated power and pitch angle data of wind turbine under different ageing levels, the data-driven models can be obtained. By comparing the model parameters in different states identified by the ARX model, results show that the degree of ageing can be reflected by the parameter changes. This demonstrates that the method can detect the ageing of wind turbines.**

I. INTRODUCTION

Wind power as a mature component of the new energy system, has been widely installed and deployed worldwide [1]. The design service life of ordinary wind turbines is about 20 years. More than 28% of in-service wind turbines in Europe have been used for more than 15 years by the end of 2020 [2]. Therefore, it is very important to evaluate the ageing of wind turbine, find out its existing faults, and ensure that the wind turbine can run to the design year.

The ageing degree of the wind turbine affect the performance of wind turbines and cause the power generation decreased [3]. There will be nearly 5% of the total wind turbine power and energy reduction, after 13 years of operation [4]. In addition, accidents such as lightning damage, falling of the machine room and bolt failure will speed up the ageing of wind turbine [2]. Even if the excessively ageing parts are replaced and the service life of wind turbine is prolonged, it is likely only part of the lost energy can be recovered [4]. Therefore, early detection of wind turbine failures and evaluate of wind turbine ageing, which can save the maintenance cost of wind farm and improve the economic efficiency [5].

Wind turbine ageing evaluation and fault diagnosis method can be divided into three categories: signal processing methods, model-based methods and data-based methods. Fourier transform is a traditional method of signal processing, which can realize signal conversion between frequency domain and time domain. However, the Fourier transform cannot describe the local characteristics of the signal in the time domain, and perform time-frequency analysis [6]. Wavelet transform can decompose the signal into different wavelengths, which can solve this problem [7]. But this method based on the assumption of linear and stationary signals. However, for actual systems, the data is most likely to be non-linear and non-stationary. Hilbert−Huang Transform (HHT) is an empirical data analysis method, and its extension is adaptive, so it can describe nonlinear and non-stationary process [8].

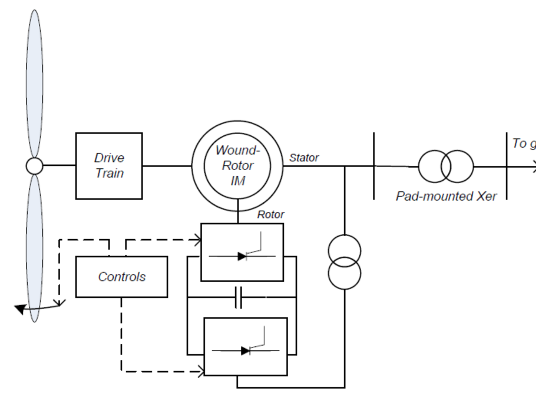

Fig. 1. DFIG wind turbine schematic [9]

The model-based approach is to use mathematical models to build a wind turbine model, and monitor the wind turbine by comparing the output difference between the model and measurements from real wind turbine. Since wind turbines are complex in structure and there will be unclear parameters, it is very challenging to simplified and determine the dynamics of overall system [10].

Data-driven methods can build the system dynamic model using input and output information, which is also referred as system identification. Diagnosis can be performed through analysing the model variations or differences. Various data analysis and processing methods are used to find the useful information and obtain the characteristic patterns of normal conditions and faults, thereby realizing fault diagnosis. A multi-objective optimized wind turbine performance model is proposed, using a neural network to capture the performance dynamic equation [11]. Its purpose is to study the effect of turbine control on its vibration and power output, and to show the optimized results of wind turbine performance. The studies have shown that the data collected at the industry-recognized frequency (0.1Hz) is not sufficient to completely reduce turbine vibration. [12] proposes an autonomous diagnostic tool that can track and diagnose structural conditions throughout the wind turbine life cycle. The

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framework relies on the symbiotic treatment of the operating environment/operating variables and the monitoring vibration response of structure. After one-year complete tracking of the obtained diagnostic index shows that the proposed tool has the potential to be incorporated into the overall structural health monitoring (SHM) damage detection framework. It is further expanded through statistical pattern recognition methods and will be explored in the next step. In order to analyse the improvement effect of yaw control optimization after several months of operation [13] used a robust multivariate linear model to quantify performance improvement. This is achieved by formulating an appropriate model for the wind turbine and analysing the residuals between model estimates and measured values before and after the upgrade.

Most existing work on data-driven based methods are for fault diagnosis. The study on wind turbine ageing is limited. There are several challenges related to ageing detection. First, ageing is a long and slow process, so it may be difficult to collect data under all ageing levels. Further, although the ageing occur on all the wind turbine components, their conditions may be different. This requires analysing multiple component conditions in order to evaluate the performance of wind turbine. Third, different components may have different dynamics and often requires sufficient sampling rates. The existing data sets, such as SCADA, often use limited sampling rate with 10 minutes averages data with a fixed sampling rate of 1 second, which may not be sufficiency.

The contributions of this paper are mainly the following aspects. Through the establishment of healthy wind turbine models with different degrees of ageing, data with different sampling rates and time lengths can be obtained. By changing the parameters of model, the ageing data of specific component can also be obtained. Because data of different sampling frequencies can be extracted, the influence of sampling rates on the experimental results can be observed. And multiple components can be detected at the same time.

II. Doubly-fed induction generator (DFIG) wind turbines

DFIG wind turbine system is a widely used system, both rotor and stator can feed power into the grid. This turbine system can get maximum energy from the wind by changing speed [14]. The blade pitch is usually used to regulate power. Although this will result in a more complex system and higher cost, more energy extraction can offset this negative effect [9]. The following describes wind turbine structure that this paper involved.

A. Rotor model

There are many aerodynamic models of turbine rotors, some of which involve aerodynamic factors of wind wheel shape [15]. Such model has many parameters, complicated equations, and mass calculation. Therefore, generally only the model of torque coefficient C_Q or the wind energy conversion coefficient C_P is considered. Because these two parameters can express aerodynamic characteristics to a certain extent.

$$T_r = 0.5\rho\pi R^3 \ V_W^2 \ C_Q. \tag{1}$$

or,

$$P_r = 0.5\rho\pi R^2 \ V_W^3 \ C_P. \tag{2}$$

Use ρ to represent air density and R to represent wind wheel radius, V_W is wind speed. C_P and C_Q can be determined by the equation of tip speed ratio λ in the stall type turbine, while in the active stall and variable speed turbines are determined by the equation of λ and pitch angle θ.

B. Pitch control system

The pitch control system can adjust the blade angle to maximize the wind energy utilization rate of wind turbine and control the balance of power and speed under different wind conditions [16]. When the wind speed is high, the attack angle of blades will be reduced to reduce the impact of wind on blades, while controlling the absorption of wind energy. When the wind speed is slow, the attack angle of the blades will be increased to ensure that the maximum wind energy is obtained. In addition, the pitch control system can also make the blades reach a safe position when the wind turbine fails or the wind speed exceeds the operating range to ensure the safety of wind turbine.

The model of pitch system , pitch angle β and its reference β_r, can be expressed as the second-order transfer function:

$$\frac{\beta(s)}{\beta_r(s)} = \frac{\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2}. \tag{3}$$

Where ξ is the damping ratio, and ω_n is the natural frequency.

C. Drivetrain model

Compared with the inertia moment of the generator and wind wheel, the inertia moment of the gearbox is very small and can be ignored. The advantage is that the number of equations is greatly reduced (only one equation), which will greatly speed up the calculation. The simplified model can be expressed as:

$$T_{gen} - T'_{wtr} = J_{ech}\frac{d\Omega_{gen}}{dt}. \tag{4}$$

Where $T_{gen} = T_{gen} + \frac{J_{wtr}}{K_{gear}^2}; T'_{wtr} = \frac{T_{wtr}}{K_{gear}^2}$. T_{wtr} is torque of wind wheel, J_{wtr} is the inertia moment of wind wheel, Ω_{gen} is the mechanical velocity of generator and K_{gear} is the gear ratio of the gearbox.

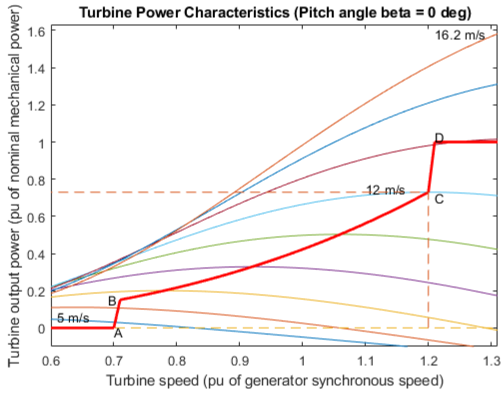

Fig. 2. Turbine Power Characteristic of DFIG

D. The rotor-side converter control system

The rotor-side converter can measure grid segment voltage and control the turbine output power. An advantage of DFIG technology is that the converter can absorb or generate reactive power, so the model can be simplified without the need to add a capacitor bank. The turbine speed and output power characteristics shown as Fig. 2. If the turbine speed is outside the range shown in the image, it will protect system by changing the angle of pitch.

E. The grid-side converter control system

The control system can be roughly divided into three parts: measurement system, outer loop and inner loop.

The measurement system mainly measures the controlled AC positive sequence current component and DC voltage. The outer regulation loop is composed of a DC regulator, which is used to output the reference current required by the current regulator, that is, the same current as the grid voltage, so as to control the active power flow. Use the current regulator to form the inner current regulation loop. The magnitude and phase of generated voltage are controlled by the current generated by the outer loop and specified reference.

III. Data-driven methods

The data-driven method uses data to build tools, and system identification is a commonly used method in building systems. Since only the relationship between input signal and output signal is considered in the system identification, there are many mathematical models can be used for fitting, which can be divided into two categories: linear and non-linear. Although wind turbine system is a typical nonlinear system, it can be approximated as a number of piecewise linear models around different operating conditions. The local linear model can simplify the modelling while enjoying good accuracy. In this paper, the linear Autoregressive with exogenous (ARX) model is used.

A. ARX model

The Autoregressive with exogenous (ARX) model has simple structure and accurate description, so it is used for system identification. The mathematical expression of ARX model can be written as follows:

$$\begin{aligned} & y(t)+a_1 y(t-1)+a_2 y(t-2)+\ldots+a_n y(t-n) \\ & =b_1 u(t)+b_2 u(t-1) \\ & +\ldots+b_m u(t-m+1)+e(t) \end{aligned} \tag{5}$$

Where $u(t)$ is input, $y(t)$ is output, and $e(t)$ is the white noise signal. n and m are the orders of $u(t)$ and $y(t)$ respectively. The model can be transformed into the following form through z transformation.

$$A\left(z^{-1}\right) y(t)=B\left(z^{-1}\right) u(t)+e(t). \tag{6}$$

In the formula, $A(z^{-1})=1+a_1 z^{-1}+\ldots+a_n z^{-n}$, $B\left(z^{-1}\right)=b_1+b_2 z^{-1}+\ldots+b_m z^{-m+1}$, and z^{-1} is called the lag operator, d is the input-output delay, n and m are the orders of $A\left(z^{-1}\right)$ and $B\left(z^{-1}\right)$ respectively. In other words, n is the number of poles and m+1 is the number of zeros.

B. ARX Model Parameter Estimation

ARX model can use least squares (LS) method to estimate the model parameters. System input $u(t)$ and output $y(t)(t=1,2,\ldots,N)$ are selected as sample. Let $p=1+max(a_n,b_m)$, and

$$Y=[y(p),y(p+1),\ldots,y(N)]^T \tag{7}$$

$$e=[e(p),e(p+1),\ldots,e(N)]^T \tag{8}$$

$$\theta=[a_1,a_2,\ldots,a_n,b_1,b_2,\ldots,b_m]^T \tag{9}$$

$$x(t)=\left[\begin{array}{c} -y(t-1) \\ \ldots \\ -y(t-n) \\ u(t-1) \\ \ldots \\ u(t-m) \end{array}\right]^T \tag{10}$$

$$X=\left[\begin{array}{c} x(p) \\ x(p+1) \\ \ldots \\ x(N) \end{array}\right] \tag{11}$$

Thus, the ARX model can be written as

$$Y=X\theta+e \tag{12}$$

Where the parameters obtained according to LS method are

$$\hat{\theta}=(X^T X)^{-1} X^T Y \tag{13}$$

When performing system identification, the order of model, delay and noise all have an impact on results. In order to observe the parameter changes under healthy and damaged conditions, a number of different ageing levels are used to simulate the turbine.

IV. Experiment

The purpose of experiment is to check whether the ageing condition of wind turbines can be determined via system identification. And when the ageing situation is gradually serious, whether the identified model can determine condition deterioration. In order to achieve this goal, the experiment considers four deteriorating cases with different damage levels: mechanical power, magnetizing inductance, pitch angle controller gain and pitch angle change rate.

The overall simulation process of the experiment can be divided into the following steps: First, a health wind turbine model need to be established. Second, changing specific model parameter to set up ageing wind turbine. For example, by reducing the pitch angle change rate of blade to simulate the damage caused by the blade bearing wear. Design 4 to 5 ageing stages for each damage, then use models to collect data. After that, using the collected data to build ARX models in different ageing level. Finally,analysed the ARX model parameters.

The health wind model used in this experiment is a modified wind farm model in MATLAB. The chosen wind speed of 10.5m/s as reference which is rated wind speed of 2MW wind turbine, and the mechanical power of 0.895(pu) which consistent 2MW turbine power characteristic. In order to study the impact of sampling rate on the identification performance, different sampling ratios have been used and it is found the sampling rate with 1s is sufficient for the purpose of this paper. Assumed that the ageing degree is aggravated by 1%, 2%, 5%, and 10%. If the ageing degree of a wind turbine reaches about 10%, it means that the system will lose about 200kW of power. Even if the ageing of system is only about 1%, it will still lose about 20kW of power. The gradual change of the power is used to simulate the ageing condition. At the same time, in order to reduce the impact of noise, each experiment will be repeated 5 times, and the model parameters obtained afterwards are the average results.

According to the different simulated ageing parts, the experiment can be divided into the following four parts.

A. Mechanical power changes

Because in the actual ageing process, ageing wind turbine can often reduce the power yield. The reduction of power is assumed to be changed gradually. By modifying the mechanical power data, it simulates that the rotor-side converter control system of the wind turbine has a fault. By decreasing the value of mechanical power by 1%, 2%, 5%, and 10%, to simulate different damage levels of the system.

Although the overall system is a nonlinear system, the local linear model can simplify modelling and at the same time has good accuracy. Thus input wind speed is selected as a constant, and then the noise signal is added. In the experiment, the wind speeds of 7m/s and 10.5m/s are selected respectively, which are the cut-in wind speed and the rated wind speed of the wind turbine.

B. Pitch angle changes

This experiment simulates the ageing situation of the wind turbine by changing the rotation rate of the pitch angle. Pick up the wind speeds of 7m/s and 11m/s as the insertion and high offset of the input square wave, respectively, and 120s is a period to leave excess reaction time for the system. 2degree/s is the reference, and then 1.8degree/s, 1.5degree/s and 1degree/s are selected as the comparison items for experiment.

C. Pitch controller gain changes

This experiment simulates the ageing of pitch controller by changing the pitch controller gain. The wind speed used is the same as the previous experiment, and the Kp 500 is used as the reference.

D. Magnetizing Inductance changes

By reducing magnetizing inductance, the ageing of generator side coil with use is simulated. The wind speeds of 10.5m/s is selected, and inductance Lm 2.9(pu) is reference.

V. Results

A. Mechanical power changes

Since the results under the two wind speeds are basically same, the following will only show the results when wind speed is 10.5m/s. After experiments and data processing, the results shown in the Fig. 3 and Fig. 4 can be obtained. In the case of sampling rates at 1s, $A(z)$ and $B(z)$ are both 10 orders. The mathematical model of mechanical power at 0.895 (pu) is used as a reference for the entire experiment. Parameters obtained after decreasing the mechanical power by 1%, 2%, 5%, and 10% are respectively subtracted from the reference, and the results obtained are shown in Fig. 3 and Fig. 4.

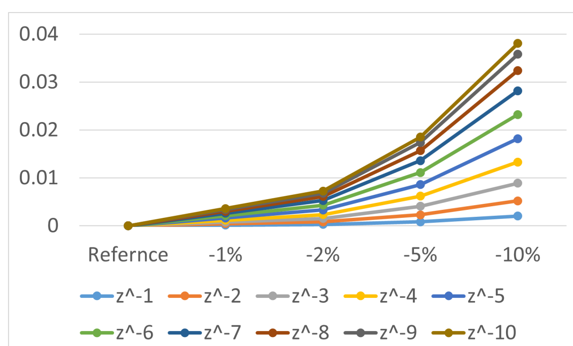

Fig. 3. The variations of parameters in $A(z)$ with the mechanical power changes

It can be seen that as the mechanical power decreases, the model parameters also decrease, and the change trend of each order parameter is consistent with the trend of mechanical power. In addition, by comparing the unit change rates of the same parameter of different models, it can be found that the unit change rates of the same order parameters are basically

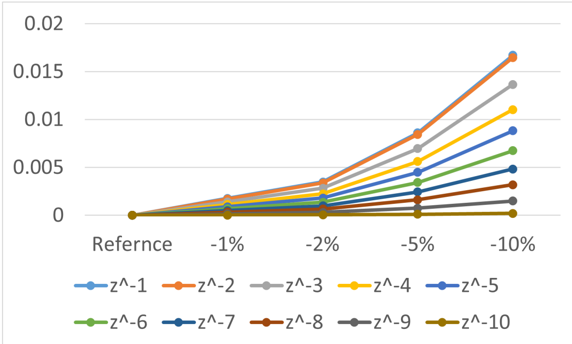

Fig. 4. The variations of parameters in $B(z)$ with the mechanical power changes

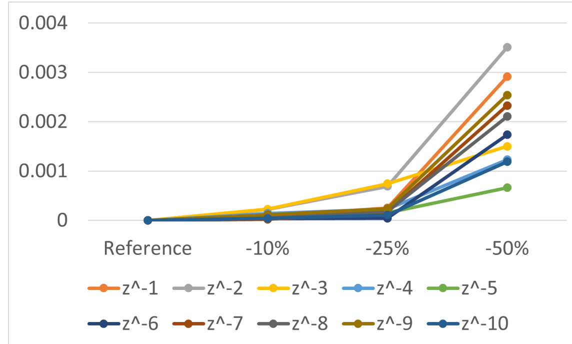

Fig. 5. The variations of parameters in $A(z)$ with the pitch angle changes

the same. Therefore, there is a linear relationship between mechanical power and mathematical model parameters. In other words, if the mechanical power of wind turbine system changes due to ageing, the parameter change can be observed from the mathematical model changes of the system. And ageing degree can be analysed by comparing them with reference model parameters.

In addition, it can be seen from Fig. 3 and Fig. 4 that although all the 20 parameters in $A(z)$ and $B(z)$ are decreasing with the severity of ageing, the reduced values are different. Assuming that the ageing of other components causes parameters changed. Since different components have different dynamic characteristics, even with the same degree of ageing, there may be a certain gap in the impact on the overall wind turbine system. The numerical variation of each parameter will be different. Generalization, we will have the opportunity to determine which components have deteriorated through the parameters change.

B. Pitch angle changes

Consistent with the experiment A, the data obtained at a sampling rate of 1s is more in line with expectations. Because the pitch angle of the wind turbine has changed, this part uses the Multiple input single output (MISO) ARX model for system identification. By comparing the experimental results of order 5, 7 and 10, it is found that the results obtained in order 10 are better. Use wind speed and pitch angle as input, generated power as output, and the results are shown in the Fig. 5. As the change rate of pitch angle decreases, the changes of parameters are proportional to the change rates of pitch angles. As the change rate of pitch angle decreases, the changes of parameters are proportional to the change rates of pitch angles.

C. Pitch controller gain changes

The MISO ARX model is also used for system identification in this experiment, and the results are shown in the Fig. 6. The results are consistent with the previous experiment. It can be seen that all the parameter changes are proportional to the gain value changes although the second delay is the most sensitive.

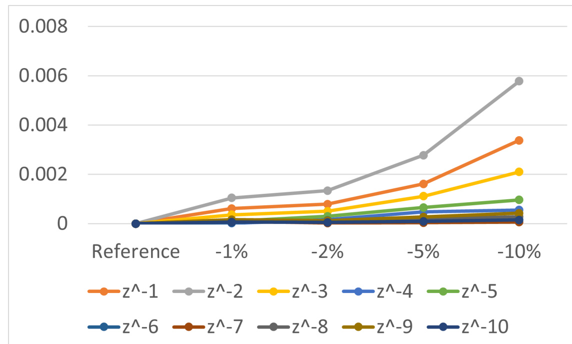

Fig. 6. The variations of parameters in $A(z)$ with the pitch controller gain changes

D. Magnetizing inductance changes

The results of changes of magnetizing inductance are show in Fig. 7 and Fig. 8. The variations of model parameters can reflect the changes of magnetizing inductance changes. However, unlike previous examples, not all of the parameters changes are proportional to the ageing severity. This may be due to that fact the magnetizing inductance can affect both active and reactive power.

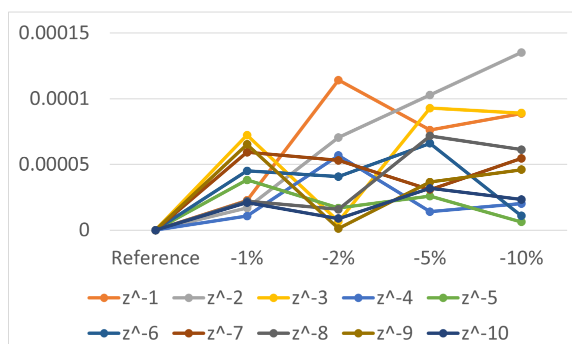

Fig. 7. The variations of parameters in $A(z)$ with magnetizing inductance changes

VI. Conclusion

This paper employed a data-driven ageing evaluation method, and uses the data obtained from the computer

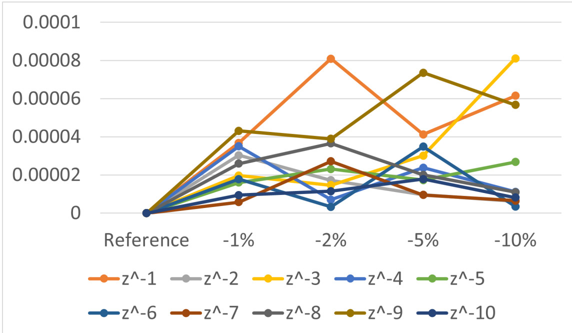

Fig. 8. The variations of parameters in $B(z)$ with magnetizing inductance changes

simulation of the wind turbine to determine the ageing deteriorating conditions. For the simulation results, the model parameters obtained by the system identification have shown that the ageing degree can be reflected on the model parameter changes. Therefore, this method can not only detect the occurrence of wind turbine ageing, but also diagnose the severity of ageing and issue a warning.

It can be obtained that under certain conditions, the ageing attributes of wind turbine system can be reflected in its data-driven model. This work validated them in these operating conditions. Future work will also consider how to analyse the ageing of different parts or different combinations of ageing problems.

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