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Optimum Setting Strategy for WTGS by Using an Adaptive Neuro-Fuzzy Inference System

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ABSTRACT

With the popularization of wind energy, the further reduction of power generation cost became the critical problem. As to improve the efficiency of control for variable speed Wind Turbine Generation System (WTGS), the data-driven Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to establish a sensorless wind speed estimator. Moreover, based on the Supervisory Control and Data Acquisition (SCADA) System, the optimum setting strategy for the maximum energy capture was proposed for the practical operation process. Finally, the simulation was executed which suggested the effectiveness of the approaches.

Keywords: Wind Energy; Data Processing; Adaptive; Takagi-Sugeno (T-S) Fuzzy; Neuro-Network

1. Introduction

Nowadays, wind energy is growing rapidly [1, 2]. The crucial problem of popularizing wind energy has become the further reduction of power generation cost. Thus, the higher efficiency and more optimal operation for wind power generation are required. In order to improve the efficiency of WTGS, the notion of maximum energy capture is introduced. And with the emergence of variable speed variable pitch technique, the operation optimization can be deepened.

In the practice, many anemometers have to be used to measure the wind speed which can derive the optimum setting values of rotor speed and generator power. And not only the single WTGS but also the wind field needs many anemometers to provide adequate information. However, due to the varied environment, the measurement may provide inaccurate signal to the system and the traditional optimum setting strategy may have some drift to the initial setting after a period of operation. Besides, the installation and maintenance of the anemometers increase the cost and reduce the reliability of the whole system.

Recently, several kinds of sensorless maximum energy capture method were proposed in the literatures. Bhowmik et al. [3] used the power coefficient polynomial to estimate wind speed by solving the polynomial roots online with an iterative algorithm. Because the polynomial was seventh order, the calculation was complex and time-consuming. Tan [4] and Simoes [5] et al. applied a two-dimensional (2D) look-up table of power coefficient and power mapping method to estimate the wind speed, but the technique needed huge memory space and suboptimum solution was often caused by the inherent slow searching mechanism. H. Li *et al.* [6] used the Artificial Neuro Network (ANN) to establish a sensorless wind speed estimator but the neuro-network is easy to be over-fitting or fall into the local minima. V. Calderaro et al. [7,8] combined the advantages of T-S fuzzy system [9], Genetic Algorithms (GA) and Fuzzy C-Means clustering (FCM). Then, an adaptive optimum setting strategy was realized. However, the GA was unstableness and also time- consuming to train the parameters of T-S fuzzy system.

In [10], the ANFIS was firstly proposed by Jang J-SR. In [11], a kind of ANFIS was applied on the data-modeling for thermal processes. In the paper, in order to improve the training efficiency and accuracy, the ANFIS was adopted which fully combined the advantages of T-S fuzzy system and neuro-network and is very useful for data-driven modeling.

In section 2, the system analysis of WTGS is carried out and the profile mapping between rotor speed, wind speed and mechanical power is discussed. In section 3, based on the characteristic data from the wind tunnel test, an adaptive sensorless wind speed estimator is firstly established by ANFIS. Then, using the wind speed estimator and the measured data source in the SCADA system for wind power generation process, the optimum setting strategy based on measured value is given. In section 4, the simulation is executed to validate the effectiveness of the approaches. And in section 5, we conclude the paper.

2. System Analysis

Generally speaking, the variable speed variable pitch WTGS include two control level, the wind turbine control level and Doubly-Fed Induction Generator (DFIG) control level [12]. From **Figure 1**, we can see that in order to realize the maximum energy capture, the optimum setting values of rotor speed ω_r and turbine mechanical power P_m are needed besides their measured values. Usually, the mechanical power extracted from the wind energy can be represented as

$$P_m = 0.5\rho\pi R^2 C_P(\lambda,\beta)V^3$$

where ρ is the air density, R is the rotor radius, $C_P(\lambda,\beta)$ is the power coefficient, $\lambda = R\omega_r/V$ is the tip-speed-ratio and β is the pitch angle. When λ and β get the optimum values, $C_P(\lambda,\beta)$ reaches the maximum value. Then, the wind turbine has the most efficiency to extract wind energy.

Here, we take the operating region below rated wind speed for example. The main operating mode is the variable speed fixed pitch operation and the main control task is the maximum energy capture. Thus, the pitch angle is fixed at zero degree to maintain the maximum power coefficient $C_P(\lambda,\beta)$. Consequently, the nonlinear profile mapping between λ, β and $C_P(\lambda,\beta)$ can be simplified to the one between ω_r, V and $C_P(\lambda,\beta)$. There are many ways to demonstrate the nonlinear profile mapping such as fitted nonlinear function and look-up table. Using the nonlinear function in [13], a schematic of the profile curve can be shown in **Figure 2**.

3. Algorithms Application

In this section, we introduce the ANFIS to establish the sensorless wind speed estimator. While considering the the possible drift of the optimum power coefficient curve to the initial setting, a novel optimum setting mechanism is proposed based on the SCADA system.

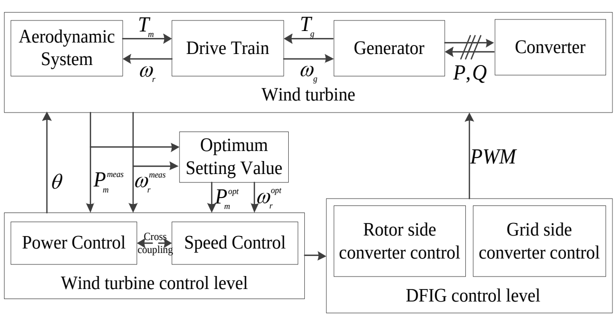

Figure 1. Wind Turbine Generation System.

3.1. Wind Speed Estimation

From the analysis in section 2, we know that a two dimensional inverse mapping between ω_r, P_m and V needs to be established. Using the characteristic data of wind tunnel test, the data-driven modeling approach, ANFIS, is introduced. The modeling mechanism is shown in **Figure 3**.

The fuzzy system mainly includes the Mamdani fuzzy system and the Takagi-Sugeno fuzzy system. Because the neuro-network usually deals with the numerical data, choosing the T-S fuzzy system which has numerical outputs is more convenient. Thus, we choose T-S fuzzy system and a kind of neuro-network to approximate the inverse mapping. For establishing the whole T-S fuzzy system, it usually includes the identification of premise parts and consequent parts. The BP neuro-network [14, 15] is used to identify the premise parameters of the T-S fuzzy system. However, it is a kind of globally approximating network which is easily to fall into the local minimums. Then, we adopt sub-clustering method [16] to partition the input space of the premise variables by which we try to compensate the disadvantages of BP neuro-network. After the determination of the number and shape of membership functions, the combination of BP neuro-network and Least Square (LS) algorithm [17, 18] is used to identify the premise structure parameters and the consequent parameters respectively.

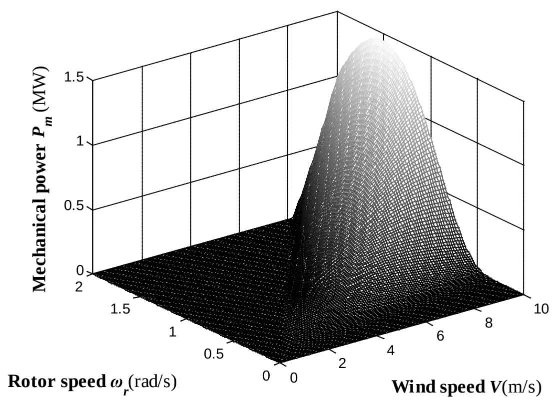

Figure 2. Wind turbine mechanical power curve.

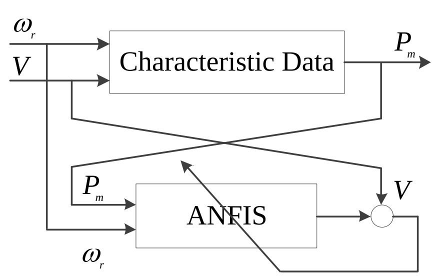

Figure 3. ANFIS for wind speed estimation.

The diagram of the algorithms is shown in **Figure 4**.

The first layer is the input layer. And each node in the second layer computes the membership degree of each input value. The third layer and the forth layer complete the fuzzy inference together. The third layer mainly deals with the premise parts of the T-S fuzzy rules. Then the consequent parts are tackled by the fourth layer. The fifth layer is the output layer which gives the numerical values. It is noted that the premise parameters are given by the BP neuro-network algorithm and the consequent parameters are determined by the LS algorithm. At last, the sensorless wind speed estimator is established.

3.2. Optimum Setting Strategy

For the WTGS control, usually, we just concern the control method more. However, in the industrial process, the correct setting values also matter a lot. As to realize the maximum energy capture in the operation process of WTGS, we need to provide the optimum setting values of rotor speed ω_r and mechanical power P_m. In general case, we use the measured wind speed values to estimate the optimum P_m. And the optimum C_P is used to set the optimum ω_r. However, in the practice, the efficiency of the wind energy conversion process may be changed and the optimum C_P may have some drift with time and varied environment. Thus, the setting values determined by the initial status of WTGS need to be updated according to the current operating status of WTGS.

Based on the SCADA system, we can establish the profile mapping between ω_r^{meas}, P_m^{meas} and V. Then, using the estimated wind speed $\hat{V}$, we can search out the primarily optimum output power $\bar{P}_m^{opt}$ and rotor speed $\bar{\omega}_r^{opt}$ corresponding to the current status, ω_r^{meas} and P_m^{meas}.

The data acquisition process can be executed as follow:

1) Regulate the rotor speed until it can be stable at a fixed value. And then, store up the measured value of $\omega_r^{meas}(i)$ into the SCADA system.

2) Measure the corresponding turbine power $P_m^{meas}(i, j)$. Meanwhile, estimate the wind speed $V(j)$ using the wind speed estimator and keep in storage.

3) Update the rotor speed to the next fixed value $\omega_r^{meas}(i+1)$.

4) Repeat step 2) and 3) until data of most operation points has been collected in the SCADA system.

5) With the collected data, a profile mapping can be established which has the same shape with **Figure 2**.

It is noted that the profile mapping is discrete. Then, the curve fitting and other approaches can be used to establish one with high accuracy. Combining the wind speed estimator and the established profile mapping, we can search out the primarily optimum setting values of $\bar{P}_m^{opt}$ and $\bar{\omega}_r^{opt}$. However, the data are acquired in the closed loop and the controller can't accurately tracking the setting values, so some compensation needs to be given according to the performance precision of the controller. The process can be shown in **Figure 5**.

Through the optimum setting strategy proposed above, we can get the optimum setting values, P_m^{opt} and ω_r^{opt}.

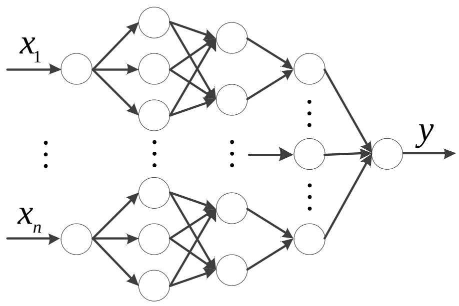

Figure 4. Train mechanism of ANFIS.

4. Simulation

Taking the 1.5 MW DFIG-based variable speed variable pitch WTGS for example, we mainly execute the approaches for fixed pitch variable speed operation mode. And for other operation modes, the processes are very the same. Using the data source in the Blade software, the characteristic data of the wind turbine for some kind of WTGS can be gotten by which we establish the wind speed estimator using ANFIS. Then, using the data source in the SCADA system, the profile mapping between ω_r^{meas}, P_m^{meas} and V can be established and the optimum setting value of ω_r can be given for the fixed pitch variable speed operation mode through searching.

The DFIG-based variable speed WTGS has the following parameters:

Rated power $P_m = 1.5MW$; turbine radius $R = 40m$;

Rated wind speed $V = 11.5m/s$;

Optimum tip-speed-ratio $\lambda_{opt} = 6.8$.

After being trained, the estimated wind speed and the error are shown in **Figure 6** and **Figure 7**. The optimum rotor speed compared with the measured rotor speed is shown in **Figure 8**. The optimum tip-speed-ratio and the practical one is shown in **Figure 9**.

From **Figure 6** and **Figure 7**, we can find that the estimated wind speed approximates accurately to the actual wind speed which shows the effectiveness of the ANFIS approach. From **Figure 8** and **Figure 9**, we can find that

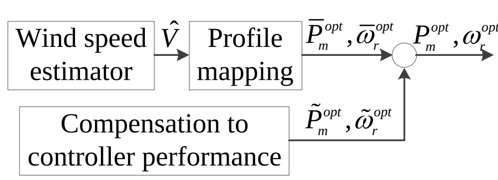

Figure 5. Optimum setting strategy.

the actual rotor speed tracks closely to the optimum rotor speed which shows the availability of the optimum setting strategy.

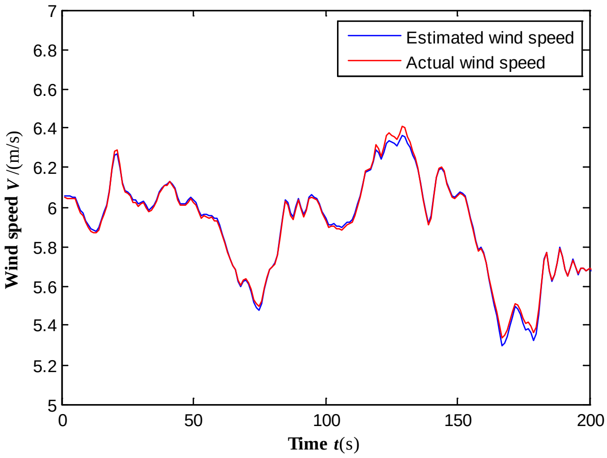

Figure 6. Comparison of estimated and actual wind speed.

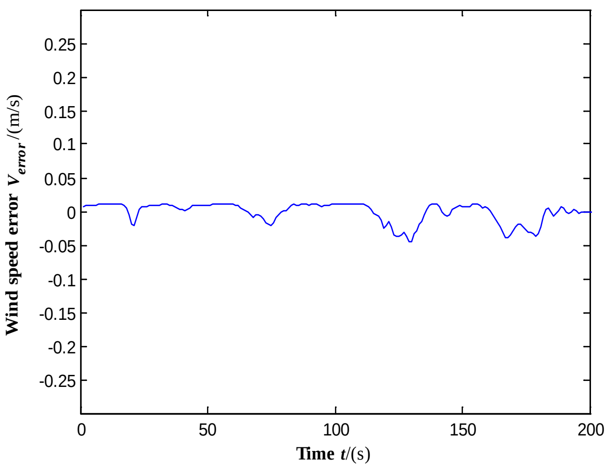

Figure 7. Error of estimated and actual wind speed.

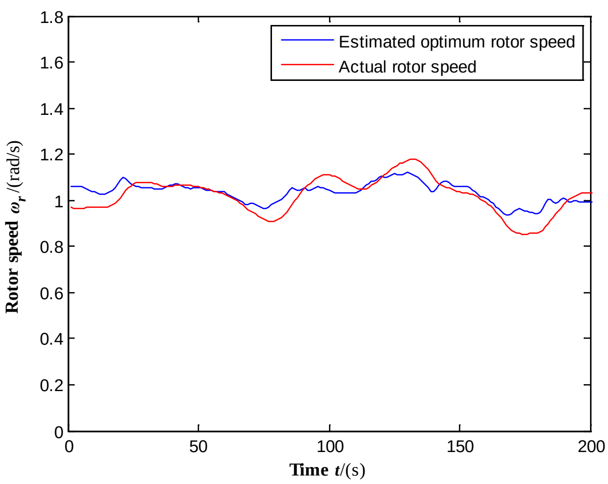

Figure 8. Comparison of optimum and actual rotor speed.

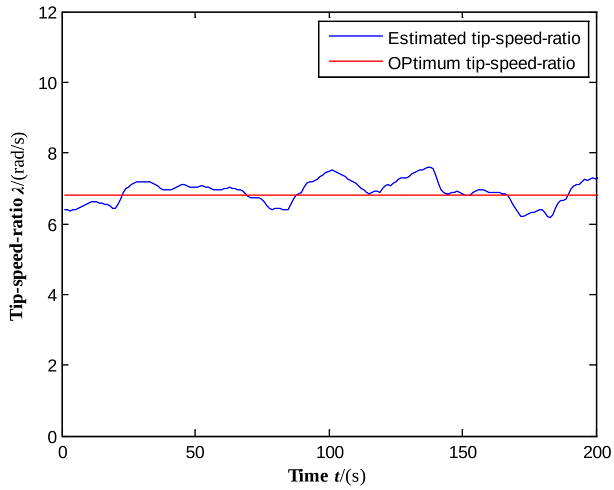

Figure 9. Comparison of optimum and actual tip-speed-ratio.

5. Conclusions

As to further reduce the cost of the wind power generation, a kind of sensorless wind speed estimator is proposed based on the ANFIS. Combining the wind speed estimation and the special data-acquisition mechanism in the SCADA system, a kind of optimum setting strategy is established. According to the simulation, the results show the effectiveness of the approaches. Especially, the approaches can not only be the optimum setting strategy but also be the scheduling setting strategy. For the modern wind power generation, the scheduling order form the grid side needs to be considered. Based on the optimum setting strategy, the way to give the setting values corresponding to the scheduling order can also be established which will be studied in future.

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