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MODELING OF AN ADAPTIVE SYSTEM OF NEURO-FUZZY CONTROL OF A WIND POWER PLANT

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ABSTRACT
Shamol energiyasini ommalashtirish orqali elektr energiyasini ishlab chiqarish tannarxini yanada pasaytirish muhim masalaga aylandi. O'zgaruvchan tezlikda shamol turbinasi ishlab chiqarish tizimini (WTGS) boshqarish samaradorligini oshirish uchun sensorsiz shamol tezligini taxmin qilish uchun ma'lumotlarga asoslangan Adaptiv Neyro-Fuzzy Inference System (ANFIS) ishlatilgan. Bundan tashqari, Nazoratni nazorat qilish va ma'lumotlarni yig'ish (SCADA) tizimiga asoslanib, amaliy ish jarayoni uchun maksimal energiya olishda optimal sozlash strategiyasi taklif qilindi. Nihoyat, yondashuvlarning samaradorligini ko'rsatadigan simulyatsiya amalga oshirildi.

1. Introduction

Wind turbines have a lower fuel cost than other renewable energy sources in large-scale applications. A wind generator’s efficacy might fluctuate depending on the situation due to various geological characteristics, climate conditions, and wind farm characteristics . Nowadays, wind energy is growing rapidly . 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. Power suppliers will have more useful data to aid in power generation planning if the total output of windy power plants (WPP) can be projected with high precision . With this information, a WPP may be managed in a flexible and intelligent way (e.g., enhanced wind farm operating schedules and reactive energy flow). Estimating wind power generation can be done using physical procedures, analytical methodologies, fuzzybased techniques, and even hybrid approaches. Because of the detection and tracking limitations imposed by WPP’s detectors and tracking systems, physical techniques must rely mostly on numerical weather forecasts. Variable factors, calculation time, time limitations, and sampling frequency all affect WPP’s capacity to provide reliable information. It is easier to predict the efficiency of a single wind turbine than the entire WPP’s output. Lowcost forecasting methods based on probabilistic and neuronetworking principles are available. A nonlinear model of the interactions between input and output information can be created based on previously observed information. However, the anticipated error may be large if additional data that was not previously included in the collection of retraining data is used as intake into such a type of system.

According to, wind farms have a large prediction error and a wide range of failures. If an abnormal wind farm is not discovered and corrected in a timely manner, it could cause lengthy outages and even lead to a lack of electricity generation. Wind farms, on the other hand, have a major challenge due to their high operational expenses. Because of this, it is becoming increasingly important to improve wind turbine O&M technology such as state tracking and wind farm problem diagnostics. Evaluating wind turbines' real-time operational conditions and discovering emergent faults requires conducting an electronic health review. Administrators of wind farms can use it as a timely reminder to prioritize and construct time-based conditionbased repair plans. A wind farm's operating costs and loss risk can be reduced by monitoring the operational state of all its wind generators. Consequently, the safety and efficiency of the wind farm have been improved.

In, the ANFIS was firstly proposed by Jang J-SR. In, 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. **From Figure 1**, we can see that in order to realize the maximum energy capture, the optimum setting values of rotor speed ωr and turbine mechanical power Pm 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, CP (λ β,) is the power coefficient, λ ω = R V r is the tip-speed-ratio and β is the pitch angle. When λ and β get the optimum values, CP (λ β,) 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 CP (λ β,) . Consequently, the nonlinear profile mapping between λ , β and CP (λ β,) can be simplified to the one between ωr , V and CP (λ β,) . There are many ways to demonstrate the nonlinear profile mapping such as fitted nonlinear function and look-up table. Using the nonlinear function , a schematic of the profile curve can be shown in **Figure 2**.

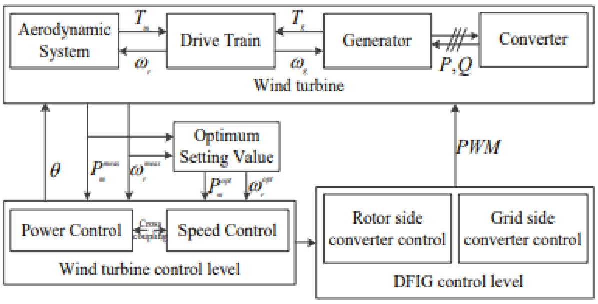

Figure 1. Wind Turbine Generation System.

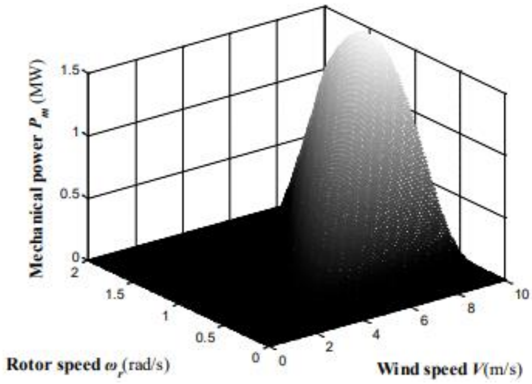

Figure 2. Wind turbine mechanical power curve.

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.

When the turbine parts are considered normal (usually functional), which is typically at the beginning of the device's lifespan, the conventional behavioral modeling is constructed. Learned systems are then used to predict signals, and the forecasting error indicates signal behavioral changes that lead to flaws in the system. The scientific community is quite interested in this technique. Autoregressive using exogenous input (ARX) modeling is used in this case to determine the status of a wind farm generator bearing using SCADA signals. Unfortunately, this approach involves human involvement in variable selection to produce a decently functioning system. Due to the large number of signals and generators that need to be inspected, human activity must be restricted. It is common for many operations to apply artificial intelligence approaches (learning capacity), and SIMAP and MARS are two of the most recent sophisticated technology that employs this strategy (MAS). There are two ways to create SCADA information typical behavioral models using artificial neural networks. Such a NN design approach is often pursued, with the creation and demonstration of NN's exceptional efficiency in this scenario being one of the most common examples.

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.**

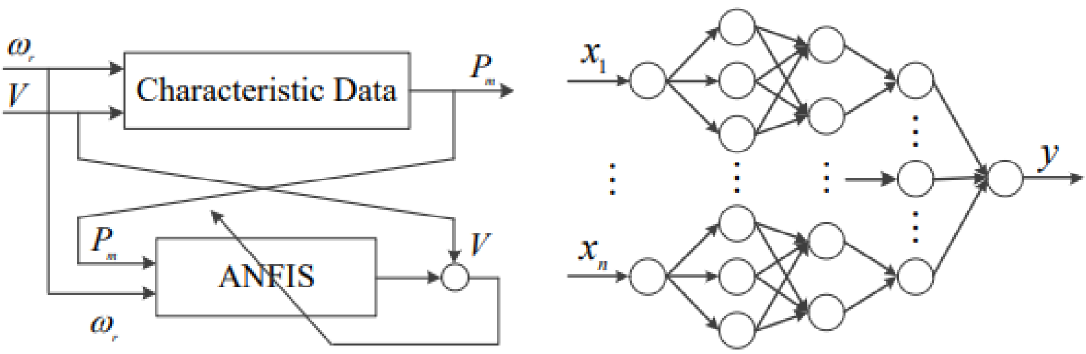

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Figure 3. ANFIS for wind speed estimation. Figure 4. Train mechanism of ANFIS.

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 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 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 is used to identify the premise structure parameters and the consequent parameters respectively.

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 establishe.

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 ω_r^{meas} (i) into the SCADA system.

2) Measure the corresponding turbine power P_m^{meas} (ij) . 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 ω_r^{meas} $(i+1)$.

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

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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} .

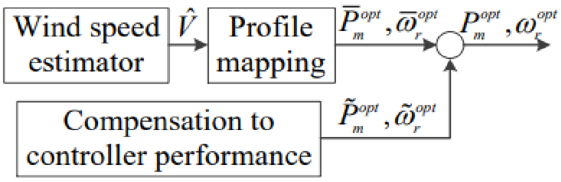


Figure 5. Optimum setting strategy.

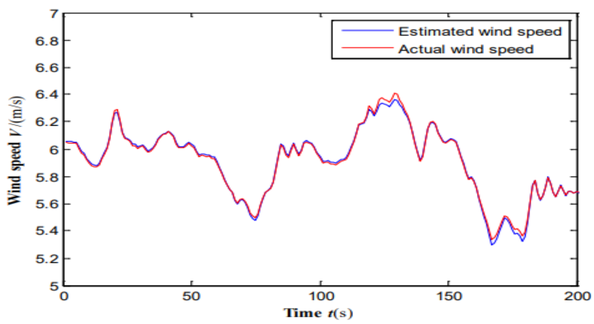
4. Simulation.

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=11.5 m/s ; Optimum tip-speed-ratio λ_{0pt}=6.8.

After being trained, the estimated wind speed and the error are shown in **Figure 6** and **Figure 7**.



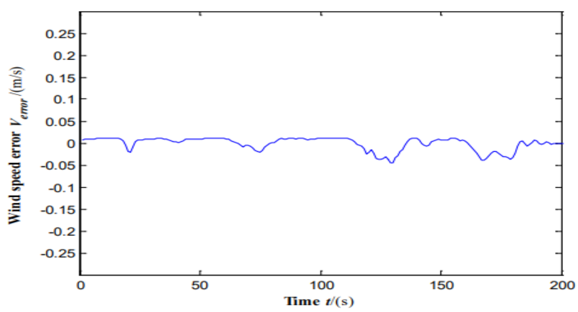


Figure 6. Comparison of estimated and actual actual wind speed .

Figure 7. Error of estimated and wind speed.

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**.

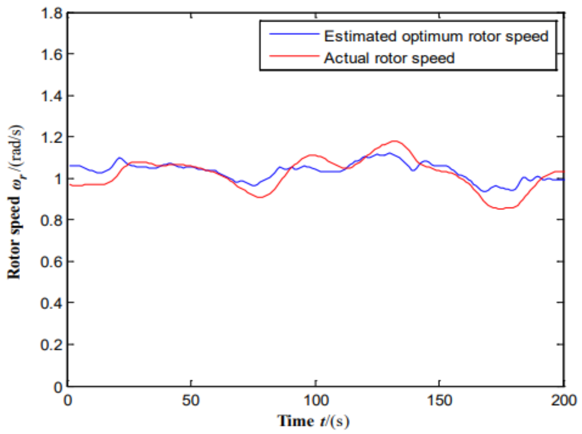


Figure 8. Comparison of optimum and actual rotor speed.

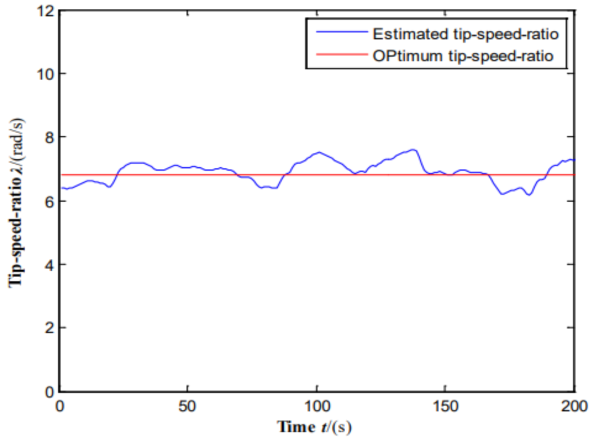


Figure 9. Comparison of optimum and actual tip-speed-ratio.

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

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.

References:

[1]. Hindavi.com
[2]. https://www.scirp.org/
[3]. .International Energy Agency, "Offshore wind outlook 2019," World Energy Outlook Special Report, International Energy Agency, 2019.
[4]. "Technology Roadmap: Wind Energy," International Energy Agency, 2009.
http://www.iea.org/publications/freepublications/publicati on/Wind_Roadmap.pdf
[5]. Carlin P.W. The history and state of the art of variable-speed wind turbine technology/ P.W. Carlin, S. Laxson, E.B. Muljadi // Technical Report NREL/TP– 500–28607, National Renewable Energy Laboratory, U.S.A. –2001.

[6]. Dawson M. H. Variable Length Wind Turbine Blade/ Dawson M. H., Lisa Barnet, Gibson Asuquo, Deborah Weems, Michael Schledorn, Marcus Farmer: Final Report DE-FG36-03GO13171. – 2006. – p.47.
[7]. Martyanov A. S., Sirotkin E. A., Solomin E. V. Adaptive control over the permanent characteristics of a wind turbine // Procedia Engineering: International Conference on Industrial Engineering (ICIE-2015). — 2015. — C. 640—646.
[8]. Martyanov A. S., Solomin E. V. Issues of windmill efficiency measurement in the field // Вопросы трансформации образования. — 2015. — C. 17—23.
[9]. Solomin E. V., Kirpichnikova I. M., Martyanov A. S. Iterative Approach in Design and Development of Vertical Axis Wind Turbines // Applied Mechanics and Materials. Energy Systems, Materials and Designing in Mechanical Engineering Collection of selected, peer reviewed papers from the International Conference for Young Scientists ―ELECTRICAL ENGINEERING. ELECTROTECHNOLOGY. ENERGY‖, June 9-12. — 2015. — C. 92—95.
[10]. Anderson M. B. An analysis of the aerodynamic forces on a variable geometry vertical axis wind turbine // Wind energy conversion 1983: Proc. of the 5th BWEA Wind Energy Conf. 1983. P. 27-29.
[11]. Korobatov D. V., Martyanov A. S., Solomin E. V. Development of control algorithms in Matlab/Simulink // Procedia Engineering: International Conference on Industrial Engineering (ICIE-2015). — 2015. — C. 922—926.
[12]. Maksimovic D., Stankovi'c A., Thottuvelil V., "Modeling and simulation of power electronic converters,"Proc. IEEE, vol. 89, pp. 898-912, 2001.
[13]. International Electrotechnical Commission et al. IEC 61400-1: Wind turbines part 1: Design requirements // International Electrotechnical Commission. – 2005.
[14]. Zhang J. et al. Pitch angle control for variable speed wind turbines //Electric Utility Deregulation and Restructuring and Power Technologies, 2008. DRPT 2008. Third International Conference on. – IEEE, 2008. – C. 2691- 2696.