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Wind Turbine Active Power Control Based on Multi-Model Adaptive Control

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Abstract

This paper proposes a multiple model adaptive control method of wind turbine active power that considers the complexity of the control model, nonlinear and strong coupling. The model is designed to reduce the negative influences of wind turbines in the process of active power control caused by different uncertain factors. We first build the multiple model of turbine operating by using subtracting cluster algorithm， based on data of a 1.5MW doubly-fed inductor generators (DFIGs) in a wind farm in Gansu, China. We use recursive least squares (RLS) algorithm to identify local model parameters. In addition， the controller is designed by adopting online optimal control model which based on a weighted index of output matching switching strategy. The controller is to realize multi-model adaptive control (MMAC). Results show that the proposed method has good control performance. The method can effectively solve the problems of wind turbines nonlinear modeling and active power control in operation.

Keywords: *Wind turbine generators, Active power control, Multi-model, Adaptive control*

1. Introduction

In many renewable energy power generation technologies, wind power is important to development for unique advantages. It has received great attention all over the world. With an increasing share of wind power in the electrical system and large-scale wind farms connected to the grid, Security, reliability, power quality and power grid scheduling of the power system will be affected by active power output of wind farms [1]. Therefore, to reduce the negative influences on the power system when the wind generator connected to the grid, it has vital significance to realize stable and reliable active power control strategy of wind turbines.

Wind turbine is a typical multivariable and complicated nonlinear system, in addition, the running environment is also complex, and has a series of uncertain factors. To reduce the influence of wind turbine output power on grid, foreign and domestic scholars have carried out researches such as adaptive gain schedule linear quadratic Gaussian control strategy on the basis of effective mean wind speed estimation in paper [2-3], reference [4] has proposed a power smoothing control strategy based on constraint factor extent-limit control, and in reference [5], a variable pitch control strategy combined with fuzzy feed forward and fuzzy PID controller is adopted. However, the methods in those papers are only under a particular condition without considering the power control during the whole wind runtime. Literatures [6-10] use different control strategies in view of turbine power smoothness of generating unit under all wind conditions from different aspects. These methods effectively reduce the fluctuations of wind generator output active power, and reduce the impact on the grid. They have achieved successful results in power smoothness control. But when

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wind speed is below the rated speed or higher than the rated. It is necessary to adopt different control strategies. When the wind fluctuates around the rated wind speed, frequent switching control strategy will cause overshoot of the transient load in the transmission chain and power output.

Multi-model adaptive control method can effectively solve complex nonlinear system control problem, thus, it has been widely used. At present, there are few applications that use this method in wind turbine control. To cope with nonlinearities in the WECS and continuous variation in the operating point, a multiple model predictive controller is proposed in [11]. It smoothes the generated power, reduces flicker emissions and provides acceptable performance throughout whole operating region, but the predictive controller design is more complicated.

To cure the above problems, this paper presents a multi-model adaptive control method for a wind turbine under full wind conditions. First, aiming at the nonlinear characteristics of wind turbine operation, multiple sub-models are used to describe dynamic characteristics of wind turbine operation. Then, based on minimum switching strategy of weighted error and accumulated error, the global model is replaced by local model that matches unit operation best. This method is equivalent to a soft switching, the switching process is smooth, and it won't cause larger fluctuation of switching output. This research studies a 1.5 MW DFIGs in a wind farm in Gansu, by collecting data of the wind turbine under different wind speeds. Simulation results prove the effectiveness of the proposed method.

2. Working Principle of the Variable-Speed Variable-Pitch Wind Turbine

Variable-speed variable-pitch wind turbine is mainly composed of pitch actuator, wind rotor, transmission part and generator. The main operation area includes two parts: partial load region, in which the wind speed is faster than cut in wind speed and below rated wind speed; full load region in which the wind speed is faster rated wind speed but below cut out wind speed. Under partial load region, the main control objective of the wind turbine is to capture the maximum wind energy. In full load region, the main control objective is to keep the output power and the generator speed at rated value.

Taking the double-fed wind power unit as an example, the variable-pitch wind turbine control principle and ideal power curve are shown in figure 1 and figure 2.

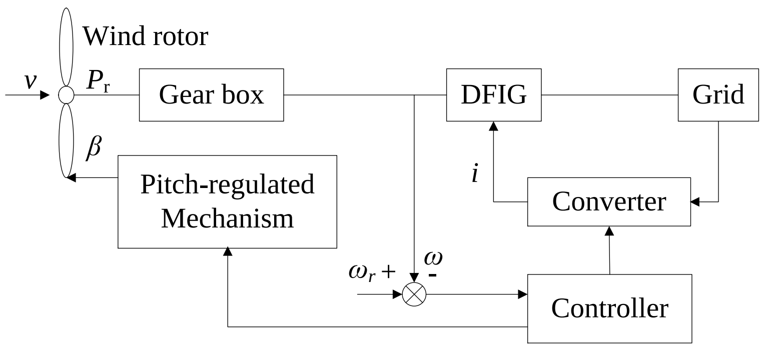

Figure 1. Wind Turbine Power Control Block Diagram

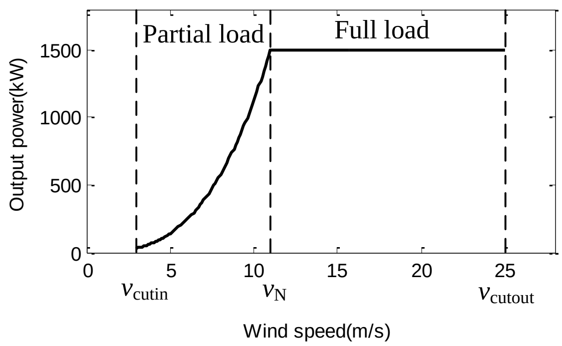

Figure 2. Ideal Power Curve for A DFIG

Therefore, output power of variable-speed variable-pitch wind turbine can be described as

$$P = \begin{cases} \eta P_{\text{r}}, & v_{\text{cutin}} \le v < v_{\text{N}} \\ P_{\text{N}}, & v_{\text{N}} \le v \le v_{\text{cutout}} \end{cases} \tag{1}$$

where

$$P_{\text{r}} = 0.5 \rho v^3 S C_{\text{P}}(\lambda, \beta) \tag{2}$$

$$C_{\text{P}} = (0.44 - 0.0167\beta)\sin\left[\frac{\pi(\lambda-3)}{15-0.3\beta}\right] - 0.00184(\lambda-3)\beta \tag{3}$$

$$\lambda = \frac{2\pi nR}{v} = \frac{\omega R}{v} \tag{4}$$

where η is the wind energy conversion efficiency, P_{r} is the wind turbine mechanical power; ρ is the air density; S is the blade swept area; C_{P} is the wind energy utilization coefficient; λ is the tip speed ratio; β is the pitch angle; v is the wind speed; ω is the wind machine spindle speed and R is the radius of wind turbines.

3. Wind Turbines Multi-Model Modeling Based On Subtractive Clustering

3.1. Multiple Model Description of the Wind Turbine Operational Process

Multi-model modeling method is an effective tool to solve the problem of nonlinear system modeling. The basic idea is to divide complex systems into multiple subintervals. In each subinterval, local linear model is built. In the operation of the system, adopting sub-model is to replace the global model [12]. Based on working conditions and nonlinear characteristics of wind turbine, multi model is used to describe dynamic characteristics of the system. The wind turbine power control process can be decomposed into multiple working points, i-th sub-model is

$$R_i : A_i(z^{-1}) y_i(k) = B_i(z^{-1}) u_i(k-d) + \zeta(k) \quad i = 1, 2, \cdots, n \tag{5}$$

where $y_i(k)$ is the prediction output of sub-model; $u_i(k\text{-}d)$ is the control variables; n is the number of model, obtained by identification with subtraction clustering algorithm; $\zeta(k)$ is the white noise sequence; $A_i(z^{-1})$ and $B_i(z^{-1})$ are polynomials, written as

$$
\begin{aligned}
A_i(z^{-1}) &= 1 + a_{i1}z^{-1} + a_{i2}z^{-2} + \cdots + a_{in_a}z^{-n_a} \\
B_i(z^{-1}) &= 1 + b_{i1}z^{-1} + b_{i2}z^{-2} + \cdots + b_{in_b}z^{-n_b}
\end{aligned} \tag{6}
$$

where n_a and n_b are orders for the input and output. Based on input and output data of power control process, formula (5) can be written in the form of least squares

$$
\begin{aligned}
y_i(k) &= -a_{i1}y_i(k-1) - \cdots - a_{in_a}y_i(k-n_a) + b_{i0}u_i(k-d) \\
&\quad + \cdots + b_{in_b}y_i(k-d-n_b) + \zeta(k) = \boldsymbol{\varphi}_i^{\mathrm{T}}(k)\boldsymbol{\theta}_i + \zeta(k)
\end{aligned} \tag{7}
$$

where $\boldsymbol{\varphi}_i^{\mathrm{T}}(k)$ is the data vector of subinterval; $\boldsymbol{\theta}_i$ is the parameter vector of sub-model to be estimated. To obtain multiple models (7), we need to determine the model structure n and parameters $\boldsymbol{\theta}_i$, we use the subtraction clustering algorithm to determine n, the least squares identification parameters $\boldsymbol{\theta}_i$.

3.2. Optimal Number of Dynamic Models Based On Subtractive Clustering

Subtractive clustering is a single fast algorithm to estimate cluster number p and the cluster center of data. With the proposed method, each data point is regarded as a possible clustering center. Then, we calculate data density around the data point to decide if the point is the clustering center [13]. Based on the operation data of the wind turbine, the number p can be obtained by the subtraction clustering algorithm.

In multiple model control, establishment of the model set is important. The more sub-models, the less negative effect that caused by piecewise linearization of the nonlinear characteristic and the higher control precision, but, too many sub-models will lead to increase of calculation. Therefore, we must determine the optimal number of the dynamic model.

The performance of clustering algorithm can be measured by using the effective index. Davies-Bouldin (DB) index [14] is one of the validity evaluation indexes for classical clustering which uses the cluster separation and intra-cluster compactness to scale the performance of clustering, defined as follows

$$
I_{\mathrm{DB}} = \frac{1}{p}\sum_{c=1}^{p}\max_{r,r\neq c}\left[\frac{S(U_c)+S(U_r)}{d(U_c,U_r)}\right] \tag{8}
$$

where p is the total number of clustering centers; $S(U_c)$ is the inner-cluster distance of c-th clustering; $d(U_c, U_r)$ is the distances between c-th and r-th clustering, $1\leq c,r\leq p$. It can be seen from the type when the number of clustering center p^* makes $S(U_c)$ minimum and $d(U_c, U_r)$ maximum, namely, separation between classes and compactness in class are the largest and the DB index is minimum, thus the clustering algorithm can be considered as the best performance, the p^* is the corresponding optimal number of dynamic model defined as

$$
p^* = \arg\min_p(I_{DB}) \tag{9}
$$

A typical measurement of intra-cluster compactness and cluster separations between classes are

$$
\begin{aligned}
S(U_r) &= \frac{1}{|U_r|}\sum_{x\in U_r}\|x - v_r\| \\
d(U_c,U_r) &= \|v_c - v_r\|
\end{aligned}
$$

where x is the element in the class U_r, v_c and v_r represent the c-th and r-th clustering center.

3.3. Multiple Model Identification

The least square method is a widely used system identification algorithm, dispense with model of controlled object, only with the system input and output data, can achieve the effect of unbiased, minimum variance, uniform convergence. In this paper, we use the method of least squares to identify the each group of clustering data, so as to obtain the unit process model set. To the *i*-th ($1<i\leqslant p^*$) clusters, RLS method is used to identify the parameters of sub-model. The RLS identification algorithm is as follows

$$\begin{aligned}
\hat{\boldsymbol{\theta}}_i(k+1) &= \hat{\boldsymbol{\theta}}_i(k)+\boldsymbol{K}(k)[y(k+1)-\boldsymbol{\varphi}_i^{\mathrm{T}}(k+1)\hat{\boldsymbol{\theta}}_i(k)] \\
\boldsymbol{K}(k+1) &= \frac{\boldsymbol{P}(k)\boldsymbol{\varphi}_i(k+1)}{\lambda_1+\boldsymbol{\varphi}_i^{\mathrm{T}}(k+1)\boldsymbol{P}(k)\boldsymbol{\varphi}_i(k+1)} \\
\boldsymbol{P}(k+1) &= \frac{1}{\lambda_1}[I-\boldsymbol{K}(k+1)\boldsymbol{\varphi}_i(k+1)\boldsymbol{P}(k)]
\end{aligned} \tag{10}$$

where $y(k+1)$ is the wind turbine output power, $\hat{\boldsymbol{\theta}}_i(0)$ is zero vector or sufficiently small vector of the initial value, $\boldsymbol{P}(0)=(10^4\text{-}10^{10})I$. Based on principle of real-time identification information updating without causing large mutation, the forgetting factor λ_1 usually choose a positive between 0.9 ~ 1.0.

4. Multi-Model Adaptive Control for Wind Turbine Power Control

4.1. Multi-Model Adaptive Control for Wind Turbine

Multiple model adaptive controller structure is shown in figure 3. Based on input and output data of wind turbines running process, p^* sub-models to identify dynamic characteristic of the operation process，the output are y_i, $i=1,2,\cdots,p^*$. At each sampling time, the system will choose the best sub-model to the closed-loop control according to the switching strategy. The paper designs a fuzzy adaptive tuning PID controller aiming at uncertainty of wind turbine power control process. The PID controller is based on the identification of multiple models and it takes some model mismatch in a mathematical model of the subspace into account. Fuzzy PID is the local controller that uses the adaptive ability of fuzzy control to correct the smaller control deviation caused by model mismatch.

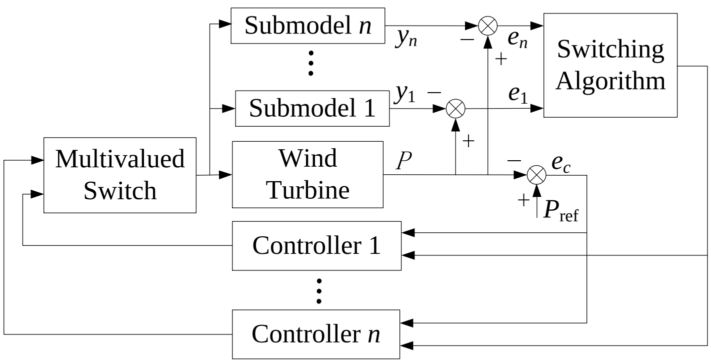

Figure 3. Multiple Model Adaptive Controller Structure

For uncertainty of wind turbine power control, and considering the mathematical model mismatch of sub-models, this paper designs a fuzzy adaptive tuning PID controller. The fuzzy PID as the local controller to correct the control error caused by small model mismatches using the adaptive ability of fuzzy control.

At each sampling point, multi-model system calculates error between the sub-model output y_i and the theoretical output power P_e. Based on the switching strategy determine wind turbine operation process real-time matching model, then design the fuzzy inference rules adjust dynamic compensation amount of PID parameters $F_1(e,ec)$, $F_2(e,ec)$ and $F_3(e,ec)$, Fuzzy rules adopt classical fuzzy inference rules [15], then the PID parameters K_p, K_i and K_d are

$$\begin{aligned} K_p &= K_{p0} + F_1(e,ec) \\ K_i &= K_{i0} + F_2(e,ec) \\ K_d &= K_{d0} + F_3(e,ec) \end{aligned} \tag{11}$$

where, K_{p0}, K_{i0} and K_{d0} are initial values of PID control parameters.

Based on the choice of optimal matching model and fuzzy adaptive controller parameter setting, the discrete PID control algorithm is

$$u(k) = K_p e(k) + K_i T_s \sum_{j=0}^{k} e(j) + K_d \frac{e(k) - e(k-1)}{T_s} \tag{12}$$

4.2. Multi-Model Switching Principle

Multi-model switching strategy is to online-determine the best matching model for the current operating conditions among several models by a performance index. To determine the best sub-model that describes the nonlinear operation of wind turbine at each moment, we use the multi-model switching strategy based on error [16]

$$J_i = \alpha_1 \left\| e_i(t) \right\|_2^2 + \beta_1 \sum_{j=1}^{g} \eta^j \left\| e_i(t-j) \right\|_2^2, \quad i = 1, 2, \cdots, m \tag{13}$$

where $e_i(t) = P_e(t) - y_i(t), \quad 1 \le i \le p^*$, represents the error of the i-th sub-model nonlinear operation process of wind generator at time t; $\alpha_1>0$ indicates the weight of error at current times; $\beta_1>0$ is the weight of error at past time; $0<\eta\le1$ is forgetting factor, represents memory effect of the error in past time; g is length of the past time considering the error. Switching performance index J_i is a criterion to evaluate matching degree of the sub-model and the nonlinear operation process. The smaller the J_i is, the sub-model is much more matching the nonlinear dynamic characteristics of the wind turbine. To this switching performance, we consider the current error and the accumulated error over time. Then we can avoid the situation of large mismatches in the system model.

5. The Simulation and Analysis

Wind turbine power control includes two aspects: the best wind turbine power control and output the dispatching specific power according to the wind farm scheduling requirements. This paper takes 1.5MW DFIGs in Guazhou wind farm in Gansu province as an object. According to the wind power control process operating data collected from scene under full wind speed, we carry out the simulation and research of the power control process. Main parameters of the wind turbine are as follows: wind turbines using power rated value of 1.5MW DFIGs, wind speed range 3~25 m/s, rated wind speed is 11m/s, rotor radius is 31.4m, air density is 1.225kg/m^3, input range of fuzzy PID controller is e=[-30kW,30kW], the error rate ec=[-60kW, 60kW], the fuzzy controller output range is $\triangle K_p$=[-0.3,0.3],$\triangle K_i$=[-0.06,0.06] and $\triangle K_d$=[-3,3].

5.1. Optimal Active Power Control of Wind Turbines

We gather 1.5MW DFIGs operation data under all wind condition and get 573 effective groups of data based on data preprocessing technology as the samples for modeling. According to the sample data of acquired wind speed v, pitch angle β and output power P, subtractive clustering algorithm and the DB cluster validity index analysis are used. Results are shown in Table 1.

Table 1. Clustering Results

Number of sub-model	Clustering center (v, β, P)	I_{DB}
3	(5.6,0,555.7);(2.6,0,74);(11.2,6.4,1506.2)	0.2655
4	(5.8,0,582.6);(1.7,90.4,0.1);(11.2,6.4,1506.2);(5.2,0,439.4)	0.1187
5	(1.6,90.4,0.1);(8.1,0,1165.4);(5.5,0,535.7); (11.5,7.1,1507.4);(3.5,0,0.1678)	0.0686
6	(6.4,0,666.7);(5.1,0,419.6);(8.1,0,1180.2); (3.2,0,131.5);(11.5,7.1,1507.4);(1.5,90.4,0.1);	0.0373
7	(6.4,0,666.7);(11.5,7.1,1507.4);(1.4,90.4,0.1);(2.8,0,91.7); (8.1,0,1180.2);(4.2,0,255.9);(5.2,0,433.7)	0.0970

From table 1 we can see that the wind power control process under full wing speed condition can be divided into six relatively concentrated work areas, the center are as follows

$$(v,\beta,P)=\{(6.4,0.00,666.7);\quad(5.1,0.00,419.6);\quad(8.1,0.00,1180.2);$$
$$(3.2,0.00,131.5);\quad(11.5,7.1,1507.4);\quad(1.5,90.4,0.1)\}$$

The pitch angle of sixth clustering center is 90.4, in this case the wind turbine is in a state of feathering, thus, its control problem can be ignored. According to the rest of the clustering center, the corresponding nonlinear model parameters of each working point are identified, which is based on the classified data. The wind speed as input of the model and the power of output, model parameters are identified by RLS

Sub-model 1： $y(k)+0.3280y(k-1)=151.8383u(k-1)+\zeta(k)$

Sub-model 2： $y(k)+0.7023y(k-1)=123.1284u(k-1)+\zeta(k)$

Sub-model 3： $y(k)-0.0120y(k-1)=-1.5315u(k-1)+\zeta(k)$

Sub-model 4： $y(k)+0.9133y(k-1)=65.4247u(k-1)+\zeta(k)$

Sub-model 5： $y(k)-0.9810y(k-1)=2.6775u(k-1)+\zeta(k)$

Simulation is carried out with MATLAB. Simulated wind speed samples as shown in figure 4, the simulation results as shown in figure 5~7. Among them, figure 5 is sub-model switching sequence. It can be seen, the identification models can cover all the working condition of unit operation. According to J_i minimum switch matching at each moment, we choose the best sub-model. Figure 6 shows wind turbine output power curve. Output of multiple model adaptive control system can effectively track the theoretical output of wind turbines. The model has a high identification accuracy, good generalization ability, and strong robustness. Multiple models can achieve a smooth handover, and the actual output power phase ratio. The method can maintain constant power output at above rated wind speed, and capture more wind energy than the actual wind power at blow rated wind speed. The error curve of adaptive multi-model approach and actual output power to the theoretical output power is in figure 7, we can see the output power of multiple model adaptive approach is closer to the theoretical output power, and can capture more energy. From figure 5 and figure 7, with the change of wind speed, multiple models adaptive method can select the best matching model according to the switching strategy, at each sampling instant. From figure 6 and 7, the output power of multiple model adaptive method is smoother, improves power quality and gets better control performance.

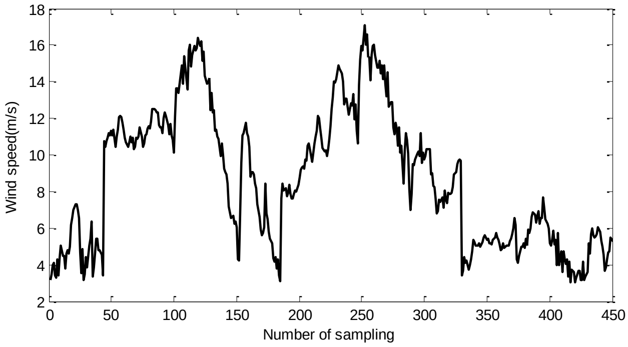

Figure 4. Simulated Wind Speed Change Curve

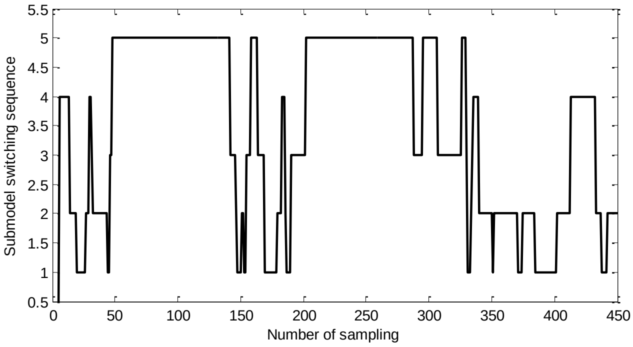

Figure 5. Sub Models Switching Figure

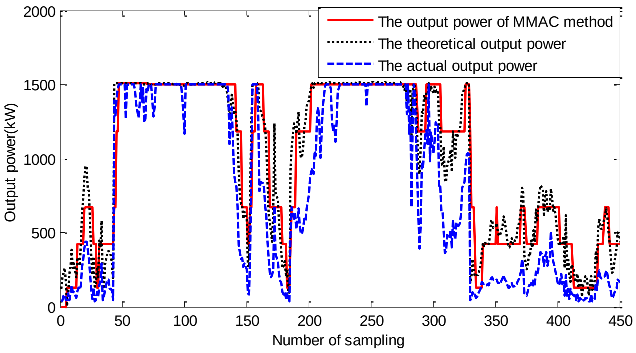

Figure 6. Wind Turbine Power Output Curve

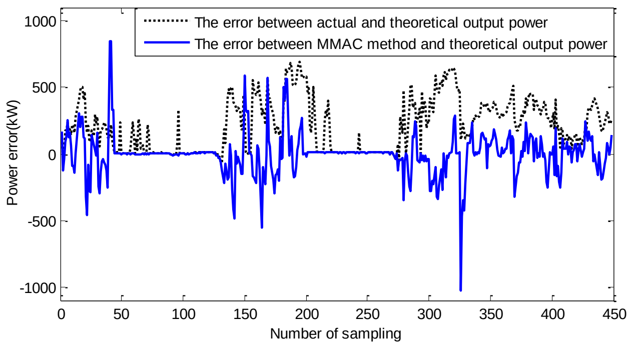

Figure 7. Wind Turbine Power Output Error Curve

We compare the output samples with theoretical output powerk, and measure the deviation of output power by calculating the standard deviation.

The standard deviation can be expressed as

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{14}$$

where x_i denotes the *i*-th sample value, σ is standard deviation, N is degrees of freedom, μ is the benchmark value of a set of data, here is the theoretical output power of wind turbine.

We take 45 sample data of output power. The theoretical output power of wind turbine is benchmark value, then the standard deviation of power output is calculated through formula (14). This processing method is to measure the deviation of output power level and validate whether the control meet the requirements of the optimal power control.

We calculate the standard deviation of actual power output sample is 300.5318 kW, and deviation degree to theoretical output power is 20.04%. The standard deviation of multiple model adaptive method output power is 144.7605 kW and deviation degree to theoretical output power is 9.65%. The calculation results show that power control precision of multiple model adaptive control method satisfy the requirements of optimal power control.

5.2. Wind Turbines Limit Control of Active Power Output

Wind power is intermittent, volatile and random. Thus, its shunt-connected generation brings a certain impact and challenge to the safety and stable operation of power grid [17]. To ensure the safety of power grid, wind farms should have active power adjustment ability that can control its output according to the dispatching department command.

In addition, wind turbine is mechanical equipment, frequent start-stop will increase wearing and operating costs. By contrast, adjusting the wind turbine control system to limit the unit output can reduce operation costs as much as possible, and make the output maintain a controllable range.

Wind farm active power control is achieved through active control module. During the grid operation, the control module receives set value given by grid scheduling. According to the real-time power generation plan, the active control module converts output scheduling command control signal to the reference active output value of each wind turbine, and assigns the signal to each unit. The wind turbine control system limits output control [18]. Thus, based on the wind turbine power generation plans and operating information, each unit has two operating modes:

1) Normal operating mode. When the power that acquired by grid dispatching command is greater than the active power output ability of the unit, then the

active power is not limited, that is, active power control module does not output control commands, wind turbine runs the best wind power tracking mode.

2) Output control mode. When the output power is greater than the active power command, the wind turbine realizes the active power limit control based on control commands given by active power control module.

In this paper, examples of a 1.5MW double-fed unit are studied and the distribution effects of active power management are analyzed. Assuming wind turbines expected to limit the maximum output to 900kW, the results shown in figure 8.

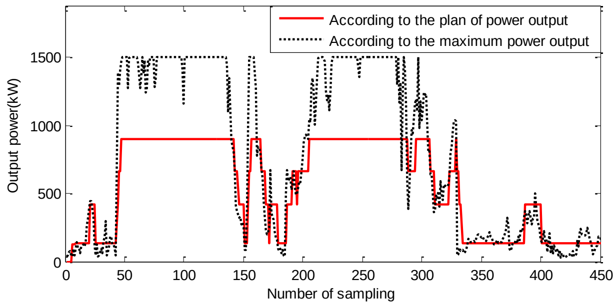

Figure 8. The Limited Power Output Control Results of Wind Turbine

Figure 8 shows that wind turbines follow the changes in the actual generation capacity variation when the desired output power is greater than the actual power generation. When the desired output power is less than the actual power generation, wind turbine power generation is limited to the expected status. Real-time control process of the power control is stable at given value. The output is controlled by limiting the unit output power. The output power of the wind turbine is able to accurately respond to changes of desired one, and it can meet scheduling requirements of the field.

6. Conclusion

This paper presents a wind turbine power control method based on multi-model adaptive control. We use subtraction clustering algorithm reasonably divide the input and output data of unit operation into several subintervals. Then we adopt the RLS algorithm to identify local model parameters and describe wind turbine operation by multiple local linear models. The models have the same structure and different parameters. Based on minimum switching performance index of weighted error and accumulated error at every moment, the global model is replaced by the local model that matches unit operation process best. Multiple model adaptive control is used to eliminate large model mismatch and fuzzy PID to improve small model mismatch. The results show that the proposed method can effectively improve the performance of wind turbine power control and follow a desired output power value in accordance with the wind farms scheduling instruction.

Acknowledgements

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