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Energy storage scheduling design on friendly grid wind power

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ABSTRACT

Smooth and accurate schedule forecast of wind power may ensure healthy and reliable running of the power grid. Energy storage systems can participate in wind power scheduling due to the ability of space-time translation of electrical energy. The reasonable strategy design is important especially on smooth and accurate forecast of wind power. Firstly, based on control indexes of volatility and forecast error of wind power, Fourier mathematical analysis is used to design one-order low pass filter to smooth the curve of auto-regression ultra-short-term prediction of wind power. Secondly, the predicting curve after smooth is used as wind power actual control target, actual output is processed to track the power forecast by storage control. Thirdly, combined with the actual state of charge (*SOC*) of the lithium battery, forecast error coefficient adjustment is innovatively introduced as dynamic error band constraint factor. Finally, schemes of complete tracking and relaxed model control are analyzed respectively by simulation to ensure the results of smoothing and accurate forecast effects of the actual wind/storage output. The designed scheme of relaxation factor control can avoid overcharge and over discharge of energy storage, reducing the frequency of charge-discharge of lithium battery, achieving the feasibility and effectiveness of energy management strategy.

Introduction

The gap changes of speed bring difficulties to the forecast of wind power [1]. With the increasing of grid capacity of wind power, the quality demand for wind power dispatching became higher and higher. The wind power generators should balance the electrical energy consumed by loads and losses at all times so as to maintain stable frequency of system [2].Scholars and engineers have made a large number of researches on wind power fluctuation and accurate forecast respectively [3,4]. How to realize smooth and high-accuracy dispatching forecast of wind power at the same time is worthy of discussion further. The existed wind power stabilization schemes include two main directions. One is enhancing the equipment itself to stabilize the output fluctuations, the other is depending on energy storage device.

For the latter, a variety of algorithms are used firstly to obtain the predicted power, then power throughput is adjusted by the energy storage. For example, time constant variable low-pass filter and hybrid energy storage are used to achieve wind power stabilization [5]. The larger time constant is, the greater energy storage configuration is required. Low energy storage capacity configuration needs relative complex algorithm [6]. In the literature [7], the wavelet packet decomposition and the energy storage state (*SOC)* are used to control the working of energy storage. The energy storage efficiency is improved to a certain extent, and the wave of output power is better suppressed.

There are also two main directions for the development of accurate schedule forecast. The first one is to increase the accuracy from the perspective of software forecast techniques. Existing methods of wind power prediction have evolved from single prediction to intelligent hybrid algorithm, and the demand of data processing has been improved. Literature [8] combines the time series model with RBF neural network model to predict wind power, so precision is higher significantly than the single model. In literature [9], fuzzy clustering analysis combined with adaptive learning is used, not only to improve precision, but also deal with the practical problems such as small sample and nonlinear. In literature [10], GA-SVM model parameters are optimized by genetic algorithm, which improves the efficiency and precision of parameter selection. Furthermore, some literatures also give out objective evaluation of wind power forecast. Due to the algorithm deficiencies in wind power prediction, such as incomplete basic sample data, low accuracy, it is suggested that the hardware configuration can be used to offset the error of software forecast methods [11].

So the other is to configure the energy storage to ensure the accuracy within the special range. Wind power of the prediction is regarded

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Nomenclature

$\Delta P_w^T(t_0)$	Wind power fluctuation in t_0 within T
$Max_{t\in[t_0,t_0+T]}^{\{P_w(t)\}}$	Maximum amount of wind power
$Min_{t\in[t_0,t_0+T]}^{\{P_w(t)\}}$	Minimum wind power
ζ	Wind power fluctuation rate
P_b	Total installed capacity of the wind farm
$P_w(t)$	the actual wind power value at t time
$P_{fors}(t)$	Wind power forecast value
e_t	The wind power prediction error at time t
σ	Real-time forecast error rate
σ_{Max}	Maximum forecast error rate
σ_{RMSE}	RMSE (root mean square error)
T	Time scale
σ_{nT}	Nth sampling period prediction error
P_{out}	Filtered output power
P_{in}	Autoregressive predictive power
ΔP_{smo}	The power difference between P_{out} and P_{in}
ΔP_{fors}	The wind power prediction curve after smooth
SOC_{for}	Prediction error
SOC_{bat}	SOC of battery
P_{HESS}	Desired actual power of hybrid energy storage system
P_{bat1}	Automatic power distribution of the lithium battery
P_{cap1}	Automatic power distribution of ultra-capacitor
P_{bat2}	Security power bottleneck module of the lithium battery
P_{cap2}	Security power bottleneck module of ultra-capacitor
P_{bat3}	Charge-discharge power considering protection of the lithium battery
P_{cap3}	Charge-discharge power considering protection of ultra-capacitor
γ	Coefficient of error band
P_w	Actual wind power
P_{for}	Forecast wind power
P_{max}	Upper limit of prediction error
P_{min}	Lower limit of prediction error
P_{fors}	Expected power of mixed energy storage system
P_{batmax}	Maximum safety power of the lithium battery
P_{capmax}	Maximum safety power of the SC
SOC_{max}	Highest value of SOC
SOC_{min}	Lowest value of SOC
Q_{bat}	Actual battery capacity used
Q_b	Rated Capacity of the battery
SOC_{capmax}	Maximum safety power of the SC
SOC_{capmin}	Minimum safety power of the SC
I_{bat}	Charge-discharge current of the battery
I_{cap}	Charge-discharge current of the battery

as amount revealed in advance to the grid, and the forecast output is tracked by participation scheduling of the energy storage device [12]. The scheme can ensure accurate schedule forecasts, but the capacity of energy storage configuration is large. In literature [13], the deviation of wind power prediction is calculated in real time, and the compensation coefficient is introduced. The charge and discharge states and the battery *SOC* are used as compensation factors to correct the control parameters to ensure the energy storage not overrun. Therefore, some scholars put forward error band from the angle of forecast standards, part errors beyond the wind power are absorbed, and the power is stabilized by the energy storage device combined with the forecast rule. The wind power forecast smoothness can be improved to a certain extent [14]. Literature [15] considers error band either in the prediction or smoothness when using the hybrid energy storage system. The energy storage capacity is increased with the decreased error band.

In this paper, the autoregressive prediction curve is smoothed by the filter, and the smoothed curve is regarded as the schedule forecast curve. Followed by the research of strategy of full tracking, the forecast error band is proposed. The corresponding dynamic control strategy is introduced innovatively by dynamic relaxation factor, which can not only protect the energy storage device, lower the energy storage configuration capacity, reduce the initial investment and cost of operation and maintenance, but also ensure the accuracy of the forecast. Furthermore, wind energy would become a stable and controllable clean energy.

Grid demand indicators of wind farm

Fluctuations stabilization function requirements of grid-connected wind power

State Grid Corporation of China makes provisions clearly in 2011 version (the technical provisions of wind farm access to the grid). The volatility limit is as shown in Table 1. The maximum power fluctuation of wind farm is divided into 10 min and 1 min. Maximum change of 10 min level can't exceed 1/3 capacity of the installed capacity, the maximum change of 1 min level fluctuations does not exceed 1/10 of installed capacity.

Accurate forecast function requirements of grid wind power

National Bureau of Energy of China issued 'the wind farm power forecast interim measures' in 2011. It can be seen that accurate schedule forecast requirements are quantified strictly, as shown in Table 2.

Smooth and accurate forecast scheme

Analysis on fluctuation stabilization correspond to prediction error control index

Wind power fluctuations calculation

The fluctuation characteristic of wind farm can be described by the fluctuation quantity. The maximum power variation of wind power within the time scale T is shown in formula (1) and Fig. 1.

$$\Delta P_w^T(t_0) = Max_{t\in[t_0,t_0+T]}^{\{P_w(t)\}} - Min_{t\in[t_0,t_0+T]}^{\{P_w(t)\}} \tag{1}$$

Formula for volatility rate calculating is shown in (2).

$$\zeta = \frac{\Delta P_w^T(t_0)}{P_b} \tag{2}$$

In formula (2) and Fig. 1, $\Delta P_w^T(t_0)$—wind power fluctuation in t_0 within T, $Max_{t\in[t_0,t_0+T]}^{\{P_w(t)\}}$—the maximum amount of wind power, $Min_{t\in[t_0,t_0+T]}^{\{P_w(t)\}}$—minimum wind power, ζ—wind power fluctuation rate, P_b—the total installed capacity of the wind farm.

Wind power prediction error calculation

Daily forecast mode is used, $P_w(t)$—the actual wind power value at t time, $P_{fors}(t)$—the forecast value, the error $e(t)$ at time t is defined as the difference between the actual wind power and the forecast, shown in

Table 1
Wind farm maximum active power fluctuation value.

Wind farm installed capacity (MW)	10 min maximum change (MW·(10 min)$^{-1}$)	1 min maximum change (MW min^{-1})
< 30	10	3
30–150	installed capacity/3	installed capacity/10
> 150	50	15