

Research on Control Strategy of Supercapacitor-Lithium Iron Phosphate Battery-Flywheel Hybrid Energy Storage System for Mitigating Wind Power Fluctuations Across Multiple Time Scales

Shaobo Yan

Henan University of Science and Technology, Luoyang 471000, China

Abstract: Aiming at the problems of reduced power quality and insufficient grid absorption capacity caused by power fluctuations in traditional wind power grid connection, this paper proposes a multi-element hybrid energy storage system composed of supercapacitors, lithium iron phosphate batteries, and flywheel energy storage to mitigate wind power fluctuations across multiple time scales. Firstly, based on the principle of Empirical Mode Decomposition (EMD), the wind power signal is decomposed into three types of fluctuation components with different time scales: high-frequency, medium-frequency, and low-frequency. Secondly, combined with the response characteristics of the three types of energy storage devices (supercapacitors with fast response, flywheel energy storage with high power density, and lithium iron phosphate batteries with excellent energy density), the high-frequency components are allocated to supercapacitors for mitigation, the medium-frequency components are processed by flywheel energy storage, and the low-frequency components are regulated by lithium iron phosphate batteries, forming a multi-time scale coordinated control strategy. Finally, a simulation model is built in the MATLAB/Simulink environment, with 24-hour actual power data of a 20MW wind farm as input, to compare and analyze the mitigation effect and economy of different energy storage combinations. The simulation results show that the proposed hybrid energy storage system can achieve full-time scale coverage of wind power fluctuations, the fluctuation range of the grid-connected power after mitigation is controlled within $\pm 2\%$, and the life-cycle cost is reduced by 18.3% compared with the traditional "battery-supercapacitor" combination, verifying the effectiveness of the hybrid system in improving the stability and economy of wind power grid connection.

Keywords: Hybrid energy storage system; Wind power fluctuation mitigation; Empirical Mode Decomposition; MATLAB/Simulink simulation

1. Introduction

With the continuous growth of wind power installed capacity, wind power is affected by factors such as wind speed, wind direction, and weather, showing significant multi-time scale fluctuation characteristics. Large fluctuations can lead to grid frequency deviation, voltage fluctuation and other problems, and even cause the "wind curtailment" phenomenon, which seriously restricts the wind power absorption capacity. A single energy storage device is difficult to meet the dual requirements of "response speed" and "energy capacity" simultaneously, while the hybrid energy storage system can achieve effective mitigation of wind power fluctuations across multiple time scales through the characteristic complementarity of different energy storage devices. After the access of large-capacity wind farms, the grid voltage stability will be affected, and relevant scholars have carried out calculation analysis and control strategy research on this problem [1].

2. Hybrid Energy Storage System and Control Strategy

2.1. Composition of Hybrid Energy Storage System

The supercapacitor-lithium iron phosphate battery-flywheel hybrid energy storage system is connected between the wind farm and the power grid. After the output power of

the wind farm is decomposed by EMD, the obtained high-frequency, medium-frequency, and low-frequency fluctuation components are mitigated by supercapacitors, flywheel energy storage, and lithium iron phosphate batteries respectively, and finally a stable grid-connected power is formed to connect to the power grid.

2.2. Power Decomposition Based on EMD

Empirical Mode Decomposition (EMD) is an adaptive signal decomposition method that does not require preset basis functions. It can decompose the wind power signal into several Intrinsic Mode Functions (IMFs) and one residual trend term according to the time scale characteristics of the wind power signal itself. The decomposition steps are as follows:

Step 1: Extract all maximum and minimum points of the wind power signal, and fit the upper and lower envelopes through cubic functions respectively.

Step 2: Calculate the average value of the envelopes, subtract the average value from the original signal to obtain the initial component. If the initial component meets the IMF conditions, it is taken as the first IMF component; otherwise, this process is repeated.

Step 3: Subtract the obtained IMF component from the original signal to get the residual signal. Take the residual signal as a new signal and repeat the above process until the last remaining signal is a monotonic function.

The Empirical Mode Decomposition (EMD) process of the wind power signal is actually to decompose the complex

fluctuations of the wind power into components of different time scales through the EMD process, providing a basis for the subsequent power allocation of the energy storage system (e.g., high-frequency fluctuations are mitigated by supercapacitors, and low-frequency fluctuations are borne by batteries/flywheels), thereby realizing the stable output of wind power.

2.3. Multi-Time Scale Coordinated Control Strategy

According to the characteristics of the three types of energy storage devices and combined with the EMD decomposition results, a component allocation strategy is formulated:

1. High-frequency components (composed of the first 2 IMF components, corresponding to second-level fluctuations): Mitigated by supercapacitors, adopting a dual closed-loop control of voltage outer loop and current inner loop to track high-frequency components in real time.

2. Medium-frequency components (composed of the middle 3 IMF components, corresponding to minute-level fluctuations): Processed by flywheel energy storage, adopting speed control mode to realize power absorption and release by adjusting the rotor speed.

3. Low-frequency components (composed of the remaining IMF components and trend term, corresponding to hour-level fluctuations): Regulated by lithium iron phosphate batteries, and adopting State of Charge (SOC) closed-loop control to avoid overcharging and over-discharging.

3. Simulation Model Construction and Parameter Setting

3.1. Simulation Platform and Data Source

The simulation platform is built based on MATLAB/Simulink. The wind farm power data adopts 24-hour actual operation data of a 20MW wind farm with a sampling interval of 10s and a power fluctuation range of 2~20MW. The grid dispatching power is set according to the typical daily load curve and updated once per hour to ensure that the total wind power generation and the total grid-connected power generation are equal within 24 hours, meeting the system charge-discharge balance constraint.

3.2. Key Parameter Setting

EMD decomposition parameters: Combined with relevant research results and engineering application practice, to balance the decomposition effect and calculation efficiency and accurately reflect the inherent characteristics of the signal, the stop iteration threshold (standard deviation criterion) $S_d = 0.3$ is set. After decomposition, the original wind farm power signal is adaptively decomposed into 9 Intrinsic Mode Function (IMF) components and 1 trend term (residual term).

Energy storage device parameters:

Supercapacitor: Rated power 4MW, rated capacity 0.3MW·h, initial State of Charge (SOC) 50%;

Flywheel energy storage: Rated power 6MW, rated speed 30000r/min, initial State of Charge (SOC) 50%;

Lithium iron phosphate battery: Rated power 8MW, rated capacity 24MW·h, initial State of Charge (SOC) 50%, charge-discharge efficiency 90%.

Control parameters: The bandwidth of the supercapacitor current loop is 100Hz, the bandwidth of the flywheel energy storage speed loop is 50Hz, and the adjustment coefficient of the lithium battery SOC loop is 0.05.

3.3. Evaluation Indicators

Three types of indicators are selected: fluctuation range, mitigation rate, and life-cycle cost, to quantify the power mitigation effect and system economy respectively. The specific definitions are as follows:

• Fluctuation range: Characterizes the maximum deviation between the grid-connected power after mitigation and the dispatching power. The calculation formula is: $\Delta P_{\max} = \max|P_g - P_g^*|$, where $\Delta P_{\max}$ is the maximum power deviation, $\max$ is the maximum value operator, P_g is the grid-connected power after mitigation, and P_g^* is the dispatching power.

• Mitigation rate: Reflects the suppression degree of wind power fluctuations. The calculation formula is: $\eta = 1 - \sigma(P_g)/\sigma(P_w)$, where σ is the standard deviation, P_g is the grid-connected power after mitigation, and P_w is the original wind power.

• Life-cycle cost: Includes initial investment cost, operation and maintenance cost, and equipment replacement cost. The calculation formula is: $C_{\text{total}} = (C_{\text{inv}} + C_{\text{op}} \times T + C_{\text{rep}} \times (T/L)) \times k_f$, where C_{inv} is the initial investment cost, C_{op} is the annual operation and maintenance cost, T is the system life cycle (20 years), L is the service life of the energy storage device, and k_f is the discount coefficient (taken as 0.06).

4. Results and Analysis

4.1. EMD Decomposition Results

After the wind farm power signal is processed by Empirical Mode Decomposition (EMD), 9 Intrinsic Mode Function (IMF) components and 1 trend residual term r_9 are obtained. Theoretically, the frequency of components $c_1 \sim c_2$ is greater than 0.1Hz (high-frequency), the frequency of $c_3 \sim c_5$ is between 0.01~0.1Hz (medium-frequency), and the frequency of $c_6 \sim c_9$ and r_9 is less than 0.01Hz (low-frequency). The decomposition results meet the frequency division requirements of the preset component allocation strategy. The effectiveness of the EMD method has been verified in the analysis of nonlinear and non-stationary time series [3], and its application in wind power signal decomposition can accurately separate fluctuation components of different time scales.

4.2. Analysis of Power Mitigation Effect

From the simulation results of grid-connected power and output power of each energy storage device, the wind power fluctuates sharply before mitigation, with a maximum deviation of 8MW; after mitigation, the grid-connected power closely tracks the dispatching power, with a maximum deviation of only 0.4MW, and the fluctuation range is controlled within $\pm 2\%$. The mitigation rate reaches $\eta = 92.5\%$, which is significantly better than the traditional "lithium battery-supercapacitor" combination (mitigation rate 84.8%). From the results, the output power of the supercapacitor fluctuates rapidly within the range of ± 4 MW, mainly mitigating second-level high-frequency disturbances; the output power of the flywheel energy storage fluctuates within the range of ± 6 MW, corresponding to minute-level medium-frequency fluctuations; the output power of the lithium iron phosphate battery changes smoothly, adjusting hour-level low-frequency trends within the range of ± 8 MW. The three types of energy storage devices have clear divisions of labor

without obvious power conflicts, realizing accurate matching and mitigation of fluctuations of different frequencies.

4.3. SOC Change and Economic Analysis

Regarding the State of Charge (SOC) changes of each energy storage device: the SOC of the supercapacitor fluctuates rapidly within the range of 40%~60%, the SOC of the flywheel energy storage changes moderately within 35%~65%, and the SOC of the lithium iron phosphate battery changes slowly within 25%~75%. All three are in the safe operation range without overcharging or over-discharging. The economic analysis results show that the life-cycle cost of the proposed hybrid energy storage system is approximately 8.5 million US dollars, which is 18.3% lower than that of the "lithium battery-supercapacitor" combination (about 10.4 million US dollars). The cost reduction is mainly due to the long cycle life of flywheel energy storage (reducing equipment replacement costs) and the low initial investment of lithium iron phosphate batteries (reducing early capital investment) [2].

5. Conclusions

The supercapacitor-lithium iron phosphate battery-flywheel hybrid energy storage system proposed in this paper adaptively decomposes the wind power signal through EMD, realizing full-time scale coverage and mitigation of "high-frequency-medium-frequency-low-frequency" fluctuations. After mitigation, the fluctuation range of the grid-connected power is $<\pm 2\%$, and the mitigation rate reaches 92.5%, which significantly improves the stability of wind power grid

connection.

The three types of energy storage devices complement each other in characteristics: supercapacitors respond quickly to high-frequency disturbances, flywheel energy storage efficiently processes medium-frequency fluctuations, and lithium iron phosphate batteries stably adjust low-frequency trends. Their SOC's are all within the safe range, with no risk of overcharging or over-discharging.

Economic analysis shows that the life-cycle cost of the system is reduced by 18.3% compared with the traditional combination, and it has high application value in large-scale wind power grid connection scenarios.

Future research can further optimize the EMD decomposition efficiency, realize forward-looking control combined with wind speed prediction data, and improve the system's ability to respond to extreme weather conditions.

References

- [1] Lin L, Sun C X, Wang Y P, et al. Calculation analysis and control strategy of power grid voltage stability after large-capacity wind farm integration [J]. Power System Technology, 2008, 32(3): 41-46.
- [2] Liu X C, Wang B B, Li Y, et al. Unit commitment and economic dispatch model for large-scale wind power accommodation based on real-time electricity price [J]. Power System Technology, 2014, 38(11): 2955-2963.
- [3] Huang N E, Shen Z, Long S R, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis [J]. Proceedings of the Royal Society, 1998, 454(1971): 903-995.