Fuzzy Empirical Mode Decomposition for Smoothing Wind Power with Battery Energy Storage System

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Abstract: The intermittency and fluctuations of wind power cause problems in integration of wind energy systems into the grid. To smooth the fluctuations of wind power, a control scheme based on fuzzy empirical mode decomposition (EMD) is proposed with the use of battery energy storage system (BESS). With this idea, the wind power signal is decomposed via EMD and filtered into two parts: the low-frequency part is taken as the target smooth wind power for grid connection, and the high-frequency part is stored by BESS before connecting to the grid to compensate for the fluctuations in the original wind power signal. A fuzzy EMD filter is developed by considering constraints on both the power fluctuation rate and the state of charge (SOC) of the BESS. The performance of the proposed strategy has been examined through case study simulations, which demonstrates improvement in mitigating wind power fluctuations and also in reducing over charging/discharging operations of the integrated BESS.

Keywords: empirical mode decomposition (EMD), fuzzy control, power smoothing, fluctuation rate, state of charge (SOC), battery energy storage system (BESS), grid connection.

1. INTRODUCTION

The inherent variation nature of wind resource raises challenges for power grid in system stability, reliability, and power quality, especially at high levels of penetration (Han et al., 2008; Luo and Ooi, 2006). Wind power fluctuations can be mitigated through different technical efforts either from the power generation side or from the distribution/storage side. Electric energy can be stored electromagnetically, kinetically, or as potential energy, using facilities such as supercapacitors, flywheels, batteries, compressed air energy storage and hydro-pumped storage, and the stored energy can also be transferred out of the storage device (Barton and Infield, 2004; Black and Strbac, 2007; Garcia et al., 2013). Thus energy storage systems equipped alongside wind power generation can be used to mitigate the wind power fluctuations (Abbey and Joos, 2007; Abbey et al., 2009).

Among various energy storage options, battery energy storage system (BESS) has the advantage of easy implementation via charging and discharging of electric energy. Since a large-scale BESS is highly expensive, it is crucial to determine the capacity of BESS when used for wind power systems. In (Wang et al., 2008), a method has been proposed to determine the required BESS capacity based on maximisation of an economic benefit objective function for the wind farm. In (Li et al., 2011), the most suitable capacity of BESS has been determined based on the long-term wind speed statistics and maximisation of a specified index considering the lifetime and cost of the used BESS. With the designed capacity of BESS, control strategies have been developed for optimal use of the available BESS, e.g., to track the the desired set points for wind power dispatching. Using the state of charge (SOC) of BESS as a feedback signal, a control scheme is presented in (Teleke et al., 2009), and model predictive control (Teleke et al., 2010a) and rule-based control (Teleke et al., 2010b) have been developed to determine the current reference for the converter which will charge/discharge the BESS accordingly. A stochastic predictive controller is established using probabilistic wind power forecasts to improve the wind power dispatch ability (Kou et al., 2015).

In the above works, it is assumed that the desired dispatch smoothing set points are either given or can be determined. This, however, is not true in most practical wind power generation systems using BESS. To address this issue, smoothing methods based on first-order low-pass filters are often used instead. In (Yoshimoto et al., 2006), a modified first-order filter is adopted to smooth power fluctuations of a wind farm with BESS. In (Jiang et al., 2013), a dual-layer control strategy, consisting of a fluctuation mitigation control layer and a power allocation control layer, is proposed, where the time constant of the first-order filter is updated by a particle swarm optimisation algorithm at the power fluctuation mitigation layer.

When used to mitigate fluctuations in wind power generation, the integrated BESS may need to be switched between charging and discharging modes frequently over its full range. This will reduce the operational lifetime of BESS. In practice, a trade-off must be made between the batteries' frequent charge/discharge cycles/amplitude and the power smoothing performance. In this work, we aim to develop a strategy that can effectively mitigate fluctuations in wind farm power generation without compromising the operational lifetime of BESS. To achieve this target, the empirical mode decomposition (EMD) will be employed to decompose the wind power signal into a set of frequency components, among which the high-frequency components are combined and stored by BESS before the gird connection so as to compensate for the wind power fluctuations. The EMD filter, compared with a simple first-order filter, is considered to be able to provide more details and options in separating the signal into different frequency ranges, and it is widely suitable for non-stationary and nonlinear data. To further enhance the filtering performance, a fuzzy tuning scheme is developed to adjust the order of the EMD filter over time by considering both constraints on the wind power fluctuation rate and the SOC of BESS.

The remaining of this paper is organised as follows. The spectrum analysis and EMD of wind power signal is presented Section 2. In Section 3, the wind power smoothing algorithm is developed based on a fuzzy design of the EMD filter. In Section 4, the proposed strategy is applied to a case study system with real wind power data. Finally, conclusions are given in Section 5.

2. EMPERICAL MODE DECOMPOSITION OF WIND POWER SIGNAL

2.1 Spectrum Analysis of Wind Power

Wind power has the characteristics of intermittency and fluctuation due to the constant variations in wind field. An example is given in Fig. 1, where the data were collected from a 100MW wind farm in China during a one-day period of time with the sampling rate of 1 minute. The fast Fourier transformation (FFT) of the amplitude power signal is given in Fig. 2, from which it can be seen that the amplitudes of low-frequency components are much larger within the low-frequency range ($0\sim10^{-4}H_Z$). Therefore, for a typical wind power signal, when filtered to keep its low-frequency components, the main energy of the original power can be retained. Such a reconstructed signal will become smoother in time domain compared to its original signal.

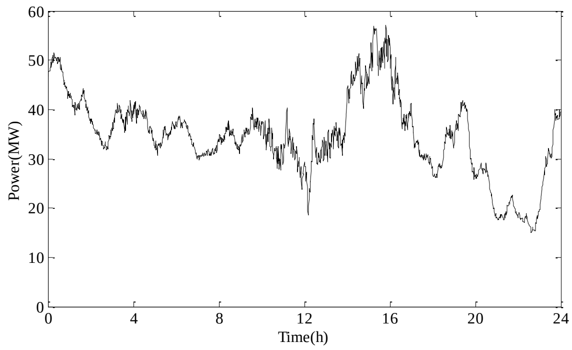

Fig. 1. Original wind power signal.

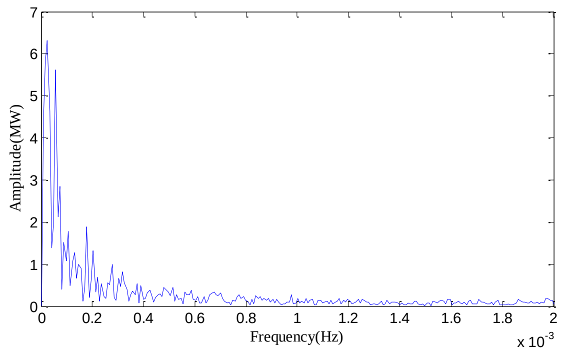

Fig. 2. Amplitude frequency characteristics of wind power.

In this work, the smoothed low-frequency components of wind power are defined as the target power signal for grid connection, and the high-frequency components of the wind power are absorbed by BESS before connecting to grid for compensation purpose.

2.2 Empirical Mode Decomposition

The EMD method proposed by (Huang et al., 1998) can be applied to a wide variety of time-series signals and has the advantages in dealing with non-stationary and nonlinear data. The essence of this method is to identify the intrinsic oscillatory modes imbedded in the data, denoted as intrinsic mode function (IMFs), by their characteristic time scales in the data empirically, and then decompose the data accordingly. Those IMFs should satisfy the following two conditions. Firstly, within the entire data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one. Secondly, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

To find all the oscillatory modes, the EMD is implemented as an iterative process. Denoting the original time series signal by $x(t)$, the main steps of EMD in this work are adapted from (Huang et al., 1998) and briefed in the following.

(1) Starting from the first iteration, set the accumulation number n=1, index i=1, and $x_1(t) = x(t)$.

(2) Identify all the local maxima and local minima in $x_i(t)$. Connect the local maxima and local minima, respectively, using the cubic spline interpolation algorithm, to obtain the maxima envelop, $e_{\max}(t)$, and the minima envelop, $e_{\min}(t)$. All data are bounded by these two envelops.

(3) Taking p=1, calculate the mean of the two envelops, which corresponds to (local) low-frequency part.

$$m_{ip}(t) = \frac{e_{\max}(t) + e_{\min}(t)}{2} \tag{2}$$

(4) Extract the (local) high-frequency IMF component by

$$h_{ip}(t) = x_i(t) - m_{ip}(t) \tag{3}$$

If $h_{ip}(t)$ satisfies the two conditions of IMF, it can be used as the identified IMF. Otherwise, $h_{ip}(t)$ will be taken as the original signal, i.e., $x_i(t) = h_{ip}(t)$, p=p+1; repeat steps (2) - (4). This sifting process continues l times until the extracted series becomes an IMF component, denoted as $c_i(t) = h_{il}(t)$. The residual signal is then $r_i(t) = x_i(t) - c_i(t)$.

(5) Update $n = n+1$, $i = i+1$, iterate on the new signal to be decomposed, $x_i(t) = r_{i-1}(t)$, repeat steps (2)-(5). This iteration process is completed when the residual signal is a monotonic function from which no more IMF can be extracted, or stopped by certain criteria.

The original signal will eventually be represented by a sum of n IMFs and a residual term, $r_n(t)$, i.e.,

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \qquad (3)$$

This decomposition can also be viewed as an expansion of the original signal in terms of the IMFs. These IMFs can serve as the basis to formulate smooth signal(s).

2.3 EMD of Wind Power Signal

Applying EMD to the real wind power signal as shown in Fig. 1, 9 IMFs are extracted from the original data. The residual signal is produced accordingly. In Fig. 3, the 1st IMF corresponds to the component of the highest frequency, and the 9th IMF presents the lowest frequency component. The residual signal (R) is a monotonic series in time domain.

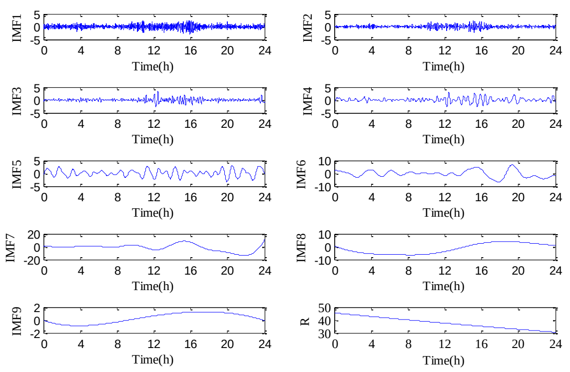

Fig. 3. Components of wind power signal from EMD.

3. SMOOTHING WIND POWER WITH FUZZY EMD

3.1 Wind Power Smoothing Strategy with BESS

In this study, all low-frequency components after k-th order, together with the residual, are combined to form the target smooth signal for grid connection, denoted as P_r. Those high-frequency components from the first order to the k-th order are combined as the input signal to BESS, denoted as $\tilde{P}_{bat}$. Due to battery losses and output limiter, the BESS output connected to grid, P_{bat}, is not the same as its input signal, $\tilde{P}_{bat}$. There's also a time delay between the battery's input and output. In this study, the BESS dynamics and the BESS charging/discharging losses are not considered, only a limiting function is applied to $\tilde{P}_{bat}$ for simplicity. The schematic diagram of mitigating wind farm power with BESS is shown in Fig. 4. The smoothed power for grid connection, P_{smooth}, is obtained from the original wind power, P_w, compensated by the stored power from BESS, P_{bat}. PCC stands for the point of common coupling to the grid.

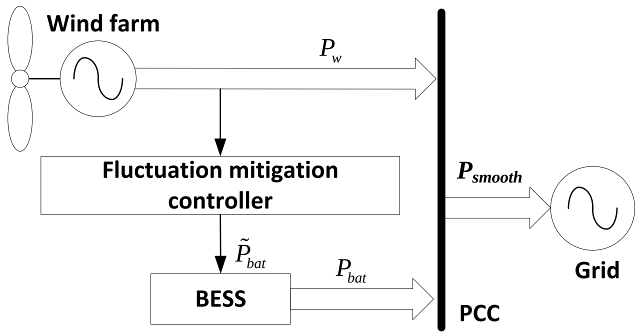

Fig. 4. Smoothing wind power with BESS.

3.2 Fuzzy Tuning Controller for EMD Filter

The order of the EMD filter, k, is used to divide the high frequency parts and the low frequency parts imbedded in wind power signal. This is a key parameter that would influence the smoothing performance. The value of k for the EMD filter can be obtained by computing the mean of the standardised accumulated modes as follows:

$$\bar{c}_m = \text{mean}\left(\sum_{i=1}^{m} \frac{1}{\text{std}(\mathbf{C}_i)} \sum_{t=1}^{T} \left(c_i(t) - \text{mean}(\mathbf{C}_i) \right) \right), 1 \le m \le n \quad (4)$$

where $\mathbf{C}_i = \left[c_i(1) \quad c_i(2) \quad \cdots \quad c_i(T) \right]^{\mathrm{T}}$, mean(·) and std(·) are mean and standard deviation functions. The order of the filter is determined to be m when $\bar{c}_m$ apparently deviates from zero, which suggests that those IMFs after the m-th component can be considered as low-frequency components. This value is used as the base value for the filter order.

In this work, a fuzzy tuning strategy is proposed to adjust the base value of k by considering both the fluctuation rate in wind power and the SOC in BESS. The fluctuation rate of wind power, δ, is calculated by

$$\delta = \frac{P_{\max} - P_{\min}}{C_{cap}} \qquad (5)$$

where $P_{\max}$ and $P_{\min}$ are the maximum and the minimum values of the wind power data within a specified window. C_{cap} is the capacity of power generation of a wind farm.

The fluctuation rate of wind power, δ, is taken as one input variable to the fuzzy tuning controller. This variable is divided into three fuzzy sets: large, medium, small. When the fluctuation rate is large, a higher filter order is chosen in order to strengthen the smoothing effect. Likewise, if the fluctuation rate falls in a small set, a lower filter order is adopted. The middle set allows the flexibility in tuning between the above two ends.

To consider the battery lifetime, the SOC of BESS is taken as another input variable to the fuzzy controller. The SOC index represents the remaining energy level of a battery device, i.e., the dischargeable energy in percentage of a battery's rated capacity. At time *t*, the SOC is calculated as follows:

$$SOC(t) = SOC(t-\Delta t) + P_{bat}\Delta t / C_{bat} \qquad (6)$$

where C_{bat} is the rated capacity of BESS, Δt is the sampling interval, $SOC(t-\Delta t)$ is the SOC value at $t-\Delta t$. The initial value of SOC is set to be 0.5.

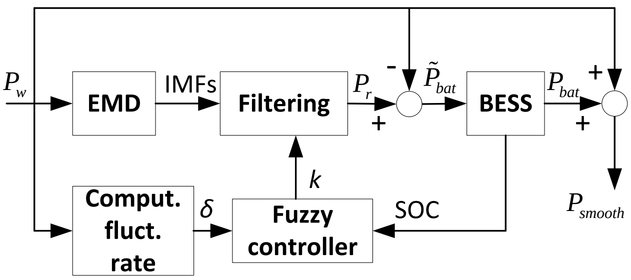

Fig. 5. Block diagram of fuzzy EMD smoothing strategy.

The schematic diagram of the fuzzy tuning controller is shown in Fig.5. Here the SOC entry is also divided into three fuzzy sets: high, medium and low. When the SOC is at a high level and the battery is in the charging operation, a smaller number for the filter order should be chosen so as to prevent the battery from charging excessively. If the battery is in the discharging state under high SOC, a larger number of *k* should be chosen so as to allow adequate discharge power of BESS for moderation. When the SOC level is low, the discharging operation should be reduced (smaller *k*), and the charging operation is allowed to be more active (larger *k*).

3.3 Design of Fuzzy Controller

The function of the fuzzy tuning controller is to determine the EMD filter order by considering two constrains: the fluctuation rate of wind power, δ, and the SOC value together with the charging or discharging operating conditions in BESS. The flow chart of the proposed fuzzy EMD smoothing strategy with BESS is illustrated in Fig. 6.

The fluctuation rate of wind power is fuzzified as three fuzzy subsets: $\{NB, ZO, PB\}$, which represents three levels: {low, medium, high}. The three membership functions of the power fluctuation rate are designed as shown in Fig. 7.

Similarly, the SOC is also fuzzified as three fuzzy subsets: $\{NB, ZO, PB\}$, which represents the SOC being {low, medium, high}. The designed membership functions of SOC are shown in Fig. 8.

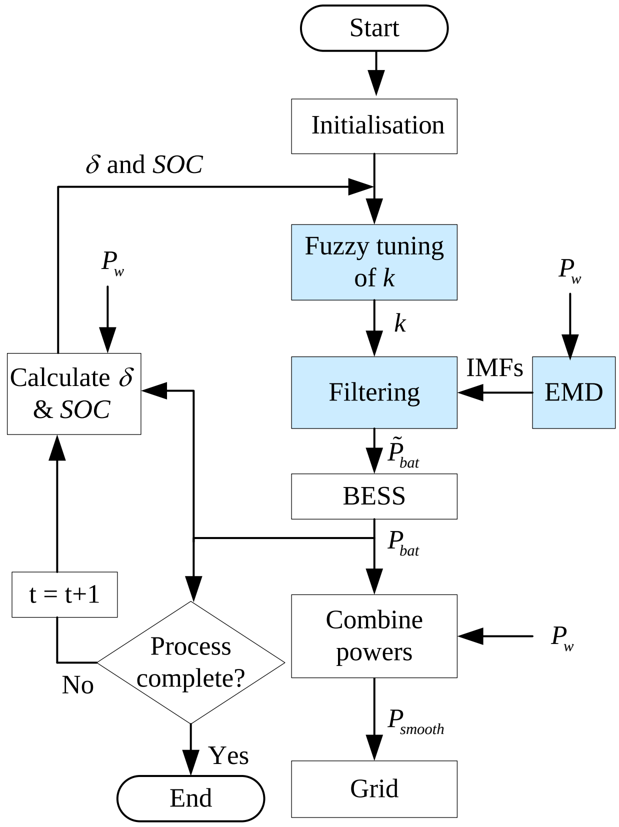

Fig.6. Flow chart of the proposed smoothing algorithm.

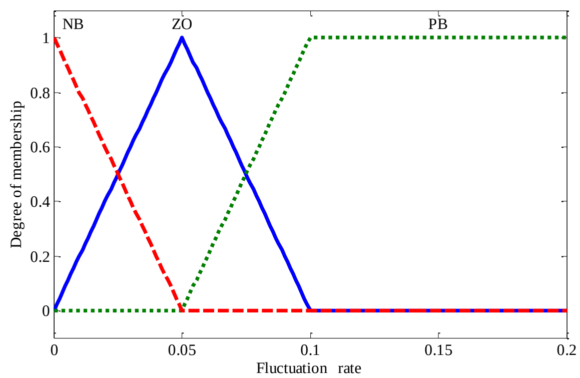

Fig.7. Membership functions for power fluctuation rate.

In this work, the Takagi-Sugeno method (Takagi and Sugeno, 1985) is adopted in developing the fuzzy inference and defuzzification process, which combines fuzzy reasoning with defuzzifacation. The output variable is the EMD filter order. In order to avoid changing the filter order frequently, the filter order is further simplified to take simply three values: $k-1$, k, $k+1$. When the output of the fuzzy controller is rounded to an integer equal to the base value, k, as calculated in (4), the order of the EMD filter is set to be k. When the output value is rounded to an integer larger than the base value, $k+1$ is used for the EMD filter order. For a rounded output with its value smaller than the base value, $k-1$ is used for the EMD filter.

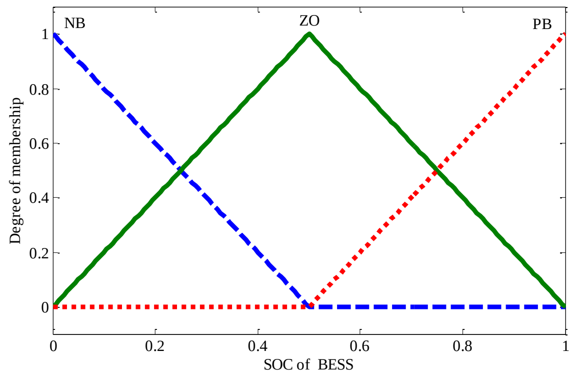

Fig.8. Membership functions of SOC.

4. SIMULATION STUDY

The collected real wind power data, shown in Fig.1, is used for the simulation study. The simulation time range is 24 hours. With the sampling rate of one minute, the data length is T=1440. For this system, the rated power and the rated capacity of battery are set to be 6MW and 6MW·h by engineering experiences. A window length is set to be 10 minutes to calculate the fluctuation rate. Using the EMD method, the original wind power signal is decomposed into 9 components. The mean of the standardised accumulated modes is calculated using (4) that gives the base value of k=5 for the EMD filter order.

The wind power curve before and after smoothing is shown in Fig. 9, from which it can be seen that the proposed method can reconstruct the signal with the same trend of the original signal effectively. Fig. 10 illustrates the evolution of power in BESS. It can be observed that the BESS can charge and discharge power in time so as to smooth the output power over the process. In Fig. 11, the fluctuation rates of the original wind power and the smoothed power are compared. The fluctuation rate of the original wind power is larger and there are a number of points at which the fluctuation rate is over a critical threshold of 10%. After the smoothing effort, the fluctuation rate is decreased to a range below 5%. This suggests that the proposed strategy can effectively smooth the wind power fluctuations.

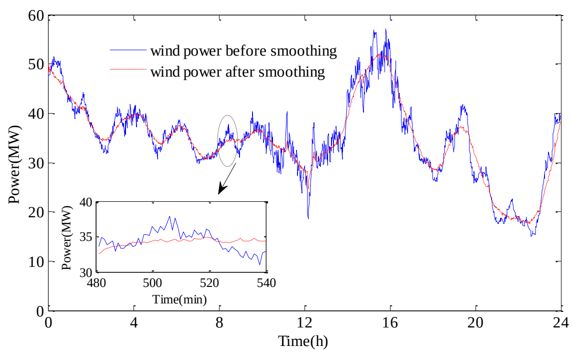

Fig.9. Wind power output with and without smoothing.

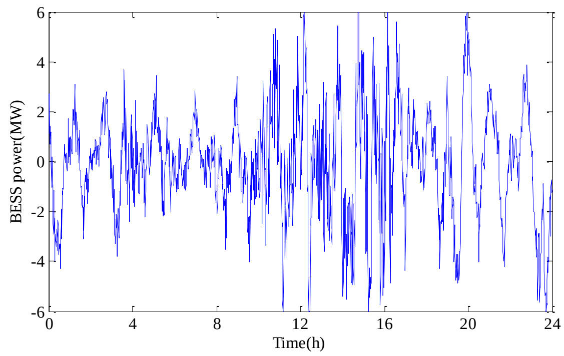

Fig.10. Power in BESS.

A further comparison is made between the proposed method and another EMD-based method that adjusts the filter order using only the SOC constraint. For both filters, the same base value of $k=5$ is used. The SOC-only design is implemented as follows. When the battery is charging and SOC>0.7, or the battery is discharging and SOC<0.3, the filter order is set to be k-1. When the battery is discharging and SOC>0.7, or the battery is charging and SOC<0.3, the filter order is set to be k+1. In all other situations the filter order is set to be 5.

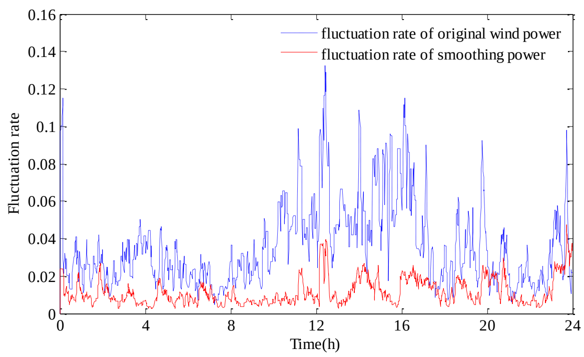

Fig.11. Fluctuation rate of original and smoothed wind power.

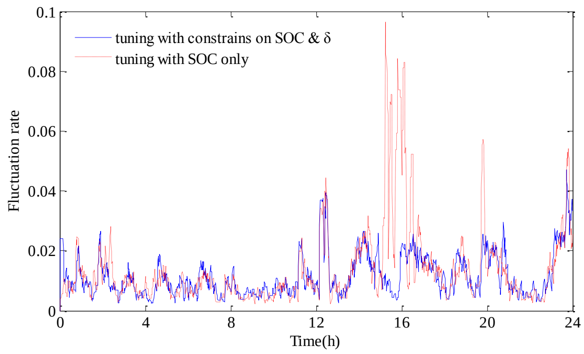

Fig. 12. Fluctuation rate profiles from two methods

The comparison results using the two filters are shown in Figs 12 and 13. From Fig. 12 on power smoothing performance, it can be seen that in both cases, the fluctuation rates are mitigated to the level below 10%. When using the SOC constraint only, the fluctuation level is higher than that using both constraints on SOC and the fluctuation rate. In the latter case, all the fluctuation rate values are actually less than 5%. The SOC values are compared in Fig. 13, from which it can be observed that both filters can keep the SOC between the range of [0.2, 0.8], the difference between the two SOC curves is very small. Keeping the SOC within a proper operation range will help to extend the battery lifetime.

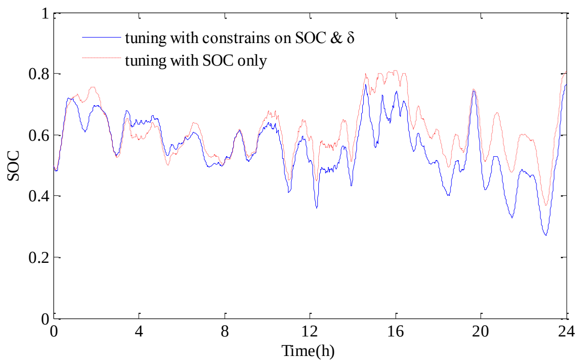

Fig. 13. Curves of SOC with changing orders of two methods

The above results demonstrate that the proposed strategy using BESS to mitigate wind power fluctuation based on fuzzy EMD can achieve satisfactory smoothing performance of wind power fluctuation as well as keep the level of SOC with the proper BESS operation range.

5. CONCLUSIONS

In this work, a new method of smoothing wind power is proposed by integrating BESS in the grid connection system. The EMD method is used to decompose the wind power signal into a set of IMF components. The low-frequency components and the residual are combined together to form the target wind power connection to grid. The high-frequency components are combined and stored by BESS to be connected to gird as a compensator. The order of the EMD filter is adaptively adjusted by a fuzzy controller based on both constraints on the fluctuation rate of power and the SOC of BESS. This strategy successfully integrates mitigation of wind power fluctuations and prolongation of the operational lifetime of BESS. The current smoothing strategy is developed based on historical data, which has an inherent delay in power compensation. Further investigations will be made to take power forecasting into account so as to avoid the delay. Experimental validation of this proposed strategy will be investigated in the future work.

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