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Optimal Sizing and Control Strategies for Hybrid Storage System as Limited by Grid Frequency Deviations

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***Abstract*—Frequency deviations of power systems caused by grid-connected wind power fluctuations is one of the key factors which restrains the increase of wind penetration level. This paper examines a combined wind and hybrid energy storage system (HESS, supercapacitor and battery) to smooth wind power fluctuations. A fuzzy based wind-HESS system (FWHS) controller is proposed to suppress the wind power fluctuations. The proposed controller takes full advantage of the complimentary characteristics of the supercapacitor and battery with the supercapacitor and battery in charge of high and middle frequency components of wind fluctuations, respectively. A differential evolution (DE) based optimal sizing method for HESS systems is introduced to evaluate the minimum capacity of HESS as being limited by grid frequency deviation. The efficiency of the proposed scheme in the paper for wind-HESS system is evaluated by a real Chinese power system.**

***Index Terms*—Hybrid Energy Storage System (HESS), Wind power, Optimal storage sizing, Fuzzy base control, grid frequency deviation, Differential Evolution.**

I. Introduction

Wind power fluctuations bring about new challenges to the safety operation of power systems. One of the main concerns is the grid frequency deviation when the level of wind power penetration is high. Especially in a low-inertia grid, speed governors and rotor inertia of synchronous generators (SGs) may not be able to accommodate the wind power variability to keep the frequency deviation within the requirement of Grid Code [1]. Hence impact of wind power fluctuations on grid frequency stability has been a topic of investigation pursued by many researchers recently. Methods based on time-domain simulations [2] and Time-Frequency Transformation [3] have been applied and proposed in the investigation to assess the impact.

Compared with the single energy storage system (ESS), the HESS is composed of a high-energy storage (ESS-E) and a high-power storage (ESS-P) where the ESS-E meets the slow, long-term energy variations and the ESS-P deals with the peak and fast transient power [4]. A hybrid energy storage system (HESS) can combine the technical merits of different types of ESSs and thus provide desired performance of power and energy capabilities [5]. Various researches have been made recently with the aim of managing the power and energy flow between ESS-E and ESS-P [6] [7]. Authors of [4] have made a detailed review of the state-of-the-art control strategies for HESS with renewable energy integrated. The control strategies of energy management of HESS can be classified into two categories which are classical control strategy and intelligent control strategy [8]. The classical control strategies include Rules Based Controller (RBC) and Filtration Based Controller (FBC) and both are widely used in energy management of ESS due to the simplicity and less computational efforts [9]. The RBC control the power set points of the HESS based on pre-defined rules and the FBC adopts the filter (e.g. low-pass filter, moving average filter and wavelet transformation) to decompose the imbalance power into high-frequency and low-frequency components. However, the classical control strategies are pre-set and rigid which are difficult to adapt to real-time system conditions [4]. Thus, intelligent control strategies such as artificial neural network, fuzzy logic controller, which are more robust and efficient as compared to classical control strategies [8], are introduced to manage the energy flow of HESS. In this paper, the proposed control strategy is based on the FBC method and also adopts the intelligent control method to automatically adjust the filter parameters in order to adapt to the real system conditions.

In term of ESS to support frequency stability, many studies have been conducted on the frequency controller design. In [10] and [11], a frequency-domain based approach was proposed to size a single ESS and battery-supercapacitor HESS system for maintaining grid power balance when penetration of wind generation is high, in order to maintain the grid frequency deviations within the required limit. However, the optimal sizing algorithm does not consider the control strategy of the HESS, which will limit its real applications. To counteract the problem of frequency deviation caused by wind power fluctuations, energy storage systems (ESSs) can be used to compensate the wind fluctuations [12] [13] or to provide extra capability of frequency response [14]–[16]. In the development of ESSs, two key factors to be examined are the ESS real-time operation strategy and sizing. As they are different issues about technical and economic aspects of ESSs, so far, they have been considered and examined separately. However, ESS control strategy may dramatically affect the sizing results.

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Moreover, storage sizing capacity cannot be verified through the real-time operation [9], if it is examined individually. Hence if those two key factors can be investigated together, a deeper insight into the issues and better strategy can be obtained. Authors of [17] presented the sizing and control methodologies for a battery based ESS to compensate wind power forecast errors. A framework for optimal sizing and energy management of smart home with battery energy storage system (BESS) and photovoltaic (PV) power generation is proposed for the goal of maximizing home economy, while satisfying home power demand using convex programming (CP) [18] [19] and randomized algorithms [20]. However, the work that has been done on ESS control and sizing, only considers a single type of ESS.

This paper proposes an optimization method and fuzzy-based control strategy for a wind-HESS system to optimally determine the size of the HESS to meet the requirement of limit on grid frequency deviation. Main contributions of this paper are as follows:

1) A fuzzy-based control strategy for combined wind- hybrid energy storage systems (HESS) considering the different SOC levels (normal, warning and alarm state) is proposed in the paper to mitigate grid frequency deviations by smoothing the fluctuations of wind power generation. The proposed method can avoid the ESS over-charging risk and at the same time prevent the ESS from operating close to the over-discharging zone, which improves the cycle life of the HESS.

2) A optimal sizing method based on differential evolution(DE) is developed to size the minimal capacity of HESS to meet the grid frequency deviation limit, while also quantifying the impact of control strategy on sizing results.

The rest of the paper is organized as follows: a general reduced order model for energy storage system has been introduced in Section II. In Section III, a fuzzy based wind-HESS system control theory, which makes full use of the merits of HESS, is proposed to smooth out the wind fluctuations. A DE based optimal sizing method for wind-HESS system to size the capacity of HESS is presented in Section IV.

II. Modeling of Hybrid Energy Storage Systems

A generalized reduced order model of energy storage system is adopted in this paper, which is shown in Fig. 1 [17]. The differences between supercapacitor and battery storage in this generalized model are the response time. Normally, the response of supercapacitor is faster than the battery (i.e. $T_{ess,s}$ of supercapacitor is larger than $T_{ess,b}$ of battery). The charging input of ESS is limited by the current SoC and the ESS power rating [21]. The general mathematical model of ESS is defined as follows:

$$\mathrm{SoC}_{t_1}\% = \mathrm{SoC}_{t_0}\% + \frac{1}{E_{ess}\cdot h}\cdot\eta\cdot\int_{t_0}^{t_1} P_{ess}dt \tag{1}$$

where, E_{ess} is the energy rating of the ESS. h is chosen to be 3600 due to the 1-second time resolution of the input data.

III. Fuzzy based Wind-HESS System Control

This section presents a brief description of the fuzzy based wind-HESS system (FWHS) control theory. As shown in Fig. 2, the supercapacitor and battery are connected to the common DC link. The Voltage Source Converter (VSC) is used to control the power flow from the supercapacitor and battery by the control reference signal from proposed FWHS system [22].

A. Wind-HESS System Smoothing Control Strategy

As being illustrated in Fig. 3, randomly variable wind power fluctuations can be decomposed into three components: high-frequency variation, middle-frequency component and low frequency variation [23], by defining two different cut-off frequencies f_H and f_L. Different variable components of wind power fluctuation can be accommodated by relevant storage techniques.

Different types of the ESS, which have different characteristic, are suitable for balancing varying components of wind power over different ranges of frequency. For example, a battery, which has relatively high energy density, is used to accommodate the component of variation range, $f_H \geq f \geq f_L$. However, a supercapacitor can respond more quickly and has relatively high power capacity, which is suitable for mitigating the high-frequency range $f \geq f_H$. The remaining low-frequency component, $f \leq f_L$ is delivered to the grid, which can be balanced by the day-ahead unit schedule. Thus, the active power of the wind power, which is the sum of battery, supercapacitor and grid power, is obtained as follows:

$$P_{wind}(t) = P_{grid}(t) + P_{sc}(t) + P_{batt}(t) \tag{2}$$

To take full advantage of the HESS device, a fuzzy based wind-HESS system (FWHS) controller has been proposed to fulfill the following two targets:

1) Functional division: two types of low-pass filters are designed: the primary filter and the secondary filter, in order to make sure that a supercapacitor is in charge of high frequency components ($f \geq f_H$) and a battery is in charge of middle frequency range ($f_H \geq f \geq f_L$).
2) HESS SoC level control: the cut-off frequencies, f_H and $f_L$of the two filters, should be adaptively adjusted according to the charging level of the battery and supercapacitor to avoid over-charging or over-discharging risk.

To explain the control scheme clearly, a simple Simulink model, which is shown in Fig. 4, is adopted to illustrate the basic control principle of FWHS. In Fig. 4 (a), The wind power is assumed to have a step change from 0 to 1. Two types of low-pass filters are used to decompose the wind power into three components: high frequency variation (green shaded area), middle frequency part (red shaded area) and low frequency one (white area, below the red line). One of the low-pass filter is the Grid primary filter, which has a larger time constant (2s in this case) and the other filter is the role dividing secondary filter, which uses smaller time constant (0.5s in this case). In practice, To smooth the wind farm out, the supercapacitor and battery are charging based on the power profile of green and red area, respectively.

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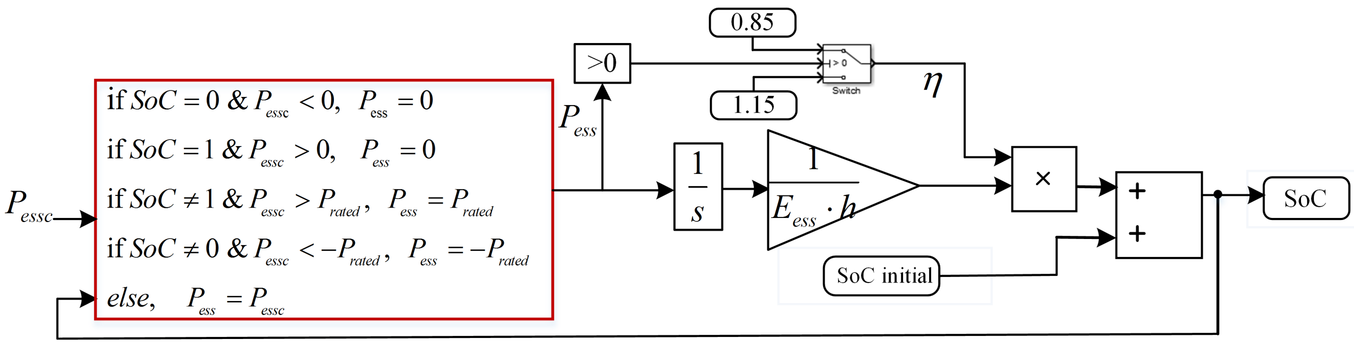

Fig. 1. Generalized reduced-order model of ESS including converter (left side) and battery (right side) model.

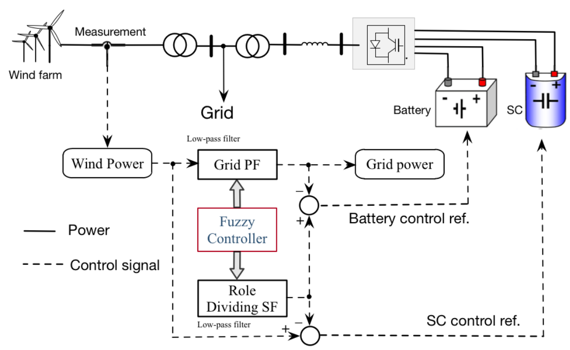

Fig. 2. The control scheme of fuzzy based wind-HESS system.

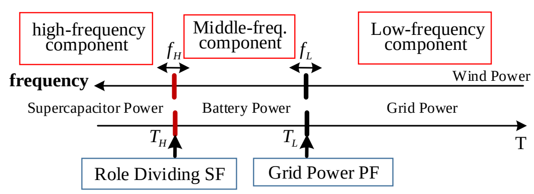

Fig. 3. Illustration of wind-HESS Smoothing principle.

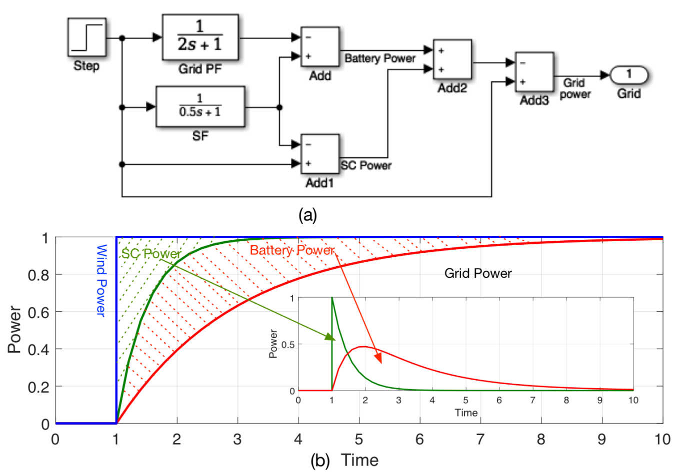

Fig. 4. Illustration example (a) A simple Simulink model; (b) Simulation results.

However, the key point of the proposed FWHS controller is how to dynamically adjust the parameters of two filters, T_H and T_L, according to the charging level of the HESS. The schematic of the proposed fuzzy based controller is shown in Fig. 5 and the individual parts are explained as follows.

B. Grid Power Primary Filter

Grid power primary filter, which is controlled by a time constant T_L, is adopted to determine how much power of HESS has to take charge of. Equation (3) represents the transfer function of the grid power primary filter:

$$G(s) = \frac{1}{1 + sT_L} \tag{3}$$

The time constant T_L is dynamically determined by the fuzzy-based controller. As shown in Fig. 5, the inputs of the grid power fuzzy controller are: 1) sum of battery and supercapacitor charging power; 2) combined SoC level of HESS. A combined SoC equation of the HESS is proposed to evaluate the SoC level of HESS, which is shown as follows:

$$SoC_{com}\% = \frac{E_{rated,s} \cdot SoC_{sc}\% + E_{rated,b} \cdot SoC_{batt}\%}{E_{rated,s} + E_{rated,b}} \tag{4}$$

The basic principles of setting T_L value are:

1) higher T_L value (yellow area in Fig. 6): As the larger the time constant T_L value is, the more wind power will get delivered to the HESS, the higher T_L value exists in the following three scenarios: a) SoC level is in the normal state and charging input is lower (middle yellow area in Fig. 6); b) ESS is in the fully charged state (SoC is higher) and charging input changes to discharge (negative, wind power starts decreasing). In this situation, as the HESS is full, it has great ability to discharge. Thus we chose higher value of T_L to let the HESS uptake more power; c) ESS is in the fully discharged state (SoC is lower) and charging input changes to charge (positive, wind power starts increasing);
2) median value (cyan area in Fig. 6): SoC level is in the normal state and absolute value of the charging input is larger than 5;
3) lower vale (blue area in Fig. 6): SoC level is higher and ESS is in the charging state; SoC is lower and ESS is in the discharging state.

The above-mentioned principles are the same as the designed results, as shown in Fig. 6. The fuzzy sets and membership functions for inputs (SoC level and Charge input) and output (T_L) are designed according to their characteristic, as shown in Fig. 6 and 7. Table I presents the fuzzy rules for grid power primary filter.

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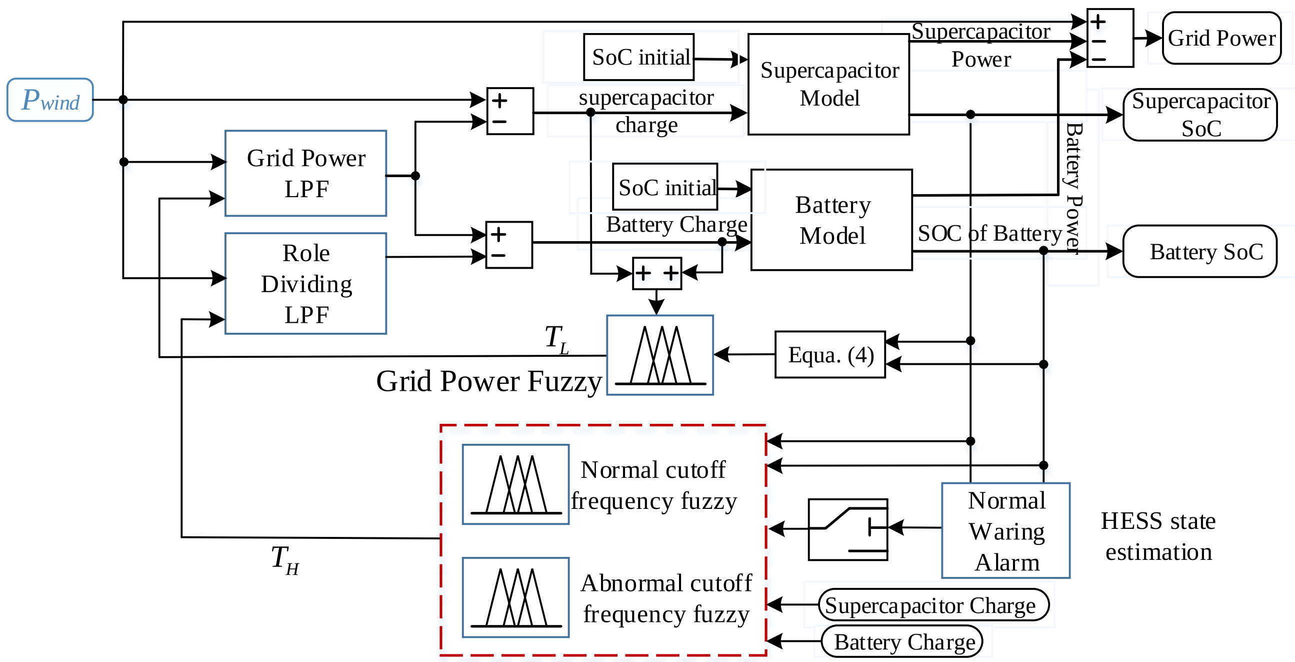

Fig. 5. Fuzzy based wind-HESS smoothing control diagram, including grid power primary filter (time constant is decided by grid power fuzzy) and role dividing filter (time constant is decided by normal and abnormal fuzzy controller).

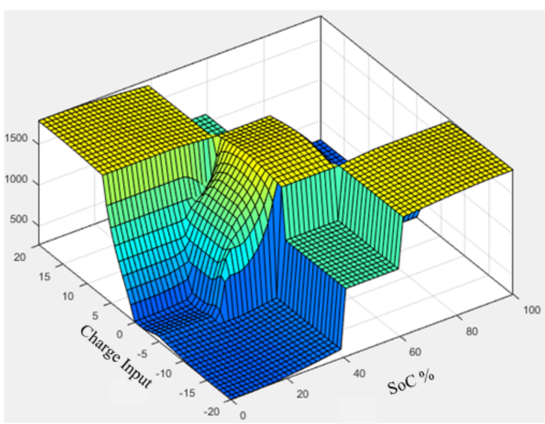

Fig. 6. Fuzzy surface of the grid power primary filter.

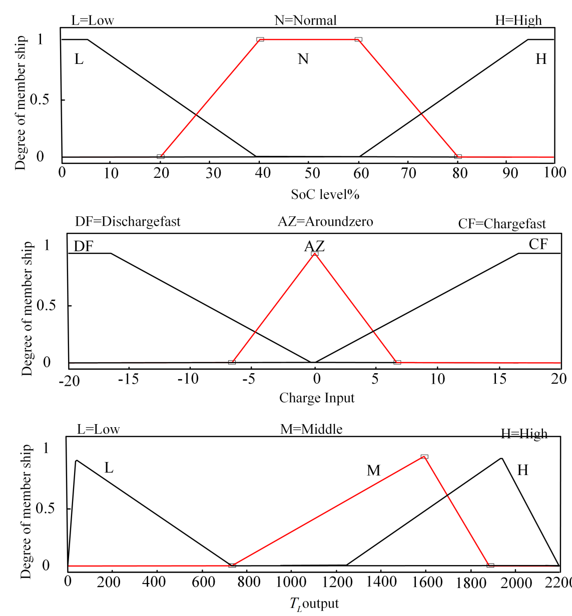

Fig. 7. Fuzzy membership function of the grid power primary filter.

C. Role dividing secondary filter

The function of Role dividing secondary filter is to determine the role of supercapacitor and battery. The transfer function of the role dividing secondary filter is the same as equation (3), except that the time constant of secondary filter is T_H. There are two switchable fuzzy-based controller used to determine the value of T_H, which are called normal and abnormal cut-off frequency fuzzy controller, as shown in Fig. 5. The principle of the switching is based on the module of HESS state estimation.

TABLE I
FUZZY RULES FOR GRID POWER PRIMARY FILTER.

T_L		Charge Input DF	AZ	CF
SoC_{com} level	L	L	L	H
	N	M	L	M
	H	H	L	L

The logic of HESS state estimation to determine the normal and abnormal level of the HESS is based on the SoC level of individual ESS, as shown in Fig. 8. The state level of HESS is classified into three states:

1) normal: the SoC of Two ESS are in the range of 20%–80%;
2) warning (Abnormal): Either the SoC of battery or super-

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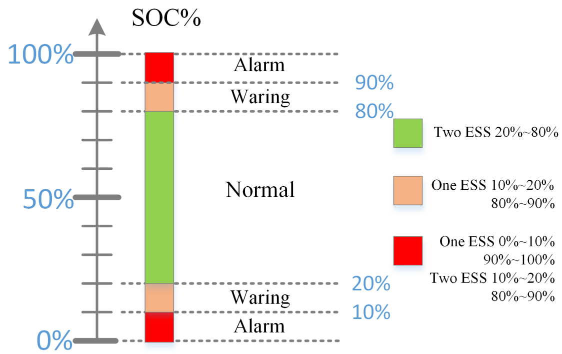

Fig. 8. HESS state estimation based on SoC operation Range.

capacitor is in the range of 10%–20% or 80% – 90%;

3) alarm (Abnormal): Two ESS are in the range of 10%–20% or 80% – 90% or one ESS is in the range of 0%–10% or 90% – 100%.

Basically, When the SoC of one ESS is larger than 80% or less than 20% (HESS is in the warning or alarm state in Fig. 8), the abnormal cut-off fuzzy controller will be active. the FWHS controller should efficiently adjust the allocation proportion of the wind power between battery and supercapacitor. For example, when supercapacitor has a higher SoC level, the time constant T_H changes to smaller value to assign more power to battery. The fuzzy rules of the two abnormal fuzzy controller are listed in in Appendix B.

IV. Optimization Method for Sizing the HESS

Different penetration level of wind power requires different size of HESS to keep the grid frequency deviation within the permitted threshold. This section proposes a differential evolution (DE) optimization method to size the HESS for this particular application.

A. Method for Sizing the HESS

Fig. 9 illustrates the procedure of the optimization method for sizing the HESS, which can be decomposed into the following sub-modules:

1) *Wind-HESS system*: It is based on the model introduced in Section III. The FWHS controller is initialized with the starting value of $P_{rated,b}, E_{rated,b}, P_{rated,s}, E_{rated,s}$.
2) *Frequency deviation simulation*: All simulations and analysis are conducted using Matlab/Simulink. A block model of the frequency simulation is shown in Fig. 10, which displays a general two-area power system frequency response model with speed governor control Wind-HESS system located in area 2 using equivalent system frequency. The parameters of the study system are derived from [24] and reported in Table V in the Appendix A.
3) *Frequency deviation assessment*: A statistical method [25] called during curve is adopted to evaluate the frequency deviation. In this paper, the maximum risk of frequency deviation Δf_{grid}^{max} is defined as 1% of percentile of frequency deviation. For example,

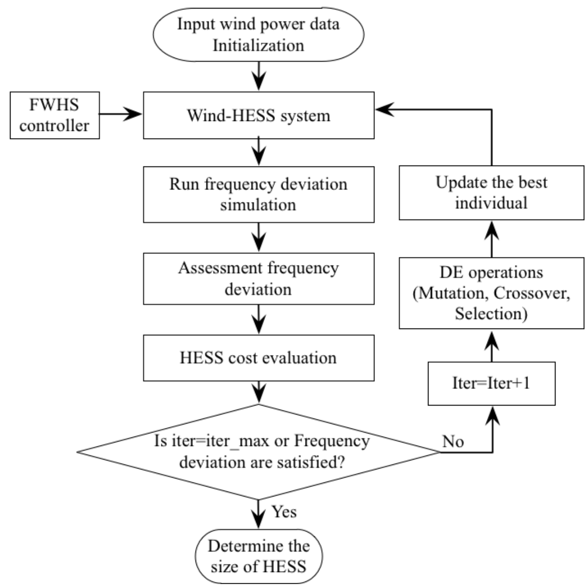

Fig. 9. Flowchart of the optimization sizing method for HESS.

from Fig. 12 it can be seen that at the position of 1% of duration of frequency deviation, Δf_{grid}^{max} is about 0.735% of the normal frequency (Point A in Fig. 12). Δf_{grid}^{max} should be within the secure frequency deviation limit, defined by the grid code.

4) *HESS Cost evaluation*: The cost of the HESS is related with the energy capacity and power capacity of individual ESS [26], which can be expressed as

$$TC_{hess} = g(\Delta f_{grid}^{max}) \cdot (TC_b + TC_s) \tag{5}$$

$$TC_b = C_{pb} \cdot P_{rated,b} + C_{eb} \cdot E_{rated,b} \tag{6}$$

$$TC_s = C_{ps} \cdot P_{rated,s} + C_{es} \cdot E_{rated,s} \tag{7}$$

where the value of $C_{pb}, C_{eb}, C_{ps}, C_{es}$ are cost coefficient of power and energy capacity and presented in Appendix A. To make sure the maximum risk of frequency deviation Δf_{grid}^{max} is within the frequency limit of grid code, a penalty cost term $g(\Delta f_{grid}^{max})$ is added in the objective function. When the maximum risk of frequency deviation Δf_{grid}^{max} is larger than the grid code limit Δf_{grid}^{code}, $g(\Delta f_{grid}^{max})$ will be set as a big value (1000 is chosen in this analysis). Thus Δf_{grid}^{max} is defined as follows:

$$g(\Delta f_{grid}^{max}) = \begin{cases} 1, & \Delta f_{grid}^{max} \leq \Delta f_{grid}^{code} \\ M, & \Delta f_{grid}^{max} > \Delta f_{grid}^{code} \end{cases} \tag{8}$$

where Δf_{grid}^{code} is chosen as 0.5% p.u. defined by the Chinese grid code [27].

5) *Differential Evolution (DE)*:: The DE algorithm is widely used for global stochastic optimization due to its simplicity, versatility and robustness [28]. The DE is used here to find the minimum cost of HESS by iteratively adjusting the power and energy capacity of HESS and make sure that the final capacity solutions meet the grid code requirement.

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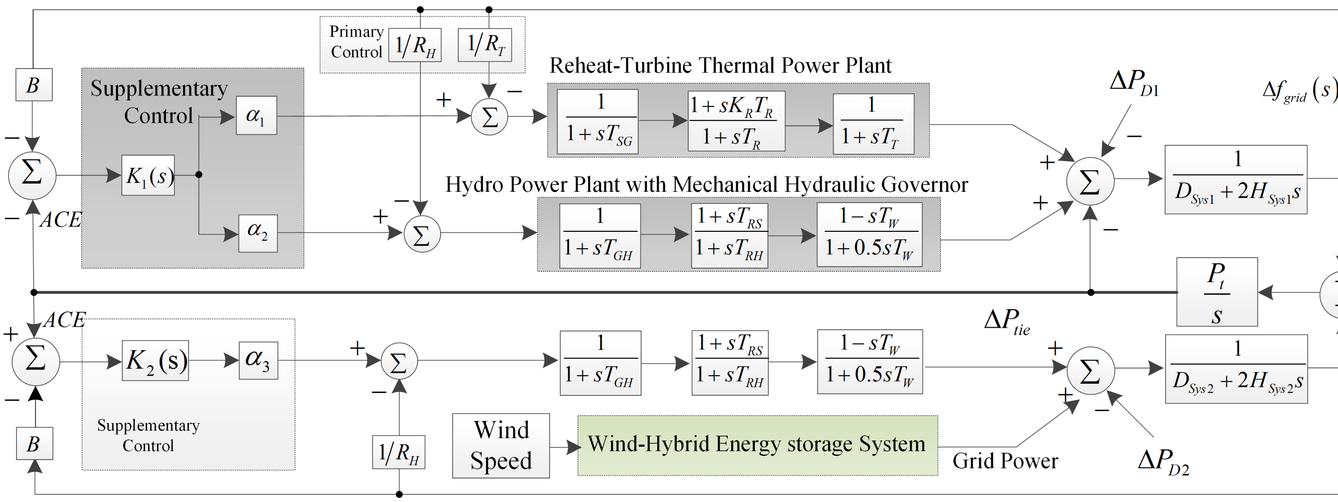

Fig. 10. Block diagram model of power system frequency response with wind-HESS system.

B. Iterative Procedure

The main steps of the proposed sizing method are summarized as follows:

Step 1) Select wind power data from the historic database of a wind farm. Initialize the parameter ranges, initial parameter values, population size and the population of the DE as $U = \{P_{rated,b}, E_{rated,b}, P_{rated,s}, E_{rated,s}\}$; set iter = 0;

Step 2) Update the power and energy capacity parameters of FWHS controller illustrated in Section III;

Step 3) Run the frequency deviation simulation using the model shown in Fig. 10.

Step 4) Evaluate the frequency deviation by computing the maximum risk of frequency deviation Δf_{grid}^{max};

Step 5) Compute the penalty cost coefficient $g(\Delta f_{grid}^{max})$ and calculate the cost of HESS by (5);

Step 6) Check the stop criteria, such as: whether $iter = iter_{max}$ or the frequency deviation are satisfied. Otherwise, the iteration goes to step 7);

Step 7) Implement the mutation, crossover, selection of DE operations introduced in [27] and update the best individual for $U = \{P_{rated,b}, E_{rated,b}, P_{rated,s}, E_{rated,s}\}$, then the iteration goes to Step 2).

V. Case Studies

The efficiency of the proposed method is investigated in a real power system [25] located in the Inter Mongolian, China, with extensive DFIG-based wind farms connected to the grid. The wind turbines are distributed within a relative small region. Thus intensive wind power fluctuations due to the high correlation of wind speed might significantly affect the grid frequency deviations. Data of wind power time series used in this paper is from a 200 MW wind farm. The annual average wind speed at the height of 70 meters in this area is approximate 8.91 m/s. The power system has four coal-fired power plants with a total 2000MW capacity.

Wind power capacity penetration level is defined as a ratio between the total amount of instantaneous power from wind farm in a certain region and the total power generation of a system at that instant [29].

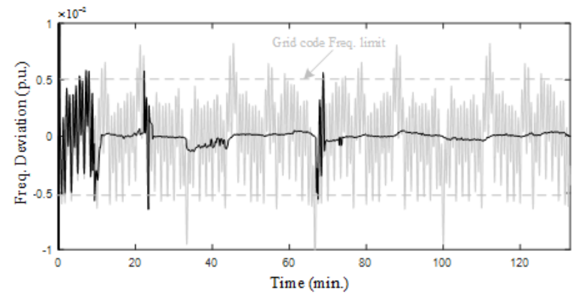

Fig. 11. Grid frequency deviation with and without HESS.

A. Controller test

Table II shows the system parameters in scenario I. The capacity of the grid-connected wind farm in this case is 1333MW. The grid frequency deviation response with and without HESS is plotted in Fig. 11. It is observed that the grid frequency deviation due to wind power penetration is dramatically smoothed by the HESS with the FWHS controller. The time duration curve of grid frequency deviation based on [25] extracted from Fig. 11 is displayed in Fig. 12. Δf_{grid}^{max}, defined as the value of 1% percentile of frequency deviation duration, is significantly reduced to about 0.48% of the normal frequency which is within the secure frequency deviation limit (0.5% ruled by the State Grid of China).

Fig. 13(a) illustrates the active power of wind (blue line), grid (green line) and HESS (black and red). It can be observed that the HESS can smooth the fluctuation of wind power effectively. Fig. 13 (b) shows that the fuzzy-based controller

TABLE II
System Parameters of the Test system in Scenario I.

Wind Penetration level %	40%
SoC initial value	20%
Power capacity of battery (MW)	120MW
Energy capacity of battery (MWh)	140
Power capacity of supercapacitor (MW)	200
Energy capacity of supercapacitor (MWh)	60

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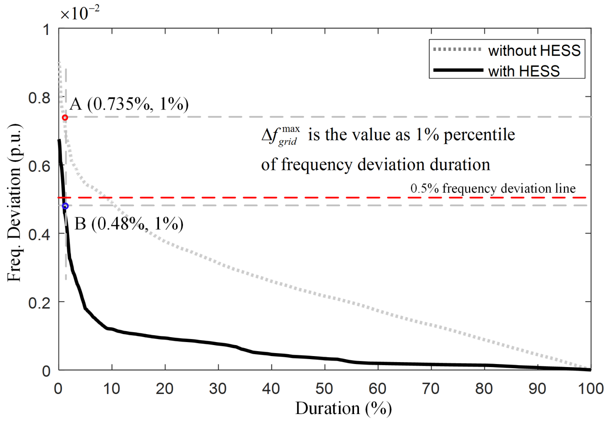

Fig. 12. Duration curve of grid frequency deviation with and without HESS.

could effectively maintains the SoC level of HESS in the normal state (i.e., between 20% and 80%) during almost the entire period. Fig. 13 (c) displays the time constant of primary filter and secondary filter given by the fuzzy-based rules according to the charging states and SoC level of HESS. At about 21:00 min, when the combined SoC level of HESS (computed by (4)) is larger than 80% (right yellow area in Fig. 6) and the charging state of battery is changed from charging to discharging (i.e. from positive to negative, shown as black line), the time constant of primary filter suddenly changed to a larger value (1702s) in order to discharge the power of HESS to avoid the SoC level from the warning case, which is the same as the design target of fuzzy controller in Section III-B.

1) Sizing Results: In term of HESS sizing, three cases are studied to evaluate the different control strategies and different wind penetration:

Case A) the wind penetration level is 40% and the initial SoC level is set as 50%;

Case B) the wind penetration level is increased to 50% and the initial SoC level is set as 80%;

Case C) the wind penetration level is 40%, the initial SoC level is set as 50% and T_H, T_L are fixed as 250 and 1000, respectively.

The dimension of the problem is four (D=4) since there are four parameters $U = \{P_{rated,b}, E_{rated,b}, P_{rated,s}, E_{rated,s}\}$ needed to be optimize. The number of population members are set to be 40 and the maximum iteration number is set to 30. The optimal sizing can be determined by use of the method shown in Fig. 9.

TABLE III
RESULTS OF SIZING HESS FOR TWO SCENARIOS.

	Case A	Case B	Case C
Wind Penetration level %	40%	50%	40%
battery Power(MW)	200	450	310
battery Energy (MWh)	440	500	460
supercapacitor Power (MW)	40	250	80
supercapacitor Energy(MWh)	680	50	680
Δf_{grid}^{max}	0.46%	0.48%	0.44%
Total cost ($10^8$$)	5.6700	10.8125	5.8618

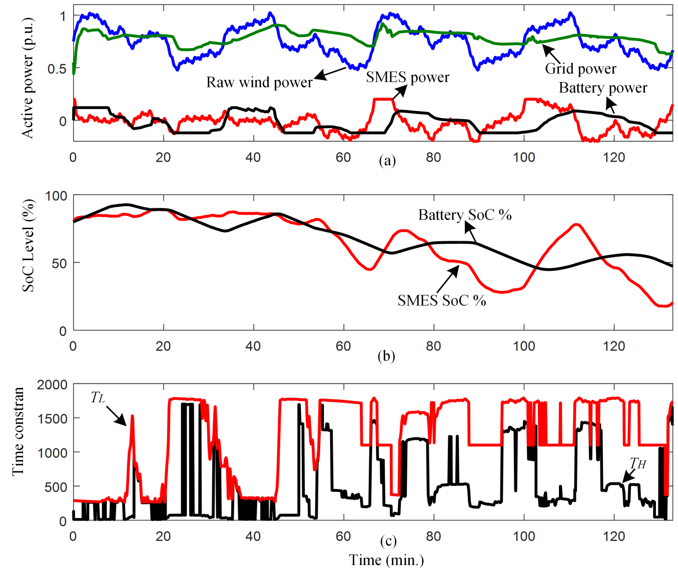

Fig. 13. Results of the FWHS controller. (a) active power of wind, grid and hess; (b) SoC level of battery and supercapacitor; (c) time constant of two filters: primary filter and secondary filter.

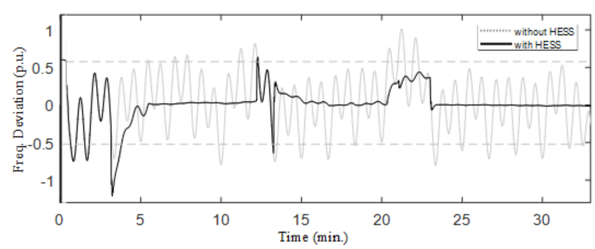

Fig. 14. Grid frequency deviation with and without HESS by the optimal sizing capacity in Case A of Table III.

The three studied cases are converged in two iterations. A summary of the results is given in Fig. 14 and Table III. As it can be seen in Fig. 13, the grid frequency deviation is smoothed effectively by the proposed HESS controller and Δf_{grid}^{max} is about 0.46% of the normal frequency which is within the secure frequency deviation limit.

Table III illustrates the optimal sizing results for three scenarios with different wind penetration level, SoC initial value and control strategies. From the computational results given in Table III, the power and energy capacity of HESS changes significantly at different expected levels of wind power penetration and different designed control strategies. The total cost of the Case B is 190.7% larger than the cost in Case A.

The proposed FWHS controller consumes the less energy storage capacity, compared with the fixed time constant controller in Case C, which proves that a better designed control strategy could save the capacity of energy storage. As the power capacity of supercapacitor is much more expensive in this analysis, less power capacity is rated for supercapacitor.

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TABLE IV
COMPARISON RESULTS WITH DIFFERENT METHODS.

Optimal method	DE	PSO
Cost (10^8 \$)	5.6700	5.8219
Time	83 mins	79 mins
Iter.	2	2

B. Comparison with PSO method

In this section, the DE method is compared with other heuristic algorithm (particle swarm optimization (PSO)). The wind penetration level is 40%. The comparison results are presented in Table IV.

As shown in Table IV, the cost of the DE method is a little lower than the PSO method, however, it is more time consuming compared with PSO method. The computation burden of these two methods are heavy, as most of the time is spent on the Simulink simulation to evaluate the objection function. However, the proposed method is a planning tool, the model can be computed preventively through offline analysis or using parallel and distributed computing techniques.

VI. CONCLUSION

This paper has proposed a fuzzy based wind-HESS system control method to suppress wind power fluctuation while considering the operating states (SoC level) of HESS. The key point of the controller is to allocate wind fluctuations with different frequency bands to the supercapacitor and the battery by dynamically adjusting the time constant of primary and secondary filter filters. The effectiveness of the proposed method has been demonstrated for a real power system.

To keep the grid frequency deviation within the permitted threshold, a collectively study of optimal storage sizing and control of wind-HESS system has been conducted in this paper. Results of the simulation have shown that the optimal sizing and control strategies could help minimize the size of HESS and also improve the cycle life of the HESS.

Future work will consider how to implement the control strategy into practice in order to further evaluate the effectiveness of this control method by means of hardware based testbed. By real time simulation, the research is able to demonstrate how this FWHS control method automatically adjust the filter parameters that can quickly adapt to the real system conditions, by taking into account the sampling rate for updating the filter parameters and its influence on the stability of hybrid system.

APPENDIX A
PARAMETERS OF THE GENERATIONS

The parameters of the generations for the test are shown in Table V. $T_{GH} = 0.2s, T_{RS} = 0.5s, T_{RH} = 28.75s, T_W = 1.0s$, The synchronizing power coefficient is $P_t = 2.0$ [24].

The cost coefficient of power and energy capacity is set as $C_{pb} = 150, C_{eb} = 125, C_{ps} = 2000, C_{es} = 400$ [11].

APPENDIX B
FUZZY RULES FOR SECONDARY FILTER

The fuzzy rules for normal secondary filter, when SoC of the battery is larger or smaller than supercapacitor (DF-Discharging fast;CS-charging slow; CF-charging fast; DS-Discharging slow), are listed in Table VI and VII, respectively.

The fuzzy rules for abnormal secondary filter, when SoC of the battery is larger or smaller than supercapacitor, are listed in Table VIII and IX, respectively.

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TABLE V
RESULTS OF SIZING ESS FOR TWO CASES.

Area	1	2
Speed regulation	$R_1 = 0.05$	$R_2 = 0.0625$
Frequency-sens. Loads coeff.	$D_1 = 0.6$	$D_2 = 0.9$
Inertia constant	$H_1 = 5$	$H_2 = 4$
Base Power (MVA)	1000	1000
Governor time constant	$T_{G1} = 0.2s$	$T_{G2} = 0.3s$
Turbine time constant	$T_{T1} = 0.5s$	$T_{T2} = 0.6s$

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TABLE VI
FUZZY RULES FOR NORMAL SECONDARY FILTER.

T_H		Supercapacitor Charge Input			
		DF	CS	CF	DS
Battery charge	DF	L	H	H	L
	DS	L	LH	H	LL
	CF	L	H	H	L
	CS	L	LH	H	LL

TABLE VII
FUZZY RULES FOR NORMAL SECONDARY FILTER.

T_H		supercapacitor Charge Input			
		DF	CS	CF	DS
Battery charge	DF	H	L	L	H
	DS	H	LL	L	LH
	CF	H	L	L	H
	CS	H	LL	L	LH

TABLE VIII
FUZZY RULES FOR ABNORMAL SECONDARY FILTER.

T_H		Charge Input	
		Discharging	Charging
Battery Charge	Discharging	L	H
	Charging	L	H

TABLE IX
FUZZY RULES FOR ABNORMAL SECONDARY FILTER.

T_H		Charge Input	
		Discharging	Charging
Battery Charge	Discharging	H	L
	Charging	H	L

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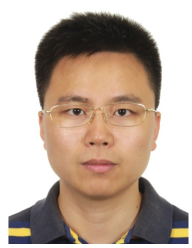

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