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Wind Power Smoothing With Energy Storage System: A Stochastic Model Predictive Control Approach

CHUANSHEN WU[1], (Graduate Student Member, IEEE), SHAN GAO[1], (Member, IEEE), YU LIU[1], (Member, IEEE), HAITENG HAN[2], (Member, IEEE), AND SUFAN JIANG[1], (Student Member, IEEE)

[1]School of Electrical Engineering, Southeast University, Nanjing 210018, China
[2]College of Energy and Electrical Engineering, Hohai University, Nanjing 210018, China

Corresponding author: Shan Gao (shangao@seu.edu.cn)

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ABSTRACT The utilization of energy storage system (ESS) is an effective method for dealing with the randomness and variability of wind power. Therefore, improving the coordination between ESS and wind power is a direction worthy of research. This study develops a two-layer stochastic model predictive control (SMPC) method for wind power smoothing on different time-scales. The proposed optimization framework smooths wind energy by adjusting the charge and discharge power of hybrid ESSs; moreover, it combines the SMPC approach and the chance constraints to address the uncertainties of wind energy. Furthermore, the previous states are taken into account, in addition to states within the rolling time horizon, to obtain optimal control of the hybrid ESSs, and capacity planning for hybrid ESSs is conducted simultaneously. The numerical results obtained through amplitude-frequency simulation comparison prove that the proposed method is superior to the conventional method in terms of minimizing the frequency fluctuation of wind power and the size of the ESS.

INDEX TERMS Energy storage system (ESS), microgrid, stochastic model predictive control (SMPC), uncertainty, wind power.

NOMENCLATURE

ACRONYMS

ESS	Energy storage system
RES	Renewable energy source
MPC	Model predictive control
SMPC	Stochastic model predictive control
SOC	State of charge

CONSTANTS

ESS_{up}	Upper layer ESS
ESS_{down}	Lower layer ESS
ESS_{hyb}	Hybrid ESS
T_{up}	Rolling time horizon of the upper layer
T_{down}	Rolling time horizon of the lower layer
Δt_{up}	Time slot of the upper layer
Δt_{down}	Time slot of the lower layer
H	State horizon
H_{up}	State horizon of the upper layer
H_{down}	State horizon of the lower layer
M	Total number of particles
a_1, a_2, a_3, a_4	Penalty parameters of the upper layer
b_1, b_2, b_3, b_4	Penalty parameters of the lower layer
N_1	Number of time slots in the rolling time horizon of the upper layer
N_2	Number of time slots in the rolling time horizon of the lower layer
L	Optimal SOC of the ESS
Det_{up}	Maximum difference coefficient between the adjacent time slots of the upper layer
Det_{down}	Maximum difference coefficient between the adjacent time slots of the lower layer
P_{wn}	Rated power of wind energy
α	Confidence parameter of the upper layer

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β	Confidence parameter of the lower layer
P_{rat_up}	Rated power of ESS_{up} per kWh
P_{rat_down}	Rated power of ESS_{down} per kWh
$SOC_{\min}$	Minimum SOC of the ESS
$SOC_{\max}$	Maximum SOC of the ESS
η_c	Charging efficiency of the ESS
η_d	Discharging efficiency of the ESS
h	Length of time slot

CONTINUOUS VARIABLES

P_W	Output of wind energy
P_{up}	Power of ESS_{up}
P_{down}	Power of ESS_{down}
P_{grid}	Combined power of wind and ESS_{hyb}
t_0	Current time
$P_{\max,i}$	Maximum of P_{sum_up} within H_{up} of the ith particle
$P_{\min,i}$	Minimum of P_{sum_up} within H_{up} of the ith particle
r_i	Mean of P_{sum_up} within Δt_{up} of the ith particle
u_i	Mean of P_{sum_up} within H_{up} of the ith particle
x_{up}	SOC of ESS_{up} at the end of time slot
x_{down}	SOC of ESS_{down} at the end of time slot
C_{up}	Capacity of ESS_{up}
C_{down}	Capacity of ESS_{down}
ΔP_{wind_up}	Difference of P_W between adjacent Δt_{up}
ΔP_{wind_down}	Difference of P_W between adjacent Δt_{down}
ΔP_{ESS_up}	Difference of P_{up} between adjacent Δt_{up}
ΔP_{ESS}	Difference of combined P_{up} and P_{down} between adjacent Δt_{down}
$P_{\max\_up}$	Rated power of ESS_{up}
$P_{\max\_down}$	Rated power of ESS_{down}
P_{sum_up}	Combined power of wind and ESS_{up}
$C_{ESS\_up}(j)$	Capacity of ESS_{up} *at* jth Δt_{up}
ΔC_{ESS_up}	Increased capacity of ESS_{up}
P_i	Value of P_{grid} of the ith particle

INTEGER VARIABLES

M_{up}	Number of particles satisfying upper layer chance constraints
M_{down}	Number of particles satisfying lower layer chance constraints

I. INTRODUCTION

Microgrids are expected to play a significant role in the future because they meet network demands locally, which reduces the purchased power from the main grid, in addition to reducing power losses, and increases the reliability indices [1]. Wind energy has attracted considerable attention over the past few decades owing to its modularity and environment-friendliness. The utilization of wind energy is an effective way to promote energy transformation in microgrids [2]. However, a significant increase in wind energy usage raises some issues with respect to the stability of the microgrid, considering its variability and stochastic nature.

A. RELATED WORK

In the literature, several studies have focused on the effective utilization of wind energy in microgrids. As a high-density and easy-to-control unit, an energy storage system (ESS) is an interesting option to reduce the risk of instability in a microgrid with wind power [3]. Shi *et al.* [4] established a wind energy storage hybrid system to analyze the fluctuation feature of wind power output in both time and frequency domains. Sattar *et al.* [5] examined the dynamic and transient performance of an ESS connected to the output of a wind energy conversion system to smooth the short-term fluctuations in the output power. Caralis *et al.* [6] investigated the role that energy storage can play in the further development of wind energy in microgrids and examined the solution of ESSs in curtailment exploitation. However, the aforementioned studies have ignored the fact that the peak-valley characteristic and the fluctuation characteristic of wind power need to be dealt with on different time-scales.

To solve this problem, a hybrid ESS can be utilized to deal with the peak-to-valley characteristic of wind power on the long time-scale and the fluctuation characteristic on the short time-scale. Wang *et al.* [7] utilized a large slower moving unit for energy shifting and arbitrage and a small rapid charging unit for smoothing. Ding and Wu [8] used a hybrid ESS based on a self-adaptive wavelet packet decomposition technique to reduce the amplitude of wind power in both high- and low-frequency domains. Abbassi *et al.* [9] utilized a hybrid ESS integrated with wind power to improve the reliability of storage units and the life cycle assessment through accommodation of fast power fluctuations. Similar studies have been conducted on the coordination of hybrid ESSs with wind energy.

It should be noted that, in real scenarios, wind power is difficult to forecast accurately over a long period of time [10]. The forecasting error increases with time and eventually leads to a large deviation between the optimal control result of the hybrid ESS and the actual demand [11]. Model predictive control (MPC) constantly incorporates newly obtained information to update the forecasting information for wind energy and, hence, can reduce the impact of the forecasting error [12]. Garcia-Torres and Bordons [13] carried out an optimal control for wind energy microgrids with hybrid ESSs using MPC, which maximized the economic benefits of the microgrid. Zhang *et al.* [14] proposed an MPC-based coordinated operation framework for a grid-connected residential microgrid considering the short-term forecast errors of wind energy.

In addition, stochastic MPC (SMPC) is applied to deal with the inherent uncertainty of wind power forecasting over a finite planning horizon [15]. SMPC uses "particles" to represent the possible cases of wind power in the future, and it is typically not possible to prevent failures in all these possible cases [16]. Chance constraints specify that the probability of failure must be below a given threshold [17]. This chance-constrained formulation is a powerful approach as it enables the user to specify a desired level of conservatism, which can be traded against performance [18]. This study focuses on the problem of chance-constrained predictive control under the stochastic uncertainty of wind power.

Although some previous studies have combined ESSs with MPC/SMPC to promote the efficient development of wind energy in different contexts, there is room for further improvement. According to the definition, MPC/SMPC uses the state variables in the rolling time horizon to calculate the control command of the rolling time horizon [19]. Many studies conducted based on this definition are valid, such as [13], [14], and [20]. In these studies, the effect of the states in a rolling time horizon on the overall evaluation index is only related to the states within the rolling time horizon, and the overall evaluation index is considered irrelevant to the states outside the rolling time horizon. For instance, through the effective coordination of ESSs and renewable energy sources (RESs), the overall cost of load supply can be minimized [21].

However, in terms of minimizing RES amplitude variation and achieving RES fluctuation suppression, the overall evaluation index is relevant to the states outside the rolling time horizon [22]. For example, when an ESS is used to improve the peak-valley characteristics of an RES, if only the states within the rolling time horizon are considered, the overall improvement effect of the peak-valley characteristic evaluation index is limited [7]. In this study, during the rolling optimization process, the states before the current moment are already known, which can be utilized effectively to achieve a better optimization effect.

Theoretically, the combined power of an ESS and wind energy can be adjusted to any value if the capacity of the ESS is sufficiently large [23]. However, considering the cost of ESSs, the capacity of an ESS should be as small as possible while meeting constraints. In this study, the capacity planning of hybrid ESSs is continuously executed through the entire optimization process.

B. CONTRIBUTIONS

A two-layer optimization framework is proposed in this study to smooth wind energy by adjusting the charge and discharge power of a hybrid ESS, which has two significant features:

1) The SMPC technology and chance constraints are combined to deal with the uncertainties of wind energy.
2) The previous states are considered in addition to states within the rolling time horizon to obtain the optimal control of the hybrid ESS.

II. SYSTEM STRUCTURE

A schematic representation of the microgrid containing a wind power harnessing system, a hybrid ESS, base loads, and a two-layer SMPC controller is presented in Fig. 1. The hybrid ESS consists of two separate units. The upper and lower layer ESSs are used for shifting and smoothing wind energy, respectively. The microgrid is connected to the power grid through a transmission line [24]. The two-layer SMPC controller is used to optimize the charge and discharge power of the hybrid ESS to obtain a suitable power that meets the requirement of the microgrid [25].

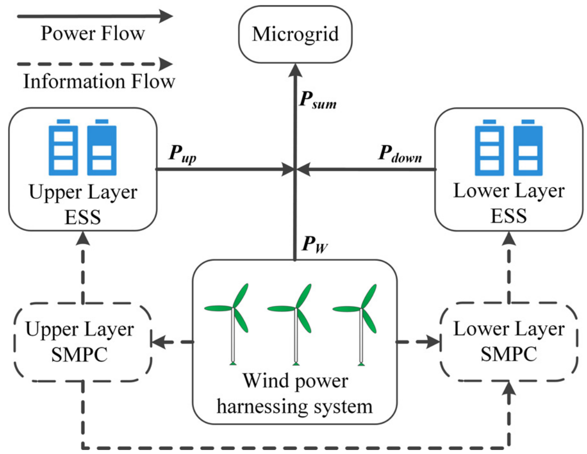

FIGURE 1. Wind power and hybrid ESS system in a microgrid.

In this study, the grid-connected power, P_{grid}, satisfies the following relationship.

$$P_{grid} = P_W + P_{up} + P_{down} \tag{1}$$

III. METHODOLOGY

A. CONVENTIONAL TWO-LAYER SMPC METHOD

A schematic of the conventional two-layer SMPC method is presented in Fig. 2 [25]. First, the upper layer SMPC optimization is performed to obtain a set of charge/discharge power of ESS_{up} within T_{up}, the first value of which is executed within the first Δt_{up}. Second, considering the actual execution power of ESS_{up}, the lower layer SMPC optimization is performed within T_{down}, and the first charge/discharge power of ESS_{down} is executed within the first Δt_{down}. Third, the rolling optimization of the lower layer SMPC continues until T_{down} involves the second time slot of T_{up}, as shown in the red part of Fig. 2. Then, the next T_{up} is optimized. This cycle continues until the optimization of the entire time horizon is completed.

B. PROPOSED TWO-LAYER SMPC METHOD

The state horizon, H, is defined as the horizon composed of state variables that affect the control commands in the rolling time horizon [25]. In the conventional two-layer SMPC method, the length of H_{up} is the same as that of T_{up}. In this study, to effectively utilize the previous states, the length of H_{up} is considered twice the length of T_{up}, and H_{up} is centered about the current time, t_0. Fig. 3 shows the structure of the proposed upper layer SMPC. The structure of the modified lower layer SMPC is similar to that of upper layer SMPC and is not shown here.

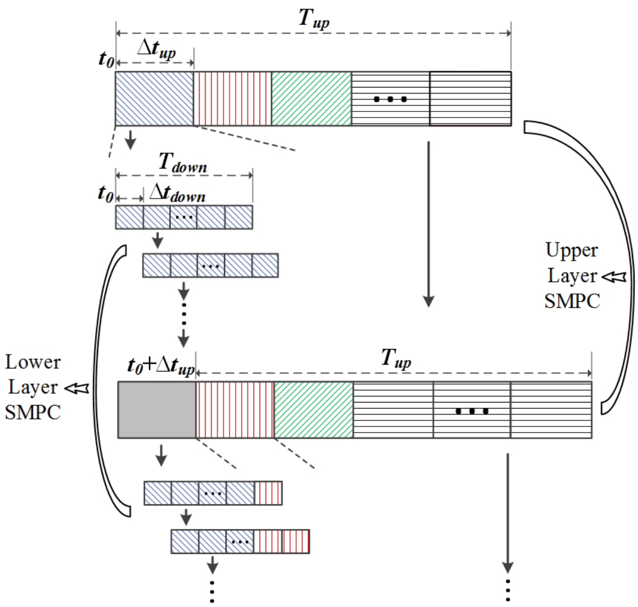

FIGURE 2. Schematic of conventional two-layer SMPC method.

Considering the previous states, the steps involved in the proposed two-layer SMPC method are presented in *Algorithm 1*, which can be understood in conjunction with Fig. 2.

Algorithm 1 Proposed Two-Layer SMPC Method

1. Initial values.
2. **While** t_0 is not at the end of entire time horizon **do**
3. Optimization of upper layer.
4. Obtain the charging/discharging power of upper layer ESS.
5. Set $n = 0$.
6. **While** $t_0 + n\Delta t_{down} + T_{down} \leq t_0 + \Delta t_{up}$ **do**
7. Optimization of lower layer.
8. Obtain the charging/discharging power of lower layer ESS.
9. $n = n + 1$.
10. **End while**
11. $t_0 = t_0 + \Delta t_{up}$.
12. **End while**

C. AMPLITUDE-FREQUENCY CHARACTERISTIC ANALYSIS

Large-scale wind power connections will result in problems with respect to frequency adjustment and wind power accommodation [26]. Therefore, it is very important that the scientific planning and economic operation of wind power describe the characteristics of wind power output with statistical methods. To evaluate the optimization effect, the amplitude-frequency characteristics of wind power and hybrid ESSs are analyzed using discrete Fourier transforms [27].

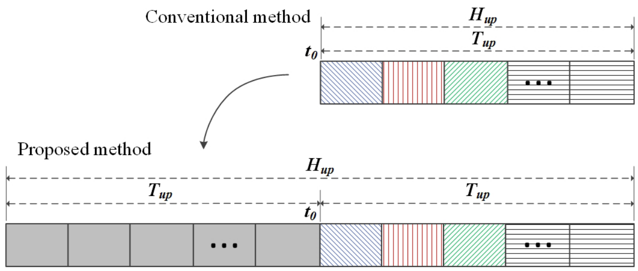

FIGURE 3. Structure of the proposed upper layer SMPC.

IV. OPTIMIZATION FORMULATION

A. MODEL OF UPPER LAYER OPTIMIZATION

The upper layer optimization dispatches wind energy on a long time-scale. The objective function of the Kth H_{up} is defined as follows.

$$\begin{aligned}\min f_1 = \frac{1}{M_{up}} \sum_{i=1}^{M_{up}} \Bigg(a_1 \left(P_{\max,i} - P_{\min,i}\right) \\ + a_2 \sum_{j=-N_1}^{N_1} \left(r_i(j) - u_i(K)\right)^2 \Bigg) \\ + a_3 \sum_{j=-N_1}^{N_1} \left(x_{up}(j) - L\right)^2 + a_4 C_{up} \qquad (2)\end{aligned}$$

where a_1 and a_2 are the penalty parameters for tuning the range and variance terms, respectively. L is the ideal energy level for the ESS, which is generally considered to be 50% of the total capacity. The upper layer optimization considers the wind energy dispatch on a long time-scale while taking into account the lifetime and cost of ESS_{up}.

For the total number of M particles, the chance constraint of the power difference between adjacent Δt_{up} is presented in (3). According to (3), the M_{up} particles that are greater than αM satisfy the chance constraint.

$$\begin{aligned}\Pr\left(-Det_{up} \cdot P_{wn} \leq \Delta P_{wind\_up} + \Delta P_{ESS\_up} \leq Det_{up} \cdot P_{wn}\right) \\ \geq \alpha \qquad (3)\end{aligned}$$

If the chance constraints cannot be satisfied, C_{up} needs to be increased to change the adjustment range of the upper layer ESS power to meet the constraints.

For the particles within M_{up}, the constraints for the power of the upper layer ESS are defined as follows.

$$-P_{\max\_up} \leq P_{up} \leq P_{\max\_up} \qquad (4)$$

$$P_{\max\_up} = C_{up} P_{rat\_up} \qquad (5)$$

The bounds of the remaining state of charge (SOC) within the upper layer ESS are defined as follows.

$$\mathrm{SOC}_{\min} \leq x_{up} \leq SOC_{\max} \qquad (6)$$

The constraint for the bounds of the combined power of the upper layer is

$$0 \leq P_{sum\_up} \leq P_{wn} \qquad (7)$$

The dynamic formula for the SOC of ESS_{up} between jth Δt_{up} and $(j+1)$th Δt_{up} is given below:

$$x_{up}(j+1) = \frac{x_{up}(j)\, C_{ESS\_up}(j) + \eta P_{up}(j)\, h}{C_{ESS\_up}(j) + \Delta C_{ESS\_up}} \tag{8}$$

where

$$\begin{cases} \eta = \eta_c, & \text{if } P_{up} \geq 0 \\ \eta = \eta_d, & \text{if } P_{up} < 0 \end{cases} \quad \text{and } j = 1, 2, \ldots, H_{up} - 1.$$

B. MODEL OF LOWER LAYER OPTIMIZATION

The objective of the lower layer optimization is to smooth the wind energy on a short time-scale. The objective function of the kth H_{down} is given by

$$\begin{aligned} \min f_2 &= \frac{1}{M_{down}} \sum_{i=1}^{M_{down}} \left(b_1 \sum_{j=-N_2}^{N_2-2} (P_i(j+2) - 2P_i(j+1) + P_i(j))^2 \right) \\ &\times \frac{1}{M_{down}} \sum_{i=1}^{M_{down}} \left(b_2 \sum_{j=-N_2}^{N_2-1} |P_i(j+1) - P_i(j)| \right) \\ &+ b_3 \sum_{j=-N_2}^{N_2} (x_{down}(j) - L)^2 + b_4 C_{down} \end{aligned} \tag{9}$$

where b_1 and b_2 are the penalty parameters for the curvature and slope terms, respectively. The lower layer optimization considers the wind power smoothing on a short time-scale while taking into account the lifetime and cost of ESS_{down}.

For the total number of M particles, the chance constraint of the power difference between adjacent Δt_{down} is given in (10). According to (10), the M_{down} particles that are greater than βM satisfy the chance constraint.

$$\begin{aligned} \Pr \big(-Det_{down} \cdot P_{wn} \leq \Delta P_{wind\_down} + \Delta P_{ESS} \\ \leq Det_{down} \cdot P_{wn} \big) \geq \beta \end{aligned} \tag{10}$$

If the chance constraints cannot be satisfied, C_{down} needs to be increased to change the adjustment range of the lower layer ESS power to meet the constraints.

For the particles within M_{down}, the constraints for the power of the lower layer ESS are given as follows.

$$-P_{\max\_down} \leq P_{down} \leq P_{\max\_down} \tag{11}$$

$$P_{\max\_down} = C_{down} P_{rat\_down} \tag{12}$$

The bounds of the remaining SOC within the lower layer ESS are defined as follows.

$$\mathrm{SOC}_{\min} \leq x_{down} \leq SOC_{\max} \tag{13}$$

The constraint for the bounds of the combined power of the two layers is as follows.

$$0 \leq P_{sum} \leq P_{wn} \tag{14}$$

The dynamic formula of the SOC of ESS_{down} is similar to (8) and is not presented here.

In this study, the energy stored in the newly added ESS_{up}/ESS_{down} is set to be half of its rated capacity [25].

V. SIMULATION RESULTS

All the simulations are carried out in MatLab (MathWork, USA) on a 64-bit Microsoft Windows with the MIQP solver in the CPLEX software package.

A. BASIC INFORMATION

The upper layer optimization requires a large-capacity and low-cost ESS to transfer the wind energy, whereas the lower layer optimization requires a fast-response and long-lifetime ESS to operate frequently to smooth the wind energy [9]. According to the characteristics of ESSs, the lead acid battery unit is selected as the ESS_{up} to store and dispatch wind energy, and the Ultra battery unit is selected as the ESS_{down} for rapid short-term smoothing [7].

The wind data used in the simulation are obtained from the Belgian electricity transmission system [27]. In this study, the forecasting error of the first time slot in the rolling time horizon is 0.5% of the actual output power. It should be noted that the forecasting error of wind power during the day is greater than that at night. Therefore, it is assumed that the forecasting error increases by 0.078% for each additional time slot between 06:00 and 18:00 and by 0.088% for each additional time slot for the remaining time period [28]. Latin hypercube sampling of the normal distribution is used to obtain the particles representing the prediction error. For the parameters of normal distribution, u is the actual output power, and σ is the forecasting error [25].

The system parameters used in the simulations are summarized in Table 1.

TABLE 1. System parameters.

Parameter	Value
P_{wn}	300 kW
P_{rat_up}/P_{rat_down}	0.2 kW/2.78 kW
$SOC_{\min}/SOC_{\max}$	0.2/0.8
T_{up}/T_{down}	360 min/90 min
$\Delta t_{up}/\Delta t_{down}$	60 min/15 min
N_1/N_2	4/4
Det_{up}/Det_{down}	0.1/0.08
$a1/a2/a3/a4$	0.1/0.795/0.1/0.005
$b1/b2/b3/b4$	0.4/0.05/0.5/0.05
η_c/η_d	0.8/1.25
α/β	0.9/0.9
L	0.5
M	100

B. RESULTS OF AMPLITUDE-FREQUENCY CHARACTERISTICS

The optimization results for the combined power curves of wind and hybrid ESS under the proposed method and conventional method are presented in Fig. 4. As shown in Fig. 4(a), if only the upper layer SMPC optimization is conducted, the curves of P_{sum_up} have better peak-valley characteristics than the wind curve in both the proposed and the conventional methods. The improvement degree of peak-valley characteristics is related to the value of Det_{up} in constraint (3). The

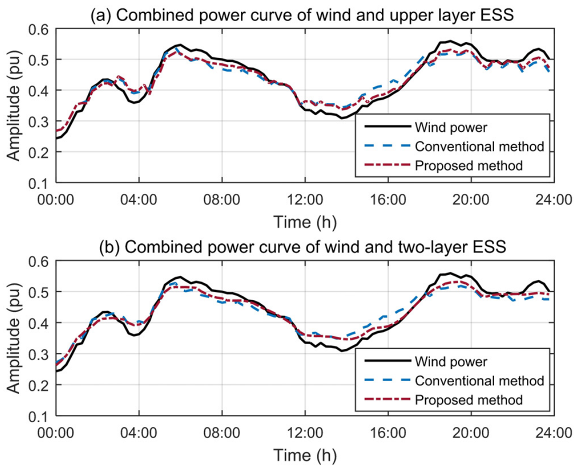

FIGURE 4. **(a) Combined power curve of wind and upper layer ESS. (b) Combined power curve of wind and hybrid ESS.**

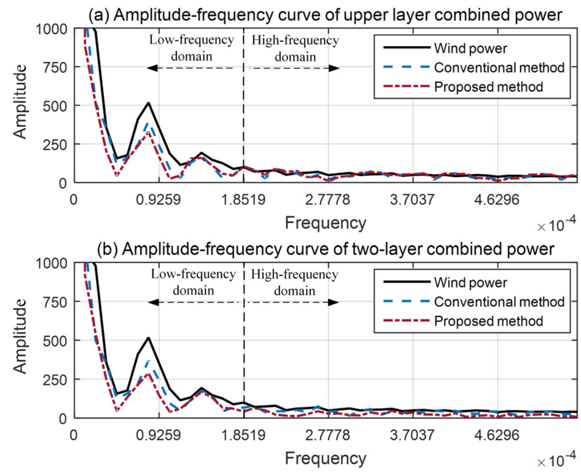

FIGURE 5. **(a) Amplitude-frequency curve for the upper layer combined power. (b) Amplitude-frequency curve for the two-layer combined power.**

larger the value of Det_{up}, the better the peak-valley characteristics; however, at the same time, a larger capacity of ESS_{up} is required. As shown in Fig. 4(b), with the optimization of the two-layer SMPC, the curves of P_{grid} are smoother than those of P_{sum_up} for both proposed and conventional methods.

To compare the optimization effect between the proposed method and the conventional method, Fig. 5 presents the amplitude-frequency characteristics of the curves in Fig. 4, which are obtained using discrete Fourier transforms. To evaluate the effect of the two-layer optimization method, the frequency domain is divided into the high-frequency domain and the low-frequency domain.

The statistical results of Fig. 5 are presented in Table 2. When only upper layer optimization is carried out, the normalized value of the mean of amplitude of the proposed method is lower than that of the conventional method in the low-frequency domain, indicating that the proposed method has a better optimization effect than the conventional method. In the high-frequency domain, the mean of amplitude of the proposed method is similar to that of conventional method, and results from these methods are slightly better than those for direct wind power usage. This is because the upper layer SMPC optimization mainly adjusts the peak-valley characteristics on the long time-scale, which is advantageous for improving wind characteristics in the low-frequency domain. In addition, after the two-layer SMPC optimization, the mean of amplitude of the proposed method is superior to that of the conventional method in both low-frequency and high-frequency domains, and both of them are better than that of direct wind power usage. This is because the lower layer SMPC optimization mainly improves the volatility on the short time-scale; hence, it is advantageous for improving wind characteristics in the high-frequency domain, thereby improving wind characteristics in the high-frequency domain.

The aforementioned results reveal that considering previous state variables in addition to present variables has a significant impact on the control command within the rolling time horizon; further, the amplitude-frequency characteristics of the proposed two-layer SMPC method are superior to those of the conventional two-layer SMPC method, and both of them are better than that of the direct wind power usage.

TABLE 2. **Statistical results of amplitude-frequency curves.**

Frequency domain	Optimization method	Analysis object	Normalized value of mean of amplitude
Low-frequency domain	/	Original wind	1
	Upper layer	Conventional method	0.6815
		Proposed method	0.5795
	Two-layer	Conventional method	0.6763
		Proposed method	0.5638
High-frequency domain	/	Original wind	1
	Upper layer	Conventional method	0.8768
		Proposed method	0.9156
	Two-layer	Conventional method	0.8019
		Proposed method	0.6577

C. RESULTS OF CAPACITY PLANNING OF ESS

The changing processes of C_{up} and C_{down} are shown in Fig. 6. C_{up} and C_{down} increase gradually in the early stage of optimization. At the end of optimization, the values of C_{up} and C_{down} of the proposed method are obviously smaller than those of the conventional method, which indicates that the proposed method has strong economic competitiveness. This is because the proposed method considers the state variables before the present time, which makes the charging/discharging power of the hybrid ESS more reasonable to meet the constraints.

Fig. 7(a) and Fig. 7(b) present the changing process of the SOC of ESS_{up} and ESS_{down}. In the two-layer SMPC optimization, the upper and lower layer SOCs are effectively controlled in the appropriate range, to avoid the impact of ESS saturation or depletion on its lifespan.

From these analyses, it is clear that, using the proposed method, not only can the fluctuation characteristics of wind

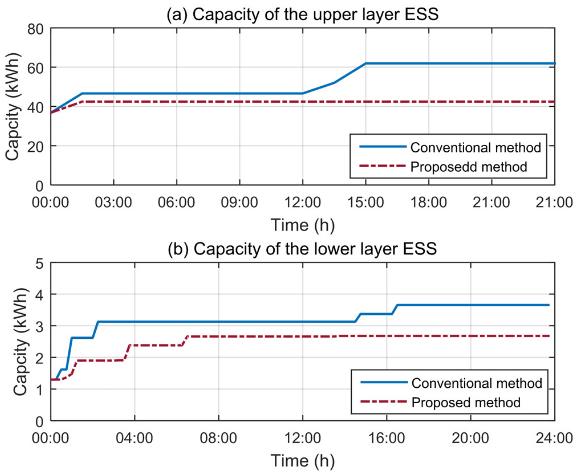

FIGURE 6. (a) Capacity of the upper layer ESS. (b) Capacity of the lower layer ESS.

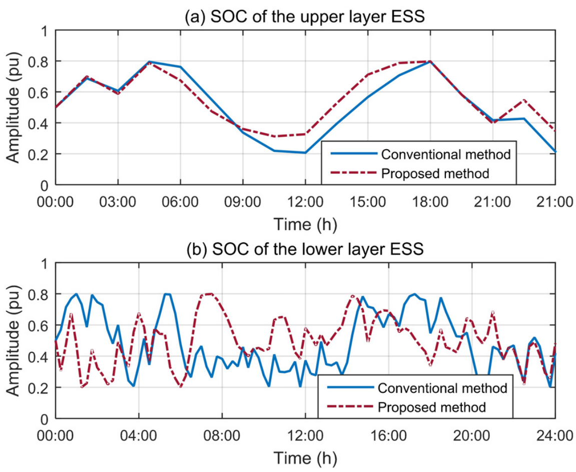

FIGURE 7. (a) SOC of the upper layer ESS. (b) SOC of the lower layer ESS.

energy be improved but the required capacity of ESS can also be effectively reduced.

D. COMPARISON OF SIMULATION RESULTS

To further verify the effectiveness of the proposed two-layer optimization method, Fig. 8 presents the ratios of the results of the proposed method to those of the conventional method after two-layer optimization for 30 days.

As shown in Fig. 8(a), after two-layer optimization, for the mean of amplitude of frequency in both low-frequency and high-frequency domains, the ratios of the results of the two methods are all less than 1, which means that the proposed method outputs better optimization results than the conventional one in all 30 different wind power situations. In addition, as shown in Fig. 8(b), for the ESS capacities in both the lower layer and the upper layer, the ratios of the results of the two methods are also all less than 1, thereby further proving the effectiveness of the proposed method. Furthermore, it is found that when the peak-valley characteristics and volatility of wind energy are not ideal, the advantage of the modified method is more noticeable.

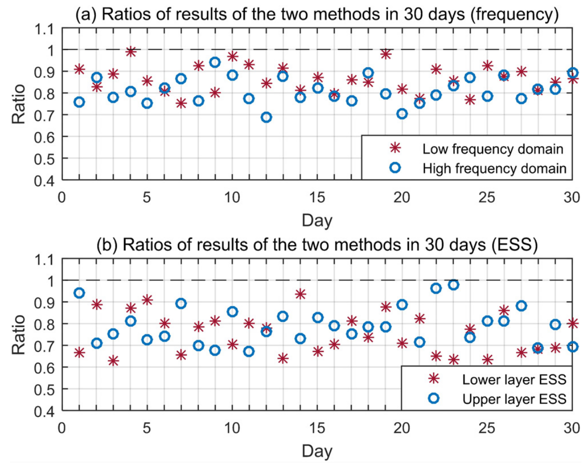

FIGURE 8. (a) Ratios of results of the proposed method to those of the conventional method in 30 days (mean of amplitude of frequency). (b) Ratios of results of the proposed method to those of the conventional method in 30 days (ESS capacities).

VI. DISCUSSION

The length of the rolling time horizon of the upper and lower layer has a significant influence on the optimization results. If the length is too long, the local improvement effect is not ideal; if the length is too short, the optimization mainly focuses on the local effect but ignores the overall effect. There are similar problems with the lengths of the time slot. In different cases, the lengths of the rolling time horizon and the time slot should be selected accordingly.

VII. CONCLUSION

A modified two-layer control method based on SMPC is proposed in this study with an aim to dispatch and smooth wind energy. In the process of SMPC optimization, the influence of the states before the current time on the control command in the rolling time horizon is considered. The experimental results demonstrate that, while considering states before the current time, the mean of amplitude of frequency of the proposed method is lower than that of conventional method, be it in the lower frequency domain or the higher frequency domain; moreover, smaller capacities for ESSs are ensured regardless of upper layer or lower layer. Future work will focus on adjusting the length of the rolling time horizon and the time slot during the optimization process according to the characteristics of wind power at different time periods.

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CHUANSHEN WU (Graduate Student Member, IEEE) received the B.S. degree from the College of Electrical Engineering and Automation, Fuzhou University, Fuzhou, China, in 2015. He is currently pursuing the Ph.D. degree in electrical engineering with the School of Electrical Engineering, Southeast University, Nanjing, China.

His research interests include microgrid management, optimal control, electric vehicle integration, and uncertain optimization.

SHAN GAO (Member, IEEE) received the Ph.D. degree from Southeast University, Nanjing, China, in 2000.

He is currently an Associate Professor with the School of Electrical Engineering, Southeast University. His research interests include power systems planning and operation, electric vehicle integration, renewable energy integration, and stochastic and distributed optimization.

YU LIU (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical engineering from Southeast University, Nanjing, China, in 2011, 2014, and 2018, respectively.

From 2015 to 2016, he was a Visiting Scholar with the University of Alberta, Edmonton, Canada. He is currently a Lecturer with the School of Electrical Engineering, Southeast University. His research interests include power systems planning and operation, integrated energy systems, and the scheduling of electric vehicles.

HAITENG HAN (Member, IEEE) received the B.S. and Ph.D. degrees in electrical engineering from Southeast University, Nanjing, China, in 2010 and 2019, respectively.

He is currently an Assistant Professor with the College of Energy and Electrical Engineering, Hohai University, Nanjing. His research interests include power systems computing, demand response, security assessment, and power systems operation and control.

SUFAN JIANG (Student Member, IEEE) received the B.S. and M.S. degrees in electrical engineering from Southeast University, Nanjing, China, in 2014 and 2017, respectively. He is currently pursuing the Ph.D. degree in electrical engineering with the School of Electrical Engineering, Southeast University.

His research interests include renewable energy integration, and optimized operation and control of power systems.