

Optimal Over-frequency Droop Control for DFIG-based Wind Farms Under Unreliable Communication

Yaxin Wang, Donglian Qi, *Member, IEEE, Member, CSEE*, Jianliang Zhang, and Yulin Chen

Abstract—Nowadays, high penetration of wind power is integrated into power grids, and WTs usually adopt the MPPT algorithm to maximize power output, which decouples the rotor speeds of wind turbines (WTs) and system frequency. Therefore, WTs cannot provide frequency support like conventional generators. To that end, especially avoiding WTs aggravating excessive power generation during over-frequency events, optimal droop control is proposed to reduce power output by fully utilizing WTs' own potential in accelerating rotors. Due to unreliable communication in a wind farm, a game theory-based distributed rotor kinetic energy optimization model is developed to obtain the ideal WT rotor speed and power reduction. Next, the optimal droop gains for WTs are designed to be proportional to their ideal power reduction. Then, not only the frequency support capability of WTs is fully activated, but also as much wind power as possible will be stored as kinetic energy into the accelerated rotor blades. Finally, the effectiveness and rationality of the proposed control are verified in MATLAB and DigSILENT.

Index Terms—Game theory, optimal droop control, over-frequency support, unreliable communication, wind power generation.

I. INTRODUCTION

LARGE-SCALE wind energy generation, such as doubly-fed induction generators (DFIG), have been integrated into grids in recent years [1], [2]. However, power electronic converters widely utilized in wind farms decouple the rotor speeds of WTs and system frequency, which makes WTs have no natural frequency modulation capability, as do conventional generators. To contribute to over-frequency events, WTs are expected to provide frequency support by reducing their power output reasonably [3], [4]. However, due to harsh environments and malicious attacks, there is potential uncertainty in communication among WTs in wind farms [5]. Therefore,

designing effective frequency control methods for WTs is of great significance, especially in grids with high wind power penetration.

A. Related Works

For safe and stable operation of the system, over-frequency indicators are regulated more stringently by the grid code, e.g., frequency peak limits specified in China and The United States are 0.5 Hz and 0.7 Hz; the rate of change of frequency (RoCoF) relay settings range from 0.1 to 1.0 Hz/s and from 0.12 to 1.2 Hz/s (in 50/60 Hz-nominal frequency, respectively) [6]. To enable WTs to contribute to frequency stability, kinds of controls have been proposed to adjust their active power output. Rotor kinetic energy control is relatively fast and effective [7]–[10] because kinetic energy mechanically stored in rotating rotors can be easily converted for a short period [11], [12]. To damp over-frequency excursions by reducing WT power output, an additional rotor kinetic energy control module is designed to increase rotor speed [13]. Rotor kinetic energy control involves two main categories: inertia emulation control [14]–[16] and droop control [17]–[20]. Inertia emulation control simulates synchronous generators' natural frequency modulation capability by detecting the RoCoF; therefore, it can provide sizeable active power support at the initial time due to the rapid variation of network frequency. In literature [21], an inertial control module is added to the DFIG rotor side converter, and then the active power reference of DFIG is adjusted to release the hidden kinetic energy for frequency regulation. However, this method only responds to the dynamic process [9], [22] and has no contribution to frequency peak/nadir. In addition, it may cause system instability when noise occurs during frequency measurement.

Unlike inertia emulation control, droop control is based on frequency deviation, and therefore it is more robust in terms of instantaneous noise [23]. Nevertheless, the same droop gains are adopted by WTs without considering the different potential abilities of each WT's rotor kinetic energy for frequency support [24]. When WT rotor speed exceeds the maximum value, the pitch angle control system is activated to reduce its power output [2]–[4], resulting in inevitable wind energy loss because of the higher pitch angle. Moreover, sudden changes in torque during primary response may lead to the turbine's stalling [9], and frequently adjusting the pitch angle increases mechanical stress. Therefore, it is a waste of wind power to activate the pitch angle control system if over-frequency

Manuscript received June 8, 2021; revised October 18, 2021; accepted December 4, 2021. Date of online publication December 4, 2021; date of current version October 5, 2024. This work was supported by National Key R&D Program of China (Basic Research Class) (No. 2017YFB0903000), and National Natural Science Foundation of China (No. U1909201).

Y. X. Wang is with China Electric Power Research Institute, Beijing 100192, China.

D. L. Qi (corresponding author, email: qidl@zju.edu.cn) and J. L. Zhang, are with the College of Electrical Engineering, Zhejiang University, Hangzhou 310027, China.

Y. L. Chen is with the State Key Laboratory of Internet of Things for Smart City, University of Macau, Macau, China.

DOI: 10.17775/CSEEJPES.2021.04360

support can still be provided by increasing rotor speeds of other WTs in wind farms [25], [26].

In other words, to fully utilize WTs' own potential in accelerating rotors, the global goal is to maximize rotor kinetic energy stored in all WTs during the over-frequency regulation process. In addition, the design of droop gains is influenced by pertinent parameters obtained via optimization. Though a centralized optimization algorithm is easier to consider in the global goal, however, due to disconnection issues, time delay, and unexpected interrupts caused by harsh environments or malicious attacks [27], complete communication structures can hardly be guaranteed all the time. The WTs within modern wind farms suffer from unreliable communication conditions. To overcome the drawbacks of centralized algorithms, such as low robustness, low scalability, and poor economic performance, research on distributed methods has been developed [5], [27]–[29]. In this paper, an optimal droop control is proposed based on a distributed optimization strategy within a game theory framework.

B. Main Contribution

Mainly due to the wake effect, WTs within a farm work in different wind speed conditions. Front-row WTs operate in or near the rated wind speed, and back-row WTs operate below the rated wind speed. During over-frequency events, compared to front-row WTs, back-row WTs are able to reduce power output by accelerating their rotors, thereby contributing to frequency regulation, as well as harvesting wind power and storing it in their blades as kinetic energy.

To enable each WT to provide an optimal over-frequency response dynamic, our contributions are concentrated in the following areas: (a) Optimal rotor kinetic energy model is designed to minimize the negative impact on the overall ability for energy production while providing frequency support. (b) A distributed optimization method for solving optimal rotor speeds is developed under the framework of a state-based potential game, thereby obtaining the ideal power reduction of each WT distributedly. (c) Optimal droop control is proposed by adaptively adjusting WT droop gains according to their ideal power reduction; then, WTs within a farm can provide fast frequency response by fully utilizing their potential in accelerating rotor blades.

II. PRELIMINARIES

A. Wind Turbine Model

The optimization object in this paper is the doubly-fed induction asynchronous wind generator in a wind farm. The wind energy captured from wind is converted into mechanical energy by the blades, and then transmitted to electric energy.

The mechanical power extracted from air flow by the WT can be expressed as follows:

$$P_{\text{wind}} = \frac{\rho}{2} \pi R^2 V_w^3 C_p(\lambda, \beta) \quad (1)$$

where ρ is air density, R is the blade radius of the WT, V_w is the wind speed upstream of the rotor, λ is the tip speed ratio, C_p is the wind energy utilization factor related to the pitch angle β and λ tip speed ratio.

$$C_p = 0.22 \left(\frac{116}{\lambda_1} - 0.4\beta - 5 \right) e^{-12.5/\lambda_1} \quad (2)$$

$$\lambda_1 = \frac{1}{\frac{1}{(\lambda + 0.08\beta)} - \frac{0.035}{(\beta^3 + 1)}} \quad (3)$$

The tip speed ratio λ is

$$\lambda = \frac{\omega_T R}{V_w} = \frac{k_g \omega R}{V_w} \quad (4)$$

where ω_T is the wind turbine rotation speed, ω is the generator rotor speed, k_g is the gear ratio of gearbox.

However, wind speed above the rotor of each WT varies from different locations because of complex aerodynamic interactions. Wake effect especially has a severe impact on the wind speed upstream of the rotor. In the Park model, which is well studied, for turbine i , wind speed V_{wi} can be expressed as follows:

$$V_{wi} = V_\infty (1 - \delta V_{wi}) \quad (5)$$

We assume uniform wind of constant speed V_∞ , and δV_{wi} represents the fractional deficit of the velocity

$$\delta V_{wi} = 2 \sqrt{\sum_{j \in N: x_j < x_i} \left(a_j \left(\frac{D_j}{D_j + 2k(x_i - x_j)} \right)^2 \frac{A_{j \rightarrow i}^{\text{overlap}}}{A_i} \right)^2} \quad (6)$$

where D_j is the diameter of the turbine j blades. A_i is the rotor-swept area of a WT i in m^2 . $A_{j \rightarrow i}^{\text{overlap}}$ is the ratio between the overlapping area and swept area of the WT i , as shown in Fig. 1. a_j is the axial induction factor of WT i . x_i is the radial distance of turbine i . k is a roughness coefficient. It has been found empirically for different environments, e.g., $k = 0.075$ for farmlands and $k = 0.04$ for offshore locations [3].

Equation (2) is a higher-order nonlinear expression, which will be fitted with a polynomial form with coefficients a_l and limited degree L as follows:

$$C_p = \sum_{l=0}^L a_l \lambda^l \quad (7)$$

and the mechanical power output of WT i is

$$P_{\text{wind},i} = \frac{1}{2} \sum_{l=0}^L \rho \pi R^2 V_{wi}^3 a_l \left(\frac{\omega_i R}{V_{wi}} \right)^l = \sum_{l=0}^L \kappa_{l,i} \omega_i^l \quad (8)$$

where V_{wi} is the wind speed upstream of the rotor, ω_i is the rotor speed, $\kappa_{l,i}$ is the artificial coefficient for mechanical power.

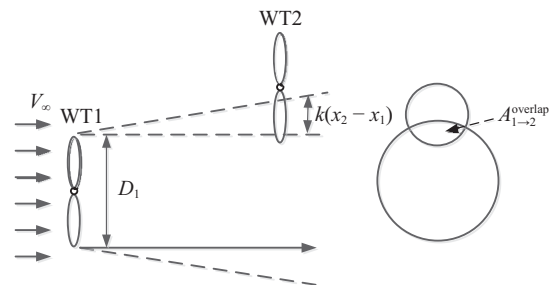


Fig. 1. Wake interaction model between two WTs.

Moreover, the wind energy utilization coefficient $C_p(\lambda, \beta)$ will only be distantly related to the tip speed ratio λ under a specific pitch angle β . To obtain the maximum value C_{pmax} , the blade tip speed λ needs to be adjusted to the optimal blade tip speed determined by the MPPT algorithm. Accordingly, the maximum mechanical power output $P_{MPPT,i}$ of WT*i* takes the form

$$P_{MPPT,i} = \max(P_{wind,i}) = \frac{\rho \pi R^5 k_g^3 C_{pmax}}{2\lambda^3} \omega_i^3 \quad (9)$$

B. Optimal Droop Control Scheme

The active power reference of WT*i* is equal to the value calculated according to the MPPT algorithm (9), as shown in (10).

$$P_{ref,i} = P_{MPPT,i} \quad (10)$$

Once the power load suddenly reduces or excessive power generation occurs, system frequency will rise due to the imbalance between supply and demand. WTs can provide frequency support by adding a droop controller.

In conventional control strategies, droop gains of DFIGs in a wind farm are generally set the same without considering the different potential abilities of each WT's rotor kinetic energy for frequency support. However, due to complex aerodynamic interactions among WTs, mainly the wake effect, wind speeds above WTs vary from different locations. According to the Park model, the WTs located upstream with high incoming wind speeds operate in the rated rotor speed. Therefore, during over-frequency events, their mechanical power output cannot be reduced by increasing rotor speeds but can only be controlled by adjusting pitch angles, which makes energy lost in vain. WTs located downstream are affected by the wake effect of WTs located upstream; therefore, they have lower incoming wind speeds. In other words, WTs located downstream operate below the rated rotor speed, so they have certain regulation margins for accelerating rotors. According to the MPPT curve, the more seriously the WT is affected by the wake effect, the greater acceleration potential its rotor has. In response to excessive power generation, WTs downstream can quickly reduce their power output by increasing rotor speeds, and harvest more kinetic energy [18], [30].

So, to relieve the excessive power generation and capture as much wind energy as possible from air, the proposed control scheme in Fig. 2 considers designing an optimal droop gain $K_{p,i}$ for each WT in a wind farm, which takes into account their great variances in potential ability in accelerating rotors during over-frequency support.

To this end, it is crucial to obtain the ideal reduction in power output, which is associated with the optimal rotor speed of each WT within a wind farm, and then droop gain settings K_P are designed according to their ideal power reduction.

III. MODEL DESIGNING

A. Modelling of Optimal Rotor Kinetic Energy for Frequency Support

An optimal rotor kinetic energy model, which considers wind energy utilization in wind farms during frequency sup-

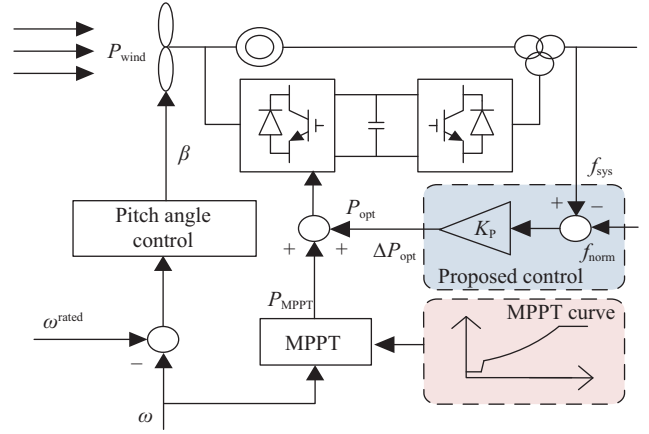


Fig. 2. Simplified active power control of DFIG.

port, is introduced for controller parameter optimization in this section.

Load reduction disturbance often occurs suddenly, resulting in the amount of generation exceeding consumption and the rise of system frequency. Conventional synchronous generators with large capacities participate in frequency regulation, but their response speed is slow. Hence, it is expected that WTs can provide a fast response by increasing rotor speeds over the initial stage of frequency support. From the perspective of energy utilization, wind farms should store as much wind power as rotor kinetic energy while compensating for the imbalance between power supply and load demand.

Objective function: Suppose a wind farm with n same-type WTs, as mentioned, the wind power stored as kinetic energy in rotating masses of WTs is expected to be maximized. Therefore, the objective function can be stated as follows:

$$\max \varphi(\omega_1, \omega_2, \omega_n) = \sum_{i=1}^n \frac{1}{2} J \omega_i^2 \quad (11)$$

where J is WT's moment of inertia, which is a basic parameter of each WT.

Constraint conditions: There are some constraints on the process of optimization. In order to ensure the system frequency will not deviate from normal value significantly, the first is to guarantee power balance. Due to the frequency response speed of conventional generators being slow, WTs are supposed to compensate for the power imbalance at the initial stage of frequency regulation, denoted by $P_{gen} = P_{exp}$. Also worth noting is to make the WT rotor speed within the upper bound, denoted by $\omega_{0,i} \leq \omega_i \leq \omega_{m,i}$. Once the rotor speed exceeds the maximum speed, it will affect the life of the bearings and burn out the coil if there is too much heat.

By combining the objective function and constraints above, the optimal rotor kinetic energy model can be expressed as follows:

$$\max \varphi(\omega_1, \omega_2, \omega_n) = \sum_{i=1}^n \frac{1}{2} J \omega_i^2$$

$$\text{s.t.} \begin{cases} P_{\text{gen},i} = \sum_{l=0}^L \kappa_{l,i} \omega_i^l \\ P_{\text{gen}} = \sum_{i=1}^n P_{\text{gen},i} \\ P_{\text{gen}} = P_{\text{exp}} \\ \omega_{0,i} \leq \omega_i \leq \omega_{m,i} \end{cases} \quad (12)$$

where $P_{\text{gen},i}$ is the active power output of WT*i*, L is the limited degree used to fit with a polynomial form of wind energy utilization coefficient, P_{gen} is the power generation of WF, P_{exp} is the expected power supply of WF after a disturbance, $\omega_{0,i}$ is the initial rotor speed prior to a disturbance, and $\omega_{m,i}$ is the upper rotor speed bound of WT*i*.

B. Distributed Optimization Strategy Designing Under the State-based Potential Game

As mentioned earlier, to fully utilize WT*s*' own potentials in accelerating rotors during an over-frequency response, the designing of droop gains is influenced by optimal rotor speed parameters obtained via optimization. However, modern wind farms usually suffer from a series of varying factors, such as communication challenges, scalability requirements, wake effects, and so on [27]. Thus, the rotor kinetic energy optimization strategy needs to be robust and effective, which ought to allow 'plug and play' for WT*s* and relax the conditions in communication security and reliability.

To that end, a distributed optimization strategy under the framework of a state-based potential game is developed to solve the model [31]–[34] due to its inherent robustness to variations.

Communication topology: We design a piecewise-constant matrix defined below to describe the communication topology in a wind farm.

$$\begin{bmatrix} N_{11} & N_{12} & \cdots & N_{1n} \\ N_{21} & N_{22} & \cdots & N_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ N_{n1} & N_{n2} & \cdots & N_{nn} \end{bmatrix}$$

where $N_{ii}(t) \equiv 1$ for all WT*s* $i \in n$, means that each turbine absolutely has its own information. If $N_{ij}(t) = 1$, the information of i can be successfully sent to j th at time t , otherwise if $N_{ij}(t) = 0$, the information of i cannot be known to j th.

According to a sequentially complete condition [34], there is minimal communication requirement for the wind farm: the cumulative effect on communication topologies during finite consecutive intervals will have at least one global accessibility.

State space: We design a state variable X as an underlying state space, each state $x \in X$ is defined as a tuple

$$x = (\omega, e) \quad (13)$$

where $\omega = (\omega_1, \omega_2, \dots, \omega_n) \in \mathbb{R}^n$ is the profile of WT rotor speeds and $e = \{e_i^k\}_{k \in M, i \in N}$ is the profile of estimation terms. The term e_i^k represents agent i 's estimate for the k th constraint.

Actions: We design a state-dependent action set $\mathcal{A}_i(x)$ for WT*i*, which permits WT*i* to change rotor speed and constraint

estimation through communication with its neighboring WT*s*. Each action $a_i \in \mathcal{A}_i$ is defined as a tuple

$$a_i = (\hat{\omega}_i, \{\hat{e}_i^1, \hat{e}_i^2, \dots, \hat{e}_i^m\}), \quad \hat{e}_i^k = \{\hat{e}_{i \rightarrow j}^k\}_{j \in N_i}$$

where $\hat{\omega}_i$ represents a change in WT*i*'s rotor speed, $\hat{e}_i^k$ represents a change in WT*i*'s estimate of the k th constraint, $\hat{e}_{i \rightarrow j}^k$ represents that WT*i* passes $\hat{e}_i^k$ to WT j .

State dynamics: For simplicity of labeling,

$$\tilde{\omega}_i = \omega_i + \hat{\omega}_i \quad (14)$$

Notably, the state dynamic of estimates is different between linear constraints and nonlinear constraints. However, their state dynamics can be concluded in the same form as follows:

$$\tilde{e}_i = \{e_i^k + \Delta e_i^k(\tilde{\omega}_i) + \hat{e}_{i \leftarrow in}^k - \hat{e}_{i \rightarrow out}^k\}_{k \in M} \quad (15)$$

where M represents the set of total constraints, including both linear constraints and nonlinear constraints. As mentioned, the bound constraints of WT rotor speed are linear constraints, and the power balance constraint in a wind farm is no-linear constraint. $\Delta e_i^k(\tilde{\omega}_i)$ represents the change of WT*i*'s estimate for the k th constraint caused by $\tilde{\omega}_i$.

Agent cost function: We design the cost function of WT*i* as two components relating to the objective function φ and the constraints for every $k \in M$

$$J_i(x, a) = J_i^\varphi(x, a) + \mu J_i^e(x, a) \quad (16)$$

where μ is a positive trade-off parameter, x represents the current state, and a represents the current action profile. For any state $x \in X$ and $a \in \prod_{i \in N} \mathcal{A}_i(x)$

$$\begin{cases} J_i^\varphi(x, a) = \varphi_i(\{\tilde{\omega}_j\}_{j \in N_i}) \\ J_i^e(x, a) = \sum_{j \in N_i} \sum_{k=1}^m [\max(0, \tilde{e}_j^k)]^2 \end{cases} \quad (17)$$

where $\varphi_i(\{\tilde{\omega}_j\}_{j \in N_i})$ is defined as $\varphi_i(\{\tilde{\omega}_j\}_{j \in N_i}) = \frac{1}{2} J \sum_{j \in N_i} \tilde{\omega}_j^2$ to satisfy $\varphi(\omega) - \varphi(\omega') = \varphi_i(\{\omega_j\}_{j \in N_i}) - \varphi_i(\{\omega'_j\}_{j \in N_i})$ [35].

$J_i^\varphi(x, a)$ is the first term of $J_i(x, a)$, which is designed to focus on global optimization. Meanwhile, $J_i^e(x, a)$ is the second term of $J_i(x, a)$, aiming to satisfy the constraints in system, like $\sum_{i \in N} e_i^k(t) \leq 0$. Hence, to consider all kinds of constraints, the equality constraint can be handled by two inequalities in forms of $\sum_{i \in N} e_i^k(t) \leq 0$ and $-\sum_{i \in N} e_i^k(t) \leq 0$.

Now the optimal rotor kinetic energy model is under the framework of a state-based potential game, which is fundamentally different from the conventional distributed optimization. In essence, a good feature of potential games (or state-based potential games) is that almost all learning algorithms ensure convergence to the Nash equilibrium. One of the feasible methods is gradient play, which converges to a stationary state Nash equilibrium in any state-based potential game [18]. At each time $t > 0$, each agent i selects an action $a_i \in \mathcal{A}_i$ according to the gradient play algorithm

$$\begin{cases} \hat{\omega}_i(t) = \left[-\eta \frac{\partial J_i(x(t), a)}{\partial \hat{\omega}_i} \Big|_{a=0} \right]^+ \\ \hat{e}_{i \rightarrow j}^k(t) = -\eta \frac{\partial J_i(x(t), a)}{\partial \hat{e}_{i \rightarrow j}^k} \Big|_{a=0} \end{cases} \quad (18)$$

where $[\cdot]^+$ represents the projection onto the closed convex set $\mathcal{A}_i^+(x(t)) \triangleq \{\hat{\omega}_i : \omega_i(t) + \hat{\omega}_i \in \Omega_i\}$, Ω_i represents the feasible set.

Accordingly, the Nash equilibrium of the game, where the optimal rotor speeds are also the state in the equilibrium point, is the optimal solution to the model in (12). Our proposed method not only can harvest wind power and store as much kinetic energy as possible, but also meets the bound constraints of WT rotor speed and the power balance constraint in the system.

IV. OPTIMAL DROOP GAINS DESIGNING FOR WTs IN A FARM

When some of the loads are shedding in a wind farm unexpectedly, to alleviate the impact of excessive power generation during over-frequency events, WTs are expected to provide frequency support, as well as utilize wind power. Their optimal rotor speeds can be obtained by solving the optimization model formatted in the last section.

In order to reduce power output by fully utilizing WT's own potential in accelerating rotor blades, the ideal power generation for WT i is

$$P_{\text{gen},i} = \sum_{l=0}^L \kappa_{l,i} \omega_{\text{opt},i}^l \quad (19)$$

where $\omega_{\text{opt},i}$ is the optimal rotor speed for WT i .

Then the ideal power reduction reference $\Delta P_{\text{red},i}$ for each WT can be represented as

$$\Delta P_{\text{red},i} = P_{\text{gen},i} - P_{\text{MPPT},i} \quad (20)$$

where $P_{\text{gen},i}$ is the ideal power generation after a disturbance, $P_{\text{MPPT},i}$ is the power output of WT i prior to a disturbance.

Droop gain represents the ability of frequency response. Based on design purposes, WT droop gain $K_{P,i}$ is designed to be proportional to its ideal power reduction reference $\Delta P_{\text{red},i}$ for the sake of simplicity in this paper, which varies from disturbance to disturbance. The optimal droop gain proposed in this paper $K_{P,i}$ (negative) can be expressed as follow,

$$K_{P,i} = \frac{\Delta P_{\text{red},i}}{\Delta f_{\text{max}}} \quad (21)$$

where $K_{P,i}$ is the optimal droop gain for WT i , Δf_{max} is the limits of frequency deviation defined by grid codes (preventing over-response).

The optimal droop control schematic diagram of the wind farm is designed in Fig. 3.

Therefore, the optimal active power reference $P_{\text{opt},i}$ for the rotor side inverter of DFIG i during the frequency response dynamic is

$$P_{\text{opt},i} = P_{\text{mppt},i} + \Delta P_{\text{opt},i} = P_{\text{mppt},i} + K_{P,i} \Delta f \quad (22)$$

where $P_{\text{mppt},i}$ is the active power reference calculated according to the MPPT algorithm, and $\Delta P_{\text{opt},i}$ represents the optimal additional active power control signal of WT i determined by the optimal droop gain $K_{P,i}$.

Due to the combined effect of the primary frequency regulation of the synchronous generators and the participation of

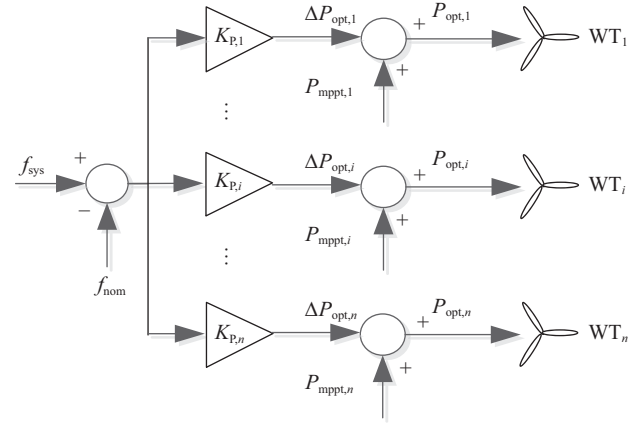


Fig. 3. Optimal droop control for wind farm.

WTs in frequency support, the system frequency decreases and then gradually rises to a new steady-state value. The WTs will not exit frequency modulation until secondary control of the system is completed. With frequency returning to the rated value, the WTs return to the MPP smoothly.

V. CASE STUDIES

A test system is a small-scale wind farm shown in Fig. 4, consisting of 16 DFIGs with each capacity of 2 MW; 4 DFIGs are connected in each feeder, and 4 feeders are connected to the main grid through transformers. SG is a synchronous generator with capacity of 32 MW, and its primary frequency control droop gain is set to 4%; PCC (Point of Common Coupling) is the common connection point between WTs and synchronous generator; P_L is the total loads of system, which is composed of some switchable loads and can be represented by 24 MW + 4 Mvar. More details about experiments in the appendix, Table AI.

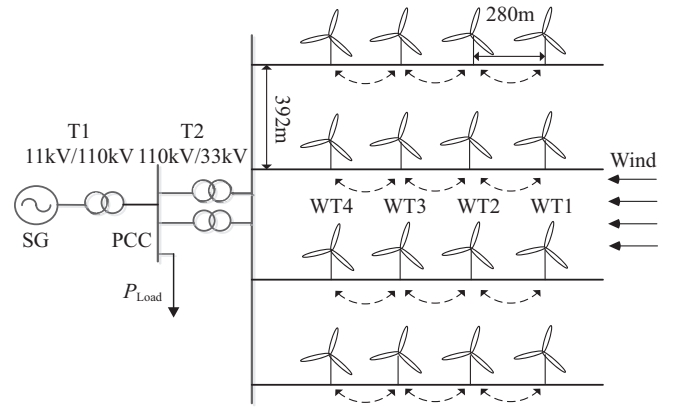


Fig. 4. The test system of a small-scale wind farm.

The spacing of two adjacent turbines in a row is 280 m, and the distance of adjacent rows is 392 m. In addition, the dotted line with a two-way arrow represents the communication topology.

A. Optimal Rotor Speeds of DFIGs Calculation Process on MATLAB

In this part, the optimal rotor speeds of WTs for frequency

support are calculated by using the proposed model mentioned in Section III.

Due to wake interactions between WTs, wind speeds of WT1, WT2, WT3, and WT4 in the same feeder are 14 m/s, 13 m/s, 12 m/s, and 11 m/s respectively. Before load reduction disturbance, the total active power generated by the wind farm was 22.4 MW (0.7 p.u.), which is reasonable to enable WTs to contribute to frequency regulation.

Some loads are cut off at time $t = 60$ s to provide over-frequency support, and the ideal active power output reduction of the wind farm is set at 1.28 MW (0.04 p.u.).

Figure 5 demonstrates the calculation process of optimal rotor speeds on MATLAB. According to the distributed optimization strategy proposed in this paper, though there is only limited communication information for each turbine, the optimal rotor speeds can still be calculated in several iterations [the optimization part can be readily solved in 0.2156s based on Dell Inspiron 13-7000 with Intel(R) Core (TM) i5-7200U CPU(R) @ 2.50 GHz]. Then the ideal power reduction for each WT within the wind farm is obtained based on their potential for accelerating rotors, as listed in Table I.

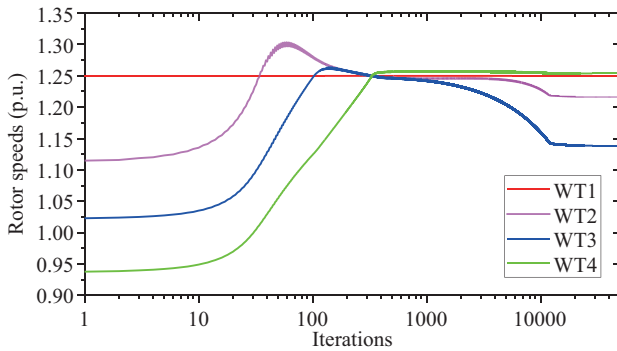


Fig. 5. Calculation process of optimal rotor speeds for four DFIGs in a row.

TABLE I
IDEAL POWER REDUCTION OF WTs

Parameters	WT1	WT2	WT3	WT4
Initial speed (p.u.)	1.2500	1.1112	1.0220	0.9369
Optimal speed (p.u.)	1.2500	1.2168	1.1388	1.2537
Power reduction (MW)	0	0.0627	0.0693	0.1880

Figure 6 shows the total kinetic energy(p.u.) stored in rotating rotors under the proposed control and traditional control [1]. Obviously, our proposed control is superior to storing kinetic energy. These energies can be released rapidly if an overload event occurs subsequently.

B. Frequency Response Dynamic of DFIGs on Digsilent

In this part, the frequency response dynamics of the wind farm are simulated based on DIgSILENT. In Fig. 7, compared to a situation without DFIGs participating in frequency regulation, the frequency peak indicator significantly decreases under droop control.

Due to the same droop gains adopted in a traditional scheme, the additional active power control signal is equal to WT1, WT2, WT3, and WT4. Before the load disturbance,

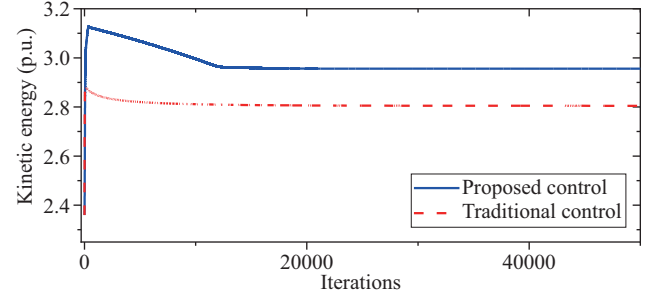


Fig. 6. The calculation process of kinetic energy storage for WTs.

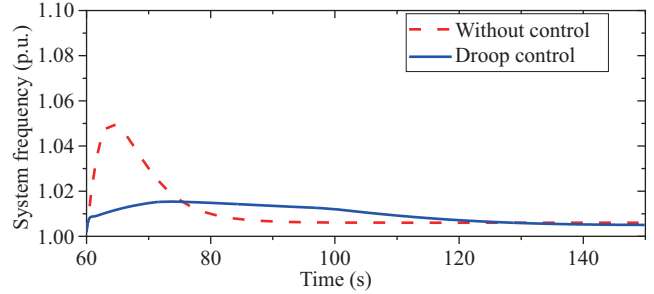


Fig. 7. Frequency response dynamics in the system.

WT1 operates on the rated rotor speed; therefore, it cannot provide over-frequency support by storing rotor kinetic energy, which forces WT1 to adjust its pitch angle under the condition that all of the other WTs still have the margin of rotor speed promotion. In our proposed control, the optimal droop gains for WTs are designed to be proportional to their ideal power reduction. Therefore, to minimize the activation of blade pitching, WT4 takes the most responsibility to increase its rotor speed and reduce power output.

To observe the difference in the over-frequency response dynamic process of WT rotor speed between traditional and proposed control, conclusions are drawn based on simulation results. Figs. 8(a)–(d) show the rotor speed of each WT after load disturbance. The lines with solid triangles represent the results of traditional control, and the lines with hollow circles represent the results of proposed control. From Fig. 8(a), the rotor speed of WT1 keeps at 1.25 (p.u.) by using the proposed droop control for the wind farms, rather than exceeding the maximum rotation value. From Fig. 8(d), the rotor speed of WT4 rises around 1.25 (p.u.) by using the proposed control. Due to the more significant additional active power control signal than the other WTs, WT4 fully utilizes its great potential in increasing rotor speed to help the wind farm reduce active power output for frequency regulation.

Compared with traditional control, the proposed method avoids activation of WT1 pitch angle control system, as shown in Fig. 8(e). Response of pitch angle control is slow, and frequent blade pitching will increase mechanical stress and fatigue. Under the same wind conditions and tip speed ratio, the higher the pitch angle, the lower the wind energy capture efficiency. After the load disturbance, the pitch angle of WT1 under traditional control still stays around $2.05(^{\circ})$. Therefore, WT1 sacrifices the ability of the wind farm to capture wind

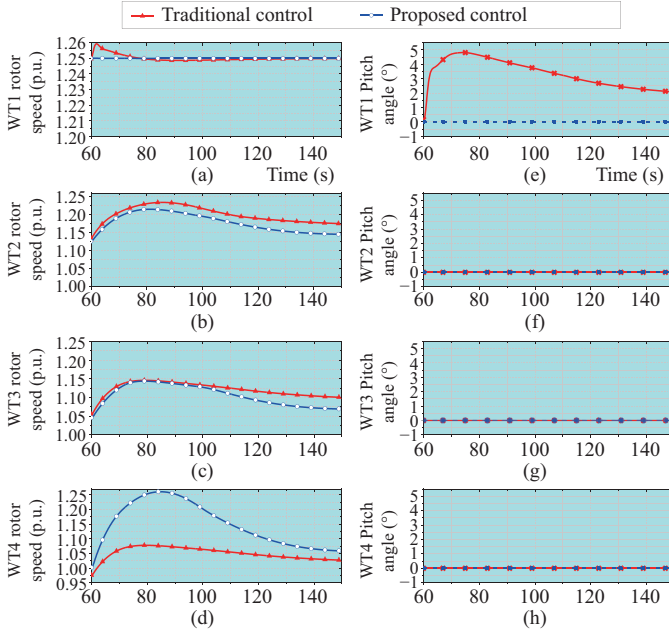


Fig. 8. The dynamic process of the WT rotor speed and pitch angle. (a) Rotor speed of WT1. (b) Rotor speed of WT2. (c) Rotor speed of WT3. (d) Rotor speed of WT4. (e) Pitch angle of WT1. (f) Pitch angle of WT2. (g) Pitch angle of WT3. (h) Pitch angle of WT4.

power. From the perspective of energy conservation, the traditional scheme is not optimal because of yielding wind energy loss. The shadow area A_1 in Fig. 9 represents more wind power captured by the proposed control than traditional control in the 60 s to 150 s. To sum up, under the optimal droop control proposed, the WTs in wind farms contribute to frequency support in a more energy-efficient way.

C. Proposed Optimal Droop Control Under Variable Wind Speed

Figure 10(a) describes the variable wind speed of front row WT1, of which the average value is 14 m/s, and the standard deviation is 0.5 m/s. Fig. 10(b) shows that, in the case of random wind speed, the proposed control can still bring downstream WT4's superiority of frequency support into full play. Therefore, as shown in Fig. 10(c), the upstream WT1 does not have to activate the pitch angle control system continually during the frequency regulation process, which verifies the effectiveness of our proposed control under variable wind speed.

VI. CONCLUSION

To deal with the over-frequency events, optimal droop control is proposed for DFIG-based wind farms, enabling the wind farm to provide frequency support and capture as much wind power as possible. Under the proposed control, upstream WTs avoid activating pitch angle control systems continually during the frequency regulation process, and downstream WTs bring their superiorities of accelerating rotors into full play. Simulation results indicate the proposed control is effective, whether under constant or random wind speeds. Therefore, the DFIGs in a wind farm with unreliable communication participate in frequency regulation more energy-efficiently.

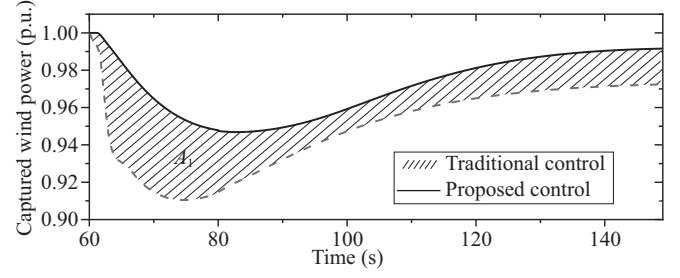


Fig. 9. The dynamic process of captured wind power for WTs.

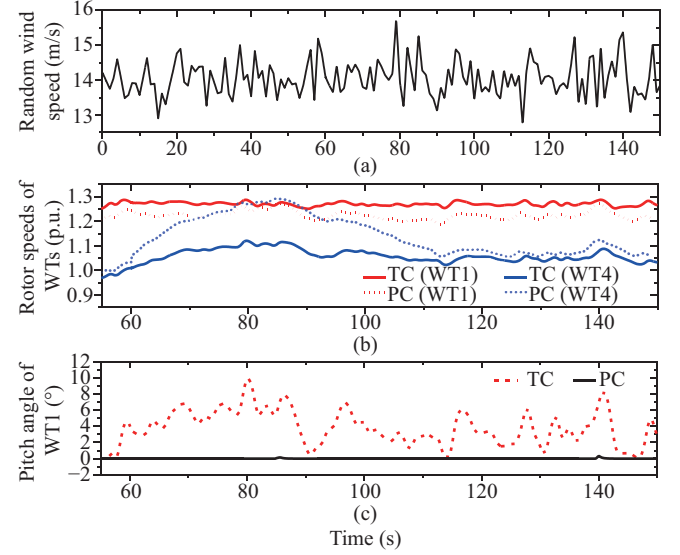


Fig. 10. Rotor speeds and pitch-angle under variable wind speeds. (a) Random wind speed for WT1. (b) Rotor speeds of WT1 and WT4. (c) Dynamic process of WT1 pitch-angle.

APPENDIX

TABLE AI
MAIN PARAMETERS

Item of DFIGs	Value	Item of SG	Value
Rated power	2 MW	Rated power	32 MW
Rated voltage	690 V	Terminal voltage	11 kV
Rated rotor speed	1.25 p.u.	Inertia constant	4 s
Inertia constant	1.55 s	Droop gain	4%
Friction coefficient	0.01 p.u.	Governor time constant	8.4 s
Rotor resistance	0.0005 p.u.	Exciter regulator gain	400
Stator resistance	0.00706 p.u.	Exciter time constant	0.01 s

REFERENCES

- [1] G. Mu, F. Z. Wu, X. P. Zhang, Z. H. Fu and B. Xiao, "Analytic Mechanism for the Cumulative Effect of Wind Power Fluctuations from Single Wind Farm to Wind Farm Cluster," *CSEE Journal of Power and Energy Systems*, vol. 8, no. 5, pp. 1290–1301, Sep. 2022.
- [2] M. Arshad, "Global status of wind power generation: theory, practice, and challenges," *International Journal of Green Energy*, vol. 16, no. 14, pp. 1073–1090, Apr. 2019.
- [3] S. Wang, J. B. Hu, X. M. Yuan, and L. Sun, "On inertial dynamics of virtual-synchronous-controlled DFIG-based wind turbines," *IEEE Transactions on Energy Conversion*, vol. 30, no. 4, pp. 1691–1702, Dec. 2015.
- [4] T. Petru and T. Thiringer, "Modeling of wind turbines for power system studies," *IEEE Transactions on Power Systems*, vol. 17, no. 4, pp. 1132–1139, Nov. 2002.
- [5] J. R. Marden, S. D. Ruben, and L. Y. Pao, "A model-free approach to

- wind farm control using game theoretic methods," *IEEE Transactions on Control Systems Technology*, vol. 21, no. 4, pp. 1207–1214, Jul. 2013.
- [6] L. S. Xiong, X. K. Liu, D. H. Zhang, and Y. H. Liu, "Rapid power compensation-based frequency response strategy for low-inertia power systems," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 9, no. 4, pp. 4500–4513, Aug. 2021, doi: 10.1109/JESTPE.2020.3032063.
 - [7] H. Z. Liu and Z. Chen, "Contribution of VSC-HVDC to frequency regulation of power systems with offshore wind generation," *IEEE Transactions on Energy Conversion*, vol. 30, no. 3, pp. 918–926, Sep. 2015.
 - [8] J. Lee, E. Muljadi, P. Srensen, and Y. C. Kang, "Releasable kinetic energy-based inertial control of a DFIG wind power plant," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 1, pp. 279–288, Jan. 2016.
 - [9] Y. J. Li, Z. Xu, J. L. Zhang, and K. P. Wong, "Variable gain control scheme of DFIG-based wind farm for over-frequency support," *Renewable Energy*, vol. 120, pp. 379–391, May 2018.
 - [10] T. C. Liu, W. X. Pan, R. Quan, and M. Y. Liu, "A variable droop frequency control strategy for wind farms that considers optimal rotor kinetic energy," *IEEE Access*, vol. 7, pp. 68636–68645, May 2019.
 - [11] Z. Zheng, G. Yang, and H. Geng, "Short circuit current analysis for DFIG-based wind generation system with Crowbar protection under grid faults," *Electric Power Automation Equipment*, vol. 32, no. 11, pp. 7–15, Nov. 2012.
 - [12] T. X. Wang, L. Ding, S. Y. Yin, J. P. Jiang, F. M. Cheng, and J. C. Si, "A NEW control strategy of DFIG-based wind farms for power system frequency regulation," in *Proceedings of 2015 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, 2015, pp. 1–5.
 - [13] B. H. Chowdhury and H. T. Ma, "Frequency regulation with wind power plants," in *Proceedings of 2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century*, 2008, pp. 1–5.
 - [14] H. J. Lao, L. Zhang, T. Zhao and L. Zou, "Innovated Inertia Control of DFIG with Dynamic Rotor Speed Recovery," *CSEE Journal of Power and Energy Systems*, vol. 8, no. 5, pp. 1417–1427, Sep. 2022.
 - [15] Y. Wang, Y. H. Meng, X. Y. Zhang, and L. Xu, "Control of PMSG-based wind turbines for system inertial response and power oscillation damping," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 2, pp. 565–574, Apr. 2015.
 - [16] Y. C. Xue and N. L. Tai, "Review of contribution to frequency control through variable speed wind turbine," *Renewable Energy*, vol. 36, no. 6, pp. 1671–1677, Jun. 2011.
 - [17] J. M. Mauricio, A. Marano, A. Gomez-Exposito, and J. L. M. Ramos, "Frequency regulation contribution through variable-speed wind energy conversion systems," *IEEE Transactions on Power Systems*, vol. 24, no. 1, pp. 173–180, Feb. 2009.
 - [18] Y. J. Li, Z. Xu, and K. Meng, "Optimal power sharing control of wind turbines," *IEEE Transactions on Power Systems*, vol. 32, no. 1, pp. 824–825, Jan. 2017.
 - [19] H. Ye, W. Pei, and Z. P. Qi, "Analytical modeling of inertial and droop responses from a wind farm for short-term frequency regulation in power systems," *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 3414–3423, Sep. 2016.
 - [20] L. Rutledge and D. Flynn, "Emulated inertial response from wind turbines: gain scheduling and resource coordination," *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 3747–3755, Sep. 2016.
 - [21] H. M. Li, X. Y. Zhang, Y. Wang, and X. R. Zhu, "Virtual inertia control of DFIG-based wind turbines based on the optimal power tracking," *Proceedings of the CSEE*, vol. 32, no. 7, pp. 32–39, Mar. 2012.
 - [22] Y. J. Li, Z. Xu, and K. P. Wong, "Advanced control strategies of PMSG-based wind turbines for system inertia support," *IEEE Transactions on Power Systems*, vol. 32, no. 4, pp. 3027–3037, Jul. 2017.
 - [23] Z. Zheng, Z. Y. Yang, and W. H. Li, "Analysis and comparison of primary frequency control technology for wind power and thermal power unit," *Electric Power Automation Equipment*, vol. 37, no. 12, pp. 92–101, Dec. 2017.
 - [24] L. Ding, S. Y. Yin, T. X. Wang, and J. L. Liu, "Active rotor speed protection strategy for DFIG-based wind turbines with inertia control," *Automation of Electric Power Systems*, vol. 39, no. 24, pp. 29–34, Dec. 2015.
 - [25] L. R. Chang-Chien, W. T. Lin, and Y. C. Yin, "Enhancing frequency response control by DFIGs in the high wind penetrated power systems," *IEEE Transactions on Power Systems*, vol. 26, no. 2, pp. 710–718, May 2011.
 - [26] K. V. Vidyandandan and N. Senroy, "Primary frequency regulation by deloaded wind turbines using variable droop," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 837–846, May 2013.
 - [27] J. Park, S. Kwon, and K. H. Law, "Wind farm power maximization based on a cooperative static game approach," *Proceedings of SPIE 8688, Active and Passive Smart Structures and Integrated Systems 2013*, 2013, pp. 86880R.
 - [28] A. Mehrizi-Sani, "Distributed control techniques in microgrids," in *Microgrid*, M. S. Mahmoud, ed. Oxford: Butterworth-Heinemann, 2017, pp. 43–62.
 - [29] Q. H. Wu, A. Bose, C. Singh, J. H. Chow, G. Mu, Y. Z. Sun, Z. X. Liu, Z. G. Li, and Y. Liu, "Control and Stability of Large-scale Power System with Highly Distributed Renewable Energy Generation: Viewpoints from Six Aspects," *CSEE Journal of Power and Energy Systems*, vol. 9, no. 1, pp. 8–14, Jan. 2023.
 - [30] J. L. Zhang, Y. J. Li, Z. Xu, D. L. Qi, and C. Y. Li, "Game theory-based optimal deloading control of wind turbines under scalable structures of wind farm," *IET Cyber-Physical Systems: Theory & Applications*, vol. 3, no. 4, pp. 224–231, Dec. 2018.
 - [31] N. Li and J. R. Marden, "Decoupling coupled constraints through utility design," *IEEE Transactions on Automatic Control*, vol. 59, no. 8, pp. 2289–2294, Aug. 2014.
 - [32] N. Li and J. R. Marden, "Design games for distributed optimization," in *Proceedings of the 50th IEEE Conference on Decision and Control*, 2011.
 - [33] N. Li and J. R. Marden, "Designing games for distributed optimization with a time varying communication graph," in *Proceedings of the 51st IEEE Conference on Decision and Control*, 2012, pp. 7764–7769.
 - [34] Z. H. Qu, *Cooperative Control of Dynamical Systems: Applications to Autonomous Vehicles*. London: Springer, 2009.
 - [35] D. Monderer and L. S. Shapley, "Potential games," *Games and Economic Behavior*, vol. 14, no. 1, pp. 124–143, May 1996.



Yaxin Wang received her Ph.D. degree in Electrical Engineering from Zhejiang University, Hangzhou, China, in 2024. Now she works in China Electric Power Research Institute. Her research interests include voltage and frequency optimization control in smart grids, and game theory-based distributed optimization with applications to power systems.



nomics, and the Journal

Donglian Qi received a Ph.D. degree in Control Theory and Control Engineering from Zhejiang University, Hangzhou, China, in March 2002. Since then, she has been with the College of Electrical Engineering, Zhejiang University, where she is currently a Professor. Her current research interests include the basic theory and application of cyber-physical power systems (CPPS), digital image processing, artificial intelligence, and electric operation and maintenance robots. She is an Editor for the Clean Energy, the IET Energy Conversion and Economics, and the Journal of Robotics, Networking and Artificial Life.



Jianliang Zhang received his Ph.D. degree in Control Theory and Control Engineering at Zhejiang University, Hangzhou, China, in June 2014. Since then, he has been working with College of Electrical Engineering, Zhejiang University (ZJU). He was a visiting scholar at The Hong Kong Polytechnic University (PolyU) (2016–2017). His current research interests include distributed optimization, with applications to energy/power systems, and cyber-physical security with applications in smart grids, etc.



cyber-physical security with application in smart grids.

Yulin Chen received the B.S. degree in Mathematics and Applied Mathematics and the M.S. degree in Electrical Engineering from Northeast Electric Power University, Jilin, China, in 2014 and 2017, respectively. He received a Ph.D. degree from the College of Electrical Engineering, Zhejiang University, Hangzhou, China, in 2021. Now, he is a Post-doctoral Fellow at the State Key Laboratory of Internet of Things for Smart City, University of Macau, Macau, China. His current research interests include distributed control of renewable energy and