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Online Assessment of Frequency Support Capability of the DFIG-Based Wind Farm Using a Knowledge and Data-Driven Fusion Koopman Method

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Abstract

The increasing integration of renewable energy in power systems causes a decrease in the frequency stability of the system. Consequently, renewable energy stations, such as wind farms (WFs), must possess adequate frequency support capabilities. To maximize the frequency support capability of the WF, it is crucial to determine the frequency support capability boundaries (FSCB) of the WF. Due to the uneven distribution of wind resources and complex operating states of wind turbines, accurate evaluation of the FSCB of the WF is challenging. To address this issue, this paper proposes a knowledge and data-driven fusion Koopman method to assess the FSCB of the doubly fed induction generator (DFIG)-based WF. The characteristics of FSCB are analyzed and a multi-dimensional indicator system is defined to precisely quantify FSCB at both theoretical and practical levels. To accurately calculate the defined indicators, a knowledge and data-driven fusion method based on Koopman-mixed integer linear programming (MILP) is proposed. The knowledge of WF frequency regulation structures is integrated to construct Koopman dictionary functions. This allows the training of historical frequency regulation data to obtain the global linearized Koopman operator for the assessment object. Subsequently, it facilitates online assessment results using real-time data. Case studies are undertaken on the four-machine two-area power system including a DFIG-based WF. Simulation results validate the rationality of the proposed indicators, the accuracy of the assessment method, and the practicality of the assessment outcomes under various operating conditions.

Keywords: Wind farm, frequency support capability, indicator system, knowledge fusion, data-driven, Koopman method

1. Introduction

In response to the challenges posed by climate change and energy security, numerous nations are actively substituting traditional fossil fuels with renewable energy[1]. Consequently, there has been a significant increase in renewable energy integration, particularly wind power in the past decade[2]. For instance, Chinese policy mandates that by around 2060, wind energy will represent 30% of the nation's total electricity demand[3]. However, wind farms (WFs) and other renewable energy stations are connected to the grid through power electronic devices, which decouples their inertia characteristics from the grid[4]. Additionally, with the increasing scale of high voltage direct current (HVDC) transmission and the rise of new types of loads such as electric vehicle charging, the proportion of power electronic devices is growing[5, 6]. This results in the low inertia and low damping characteristics of the grid, significantly affecting its frequency stability[7, 8]. Therefore, to ensure system frequency security, it is essential for renewable energy stations such as WFs to have frequency support capabilities[9, 10].

The doubly fed induction generator (DFIG) is one of the most common types of wind turbines (WTs)[11]. To enable the DFIG-based WF to have frequency support capabilities, extensive research has been conducted on active

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frequency regulation control such as deloading control[11–13] and rotor kinetic energy control[9, 14, 15]. Nevertheless, the frequency support capability has not been fully utilized in these studies. This may lead to further frequency drops due to insufficient capabilities, or wasted capabilities from an excess of power resources[16–18]. Therefore, it is crucial to evaluate the frequency support capability boundaries (FSCB) of the WF to allocate and dispatch the regulating power of each plant appropriately[19]. Unlike synchronous machines, the FSCB of DFIG-based WF is influenced by wind resources and their operational conditions[13, 20]. This makes accurate quantification and estimation challenging.

To reasonably quantify the FSCB, Ref.[21] defines the frequency regulation capability coefficient of WTs based on rotor speed and converter capacity limiting factors. Ref.[22] calculates the steady-state equivalent droop coefficient expression of a WF based on a small disturbance model. Ref.[23] computes the time-varying theoretical true values of the equivalent droop and inertia coefficients of the WF. These indicators are only suitable for internal power distribution within a WF, as the active power is not accurately calculated and the indicators are indirectly related to FSCB. To address this issue, Ref.[24] calculates the boundary value of transient additional power under safety operation constraints in a WF. Ref.[25] further divides the indicators into two energy forms: rotational kinetic energy (RKE) and deloading reserve power (DRP). These studies provide a more reasonable evaluation of FSCB, and their indicators are also applicable to power dispatch at the system level. However, they do not consider the characteristics of the FSCB at both theoretical and practical potential levels, resulting in relatively idealized evaluation results.

To accurately evaluate the FSCB, Refs.[21–25] establish simplified models for WF frequency regulation. Based on knowledge models, these studies derive analytical expressions for FSCB or calculate numerical solutions using methods such as nonlinear programming. However, the evaluation accuracy of knowledge-driven methods is limited by the accuracy and complexity of the knowledge models. The above references primarily focus on single WT or WF equivalent to an aggregated WT, considering average wind speed models. When employing a more precise but complex wake effect wind speed model, the operating states of individual WT within the WF vary significantly. This results in extremely complicated analytical expressions or a substantial increase in the number of programming equations, making it difficult to quickly and accurately solve the results. Refs.[26–29] use data-driven methods, such as artificial neural networks, genetic algorithms, graph neural networks, and Bayesian reinforcement learning to evaluate power output and flow field prediction of the WF. However, these methods lack the incorporation of domain knowledge, making it difficult to reflect internal system relationships, and the interpretability of the results remains questionable. In the actual operation of WF, it is challenging to collect frequency regulation data under extreme scenarios, thus making it difficult to ensure the accuracy of training results across a global scope. The low interpretability and high difficulty in data acquisition highlight a significant limitation in the application of purely data-driven approaches for assessing the FSCB of the WF.

The concept of the Koopman operator was first introduced in [30], and the extended dynamic mode decomposition (EDMD) algorithm was later proposed in [31]. It broadened the application scenarios of the Koopman operator. Ref.[32] utilizes the Koopman operator to assess the boundary droop coefficient of the WF. However, it does not incorporate domain knowledge, using only universal functions as Koopman dictionary functions, which results in suboptimal fitting accuracy. Ref.[33] uses Koopman operator to enable model predictive control (MPC) of the WF. Limited knowledge is integrated into the construction of Koopman dictionary functions, making it suitable only for short-term predictions of rotor speed. However, if this method is applied to the FSCB evaluation, the errors will be exceptionally large.

To address the above issues, this paper first studies the characteristics of FSCB. Then, an assessment indicator system is defined based on multi-energy forms such as RKE and DRP, and multi-assessment levels such as theoretical and practical levels. Compared to existing references, the defined indicators are more widely applicable, suitable for both power distribution within a station and power dispatch between stations. To calculate these indicators accurately, an online data-driven Koopman-MILP assessment method integrated with the physical knowledge is proposed. This method offers higher precision without relying heavily on accuracy of the physical model knowledge. And it is applicable to evaluating the WF considering wake effects, rather than the WF equivalent to an aggregated WT. Dictionary functions based on the knowledge of WF frequency support structure provide more interpretable outcomes and enhance safety by not requiring extreme condition data. Finally, case studies are conducted on the four-machine two-area power system including a DFIG-based WF using the proposed indicator system and methods. Simulation results show that the proposed method evaluates the FSCB of the WF adequately and effectively. Overall, in the context of a high penetration of renewable energy sources, this paper addresses the reasonable estimation and utilization

of the FSCB of the DFIG-based WF. The main contributions are listed as follows:

- A multi-dimensional indicator system is defined to measure the FSCB of DFIG-based WF specifically, providing comprehensive and thorough quantitative assessment. It is achieved by considering multiple energy forms such as RKE and DRP, at both theoretical and practical levels. These indicators provide significant guidance for single-unit frequency regulation control, station-level power distribution, and system-level power dispatch.
- A knowledge and data-driven fusion method based on Koopman-MILP is proposed to calculate the defined indicators. Unlike traditional nonlinear methods, it is unaffected by model accuracy and reduces solving time from several seconds to a few hundred milliseconds. This method fully exploits the frequency support capability while ensuring safe operation.
- A Koopman dictionary function form incorporating the knowledge of DFIG-based WF frequency regulation structures is proposed to further improve the assessment accuracy. Compared to universal functions without integrated knowledge, it enhances the fitting accuracy by nearly an order of magnitude. It also significantly reduces computational complexity and enhances the interpretability of data-driven training results.
- The WF considering wake effects is analyzed and evaluated. Compared to the WF equivalent to an aggregated WT, the mutual influences among the WTs within the WF are more accurately reflected, providing more reliable and precise assessment results.

The rest of the paper is organized as follows. Section 2 studies the characteristics of FSCB and defines a multi-dimensional indicator system based on these characteristics. Section 3 proposes the online Koopman-MILP assessment method. Section 4 evaluates the FSCB of a DFIG-based WF under various operating conditions, demonstrating the rationality and applicability of the proposed assessment method. Section 5 discusses potential application scenarios of the proposed assessment indicators and methods. Section 6 summarizes the conclusions.

2. Definition and analysis of quantitative indicator system for FSCB of the DFIG-based WF

2.1. Theoretical potential value indicators

When an active power disturbance occurs in the power system, the WF adjusts its active power to provide frequency support. The active power response of the WT can be divided into two components based on energy sources: the RKE stored in the rotor and the DRP stored in wind energy, as shown in Fig.1. Specifically, the RKE component mainly contributes to the short-term inertia response stage immediately after the disturbance, providing short-term support. In contrast, the DRP component primarily acts during the primary frequency regulation (PFR) stage, providing long-term support. Therefore, it is essential to quantify and assess FSCB from a multi-time scale and multi-energy form perspective.

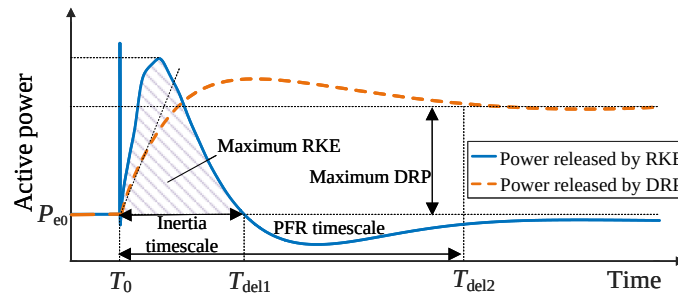


Figure 1: Active power response of the WT

2.1.1. Available RKE on the inertial time scale

The RKE stored in the rotor plays a crucial role in the early stages of frequency support, providing inertia support and initial PFR[9, 14]. However, this part of FSCB is limited. The RKE that DFIG WTs can release is mainly constrained by the minimum rotor speed. If the rotor speed drops below the safe speed range, the WT will exit frequency regulation. This can lead to secondary frequency drops and other incidents[34].

The theoretical potential value of RKE released by a single DFIG WT can be calculated using Eq.(1):

$$\Delta E_{k,T} = \frac{1}{2}J \cdot \omega_{r,0}^2 - \frac{1}{2}J \cdot \omega_{r,\min,set}^2 \quad (1)$$

where, J represents the mechanical rotational inertia of the WT. $\omega_{r,0}$ denotes the initial rotor speed of the turbine prior to frequency support. $\omega_{r,\min,set}$ signifies the set lower limit of safe rotor speed, typically taken as 0.7 p.u.[35].

The theoretical potential value of RKE in the DFIG-based WF can be calculated using Eq.(2):

$$\Delta E_{k,T} = \frac{\sum_{i=1}^l S_i \Delta E_{k,i,T}}{\sum_{i=1}^l S_i} \quad (2)$$

where, S_i is the capacity of the i -th WT. $\Delta E_{k,i,T}$ represents the releasable RKE of the i -th WT. l is the number of WTs in the WF.

2.1.2. DRP at PFR time scale

Within the PFR time scale, the DRP stored in wind energy plays a significant role in frequency support. Overspeed deloading and pitch angle control are typical reserve power schemes for DFIG WTs. However, pitch angle control can cause mechanical wear due to repeated operation, affecting the normal functioning of WTs[9]. Therefore, this paper primarily considers the overspeed deloading scheme.

Unlike the rapid response of the RKE component, the DRP component responds more slowly. This slower response is due to its dependence on rotor speed, constrained by mechanical limitations. Generally, DRP takes tens of seconds to increase from the initial to the steady-state value[11]. Within the PFR time scale, just using steady-state extra power generation as an indicator cannot fully measure the release potential of DRP. Given the slower response of the DRP component, this paper defines the average additional power generated within the PFR time scale as the DRP assessment indicator.

The mechanical power P_m captured by the WT can be expressed as[36]:

$$\begin{cases} P_m = \frac{1}{2}\rho C_p(\lambda, \beta)\pi R^2 V_w^3 \\ C_p(\lambda, \beta) = 0.22 \left(\frac{116}{\lambda_i} - 0.4\beta - 5 \right) e^{\frac{-12.5}{\lambda_i}} \\ \frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \end{cases} \quad (3)$$

where, $\lambda = \omega_r R / V_w$ represents the tip speed ratio. β represents the pitch angle. ω_r represents the rotor speed. R represents the blade radius. V_w represents the wind speed. ρ represents the air density. C_p represents the wind energy utilization coefficient. λ_i is an intermediate variable. By performing a Taylor series expansion of C_p at the steady-state operating point and ignoring higher-order terms, it can be expressed as a second-order polynomial:

$$C_p(\lambda, \beta) = c_2 \lambda^2 + c_1 \lambda + c_0 \quad (4)$$

Given that $c_2 = -0.0101$, $c_1 = -0.0042\beta + 0.2077$, and $c_0 = 0.0243\beta - 0.6140$ are linear functions of β , Eq.(3) can be rewritten as follows:

$$P_m = \frac{1}{2}\pi\rho R^2 (c_0 V_w^3 + c_1 R V_w^2 \omega_r + c_2 R^2 V_w \omega_r^2) \quad (5)$$

The operating point where a WT achieves maximum power output is called the maximum power point (MPP). As wind speed changes, the rotor speed for maximum power output also changes, forming the MPP operating curve. The power peak P_{mpp} is obtained at the apex of this curve.

$$P_{\text{mpp}} = \frac{1}{2} \pi \rho R^2 \left(c_0 - \frac{c_1^2}{4c_2} \right) V_w^3 = k_{\text{opt}} V_w^3 \quad (6)$$

where, k_{opt} is the fitting coefficient of the MPP curve.

When the WT uses an overspeed deloading strategy, its operating point is fixed on a predefined deloading curve. The relationship between the initial deloading output power $P_{\text{m},0}$ and the MPP output power P_{mpp} is as follows:

$$P_{\text{m},0} = (1 - k_{\text{del}}) P_{\text{mpp}} \quad (7)$$

where, k_{del} is the derating coefficient of the WT, generally set as a percentage.

Therefore, the theoretical potential value of the steady-state DRP increase is the difference between the MPP output power and the deloaded operating point output power:

$$\Delta P_{\text{m},T} = P_{\text{mpp}} - P_{\text{m},0} \quad (8)$$

Building on Eq.(8), the expression for C_p is further simplified to calculate the maximum response speed of DRP:

$$\begin{cases} P_{\text{m}}(t) \approx k_1 \omega_r(t) + b_1 \\ T_{\text{m}}(t) = \frac{P_{\text{m}}(t)}{\omega_r(t)} \approx k_2 \omega_r(t) + b_2 \end{cases} \quad (9)$$

where, k_1 , b_1 , k_2 , and b_2 are the coefficients of the linear and constant terms from the Taylor expansion of the mechanical power P_{m} and mechanical torque T_{m} .

Load constraints limit the rapid response of DRP. Based on different time scales, load constraints are categorized into instantaneous extreme load constraints and long-term fatigue load constraints[37]. Variations in electromagnetic torque are a significant cause of load fluctuations. Research shows that limiting electromagnetic torque within a range prevents the load from exceeding its limits[38]. According to the rotor motion equation:

$$\left. \frac{d\omega_r(t)}{dt} \right|_{\text{max}} = \frac{T_{\text{m}}(t) - T_{\text{e,max,set}}}{J} \quad (10)$$

where, $T_{\text{e,max,set}}$ signifies the set higher limit of electromagnetic torque, typically set as 1.2 p.u..

When the WT applies the maximum torque, its DRP response speed is fastest. According to Eq.(9) and Eq.(10), the following is obtained:

$$P_{\text{m}}(t) = b_2 e^{\frac{k_2 t}{J}} + \left(\frac{k_1}{k_2} (T_{\text{e,max,set}} - b_2) + P_{\text{m},0} \right) \quad (11)$$

Thus, the time t_{m} required for the WT to reach the MPP at maximum speed is:

$$t_{\text{m}} = \frac{J}{k_2} \ln \left(\frac{P_{\text{mpp}} - P_{\text{m},0}}{b_2} - \frac{k_1}{b_2 k_2} (T_{\text{e,max,set}} - b_2) \right) \quad (12)$$

Combining Eq.(9) to Eq.(12), considering that the DRP of the WT is released at the maximum response speed and remains constant after reaching the MPP, the average power increase within the PFR time scale is:

$$\begin{aligned} \overline{\Delta P_{\text{m},T}} &= \frac{\int_0^{t_{\text{m}}} (P_{\text{m}}(t) - P_{\text{m},0}) dt + \int_{t_{\text{m}}}^{T_{\text{del}2}} (P_{\text{mpp}} - P_{\text{m},0}) dt}{T_{\text{del}2}} \\ &= (P_{\text{mpp}} - P_{\text{m},0}) \alpha \end{aligned} \quad (13)$$

where, $T_{\text{del}2}$ represents the PFR time scale, typically 30 seconds[12]. α is a correction factor based on the steady-state difference of DRP. It is calculated using:

$$\alpha = \frac{\frac{b_2 J}{k_2} e^{\frac{k_2 t_{\text{m}}}{J}} + \frac{k_1 t_{\text{m}}}{k_2} (T_{\text{e,max,set}} - b_2) + (P_{\text{mpp}} - P_{\text{m},0})(T_{\text{del}2} - t_{\text{m}})}{(P_{\text{mpp}} - P_{\text{m},0}) T_{\text{del}2}} \quad (14)$$

Eq.(13) and Eq.(14) can serve as theoretical potential value indicators for the DRP component of the FSCB to a single DFIG WT on the PFR time scale. Similarly, the theoretical potential DRP of a DFIG-based WF can be calculated using a capacity-weighted sum.

$$\overline{\Delta P_{m,T}} = \frac{\sum_{i=1}^l S_i \overline{\Delta P_{m,i,T}}}{\sum_{i=1}^l S_i} \quad (15)$$

2.2. Practical potential value indicators

In subsection 2.1, the theoretical potential of the FSCB of the DFIG-based WF is calculated under ideal conditions. This includes the maximum available RKE at the inertia time scale and the maximum average increase of DRP at the PFR time scale. However, during actual frequency support, the performance of FSCB of the DFIG-based WF is further constrained by safety operational limits under specific frequency regulation schemes. These constraints prevent FSCB from reaching its theoretical potential. This section explores the practical potential of FSCB under specific frequency regulation schemes.

2.2.1. Safety operational constraints of DFIG WTs

In operations of WT, rotor speed, extreme load limits, and the capacity of the rotor-side converter are major constraints limiting the exploitation of FSCB. These constraints are referred to as Constraint 1, Constraint 2, and Constraint 3.

Constraint 1: rotor speed limit constraint

$$\omega_{r,\min,\text{set}} \leq \omega_r \leq \omega_{r,\max,\text{set}} \quad (16)$$

where, $\omega_{r,\min,\text{set}}$ is the set safety lower limit of rotor speed, typically taken as 0.7 p.u.. $\omega_{r,\max,\text{set}}$ is the set safety upper limit of rotor speed, generally taken as 1.2 p.u.[35].

Constraint 2: extreme load constraint

$$T_e = \frac{P_e}{\omega_r} \leq T_{e,\max,\text{set}} \quad (17)$$

where, $T_{e,\max,\text{set}}$ is the set upper limit of torque, typically taken as 1.2 p.u. [38].

Constraint 3: rotor-side converter capacity constraint

$$-P_{r,\max,\text{set}} \leq P_r \leq P_{r,\max,\text{set}} \quad (18)$$

where, $P_{r,\max,\text{set}} = \sqrt{S_r^2 - Q_r^2}$. Q_r represents the reactive output of the rotor-side converter. S_r is the capacity of the converter. In the scenario where the reactive component is zero, it is generally valued at 0.3 p.u. [39].

In the case of per-unit parameters, Eq.(19) allows for the conversion of electromagnetic power of WT into rotor-side terms according to the slip ratio relationship:

$$P_r = P_e \left(1 - \frac{1}{\omega_r}\right) \quad (19)$$

The safety operational constraints create a feasible region for frequency support by DFIG WTs, as shown in Fig.2. Constraint 1 is perpendicular to the ω_r axis. Constraint 2 is a straight line with a slope set by $T_{e,\max,\text{set}}$. Constraint 3 consists of a pair of symmetrical hyperbolic curves due to its bidirectional nature. Together, these constraints define the safe operational feasible region for WT. The two hyperbolic curves are symmetrical because Constraint 3 includes both positive and negative directions. If the operational trajectory of the WT exceeds the boundaries of this feasible region, it poses a safety hazard.

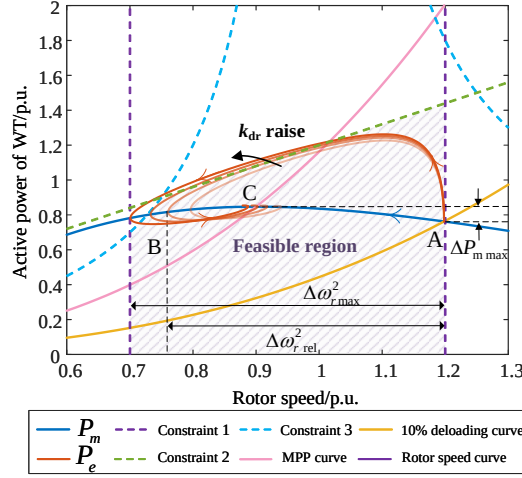


Figure 2: Feasible region of DFIG WT operating trajectories under safety constraints

2.2.2. Operational constraints in typical frequency regulation control methods

The trajectory shape in Fig.2 varies with different frequency regulation methods, affecting the practical potential of FSCB. This paper uses a typical frequency support scheme combining droop control with overspeed deloading to explain the practical potential value indicator[40].

When a DFIG-based WF detects a frequency disturbance Δf , it adjusts power command according to the preset droop coefficient k_{dr} . Then it is added to WT stator power reference command $\Delta P_{s,ref}$:

$$\Delta P_{s,ref} = k_{dr} \cdot \Delta f \quad (20)$$

Assuming the electromagnetic response of the converter is negligible, the total reference power command $P_{s,ref}$ serves as the actual power output. The stator power P_s is equal to the per unit value of the electromagnetic torque T_e :

$$P_{s,ref} = P_s = T_e \quad (21)$$

The system frequency deviation is represented by a first-order differential equation:

$$\Delta f = \frac{\Delta P_L + P_e - P_{e,0} + \Delta P_g}{2Hs + D} \quad (22)$$

where, H is the equivalent inertia of the power system. D is the equivalent damping of the system. ΔP_L represents the system power disturbance. ΔP_g is the power deviation of the synchronous machines. $P_{e,0}$ is the electromagnetic power of the WT at the initial moment of frequency regulation.

Under the constraints from Eq.(20) to Eq.(22), the operational trajectory of DFIG WT is restricted, as shown in Fig.2. Initially, the WT operates at the overspeed load shedding point A. Upon disturbance, it provides power support via droop control, ensuring the operational trajectory stays within the feasible region. After passing the lowest rotor speed point B, it eventually returns to point C. The difference in squared rotor speeds between points A and B represents the maximum release of RKE during frequency support. The power difference between points A and C reflects the ultimate release of DRP.

By adjusting the droop control coefficient, the operational trajectory of the WT can be made tangent to the boundary of the feasible region. Thus it reaches the boundary of the operational state. At this state, the amounts of RKE released and DRP released represent the practical potential of the FSCB under droop control. For example, when the operational trajectory is tangent to the rotor speed constraint boundary, the theoretical potential of the RKE is fully released. However, before this theoretical potential is fully released, the operational trajectory already crosses the torque and converter capacity constraint boundaries. Therefore, the practical potential value of the RKE under this condition is less than its theoretical potential.

2.2.3. Definition and calculation of practical potential value

The practical potential of a DFIG-based WF is the maximum FSCB under specific frequency control actions, considering multiple safety operational constraints. Essentially, it is a nonlinear time-series optimization model.

The optimization objectives of the model are the practical potential values of the RKE and DRP components:

$$\max \Delta E_{k,P} = \frac{1}{2} J(\omega_{r,0}^2 - \omega_{r,\min}^2) \quad (23)$$

$$\max \overline{\Delta P_{m,P}} = \frac{\int_0^{T_{del2}} (P_m - P_{m,0}) dt}{T_{del2}} \quad (24)$$

Eq.(23) calculates the practical potential of RKE, where $\omega_{r,\min}$ represents the lowest rotor speed achievable under the various constraints. Eq.(24) calculates the practical potential of DRP under the various constraints, where T_{del2} represents the PFR time.

Combining Eq.(16) to Eq.(24) and after discretizing them through finite difference methods, the complete optimization model is represented:

$$\left\{ \begin{array}{l} s.t. \text{ for all } i \in \{1, 2, \dots, l\} \ t \in \{0, 1, \dots, N_t\} \\ \max \Delta E_{k,P} = \frac{\sum_{i=1}^l S_i \cdot 0.5 J_i (\omega_{r,i,0}^2 - \omega_{r,i,\min}^2)}{\sum_{i=1}^l S_i} \\ \text{or } \max \overline{\Delta P_{m,P}} = \frac{\sum_{i=1}^l S_i \cdot \sum_{t=0}^{N_t} (P_{m,i}(t) - P_{m,i,0})}{N_t \sum_{i=1}^l S_i} \\ \omega_{r,i}(t+1) = \frac{\Delta T \cdot (T_{m,i}(t) - T_{e,i}(t))}{J_i} + \omega_{r,i}(t) \\ P_{m,i}(t) = \frac{1}{2} \rho C_p(\lambda, \beta) \pi R^2 V_{w,i}^3 \\ T_{m,i}(t) = \frac{P_{m,i}(t)}{\omega_{r,i}(t)} \\ T_{e,i}(t) = P_{s,i}(t) = P_{s,ref,i}(t) = k_{opt} \cdot \omega_{r,i}^2(t) - k_{dr} \cdot \Delta f(t) \\ P_{e,i}(t) = T_{e,i}(t) \cdot \omega_{r,i}(t) \\ \Delta f(t+1) = \Delta f(t) + \frac{\Delta T}{2H} \cdot [\Delta P_L + \sum_{i=1}^l (P_{e,i}(t) - P_{e,i,0}) + \Delta P_g(t) - D \Delta f(t)] \\ \omega_{r,\min,set} \leq \omega_{r,i}(t) \leq \omega_{r,\max,set} \\ T_{e,i}(t) \leq T_{e,\max,set} \\ -P_{r,\max,set} \leq P_{e,i}(t) \cdot (1 - \frac{1}{\omega_{r,i}(t)}) \leq P_{r,\max,set} \end{array} \right. \quad (25)$$

where, i denotes the i th WT. l is the number of WTs in the WF. N_t represents the total time series, corresponding to the time scale T_{del2} of the discretized quantity. ΔT is the discrete time step. t is the number of discrete time series.

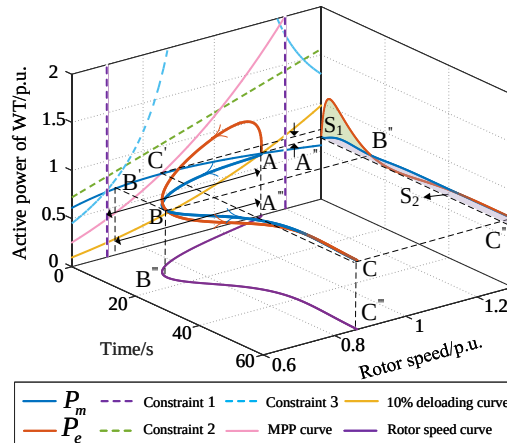


Figure 3: Three-dimensional operational trajectory of the DFIG WT

Fig.3 illustrates the relationship between theoretical and practical potential indicators under various constraints. The electromagnetic and mechanical power trajectories are plotted in three-dimensional space. Initially, both power components are equal, maintaining at the load shedding operation point A. After a disturbance, the operational trajectory passes through point B, the lowest rotor speed, and eventually returns to the steady-state operation point C. $A'B'C'$, $A''B''C''$, and $A'''B'''C'''$ represent the projections of points ABC on the power-rotor speed plane, power-time plane, and rotor speed-time plane respectively. The electromagnetic power trajectory and mechanical power trajectory projected onto the power-rotor speed plane, as shown in Fig.2. It must be ensured that the operational trajectory always remains within the feasible region. Projecting the electromagnetic and mechanical power trajectories onto the power-time plane, the intersection of the two trajectories is point B'' . Thus, the equation $d\omega_r/dt = (T_m - T_e)/J = 0$ leads to $P_m = P_e$. The area enclosed by the two projected curves between times A'' and B'' is defined as S_1 , and the area enclosed by the mechanical power curve and the initial power over the PFR time scale is S_2 . Therefore:

$$\Delta E_{k,P} = \int_0^{T_{del1}} P_e(t)dt - \int_0^{T_{del1}} P_m(t)dt = S_1 \quad (26)$$

$$\overline{\Delta P_{m,P}} = \frac{\int_0^{T_{del2}} (P_m(t) - P_{m,0})dt}{T_{del2}} = \frac{S_2}{T_{del2}} \quad (27)$$

where, T_{del1} is the time difference corresponding to A'' and B'' .

Thus, the practical potential of the FSCB under safety operational constraints can be represented by areas S_1 and S_2 in Fig.3.

In summary, the indicator system for quantifying the FSCB across multiple time scales, forms of energy, and levels of assessment is listed in Tab.1. When the wind speed, rotor speed, and disturbance status variables are measured under quasi-steady conditions, the FSCB of the DFIG-based WF can be evaluated.

Table 1: The indicator system for quantifying the FSCB

	Theoretical potential value indicators	Practical potential value indicators	Potential utilization
Available RKE on the inertial time scale	$\Delta E_{k,T}$	$\Delta E_{k,P}$	$\frac{\Delta E_{k,P}}{\Delta E_{k,T}} \times 100\%$
DRP at PFR time scale	$\overline{\Delta P_{m,T}}$	$\overline{\Delta P_{m,P}}$	$\frac{\overline{\Delta P_{m,P}}}{\overline{\Delta P_{m,T}}} \times 100\%$

3. Knowledge and data-driven fusion Koopman-MILP method for online assessment

Eq.(25) has a nonlinear and complex temporal structure, making it difficult to obtain an analytical expression. A common method is to input it into an optimization solver for a numerical solution. However, nonlinear optimization solvers are slow and often fail to find a globally optimal solution. To address this issue, this paper proposes a knowledge and data-driven fusion Koopman-MILP method, enabling accurate online assessment of the practical potential indicators of FSCB. As shown in Fig.4, first, Koopman training is performed on historical frequency regulation data to obtain a high-dimensional global linearization model of the WF using physical knowledge. Second, after collecting necessary operational data, MILP is used for online computations to obtain precise assessment results.

3.1. Koopman data training with integrated knowledge

3.1.1. Selection of input variables

The Koopman operator describes the linear evolution of observable state variables of nonlinear systems in high-dimensional space. The WF system is a complex nonlinear system with two types of operational variables. One is the state variable $\mathbf{u}_t$. It evolves continuously during the frequency support process and determines the system state at each moment, as shown in Eq.(28). The other is the control variable $\mathbf{v}_t$. It remains temporarily constant during the

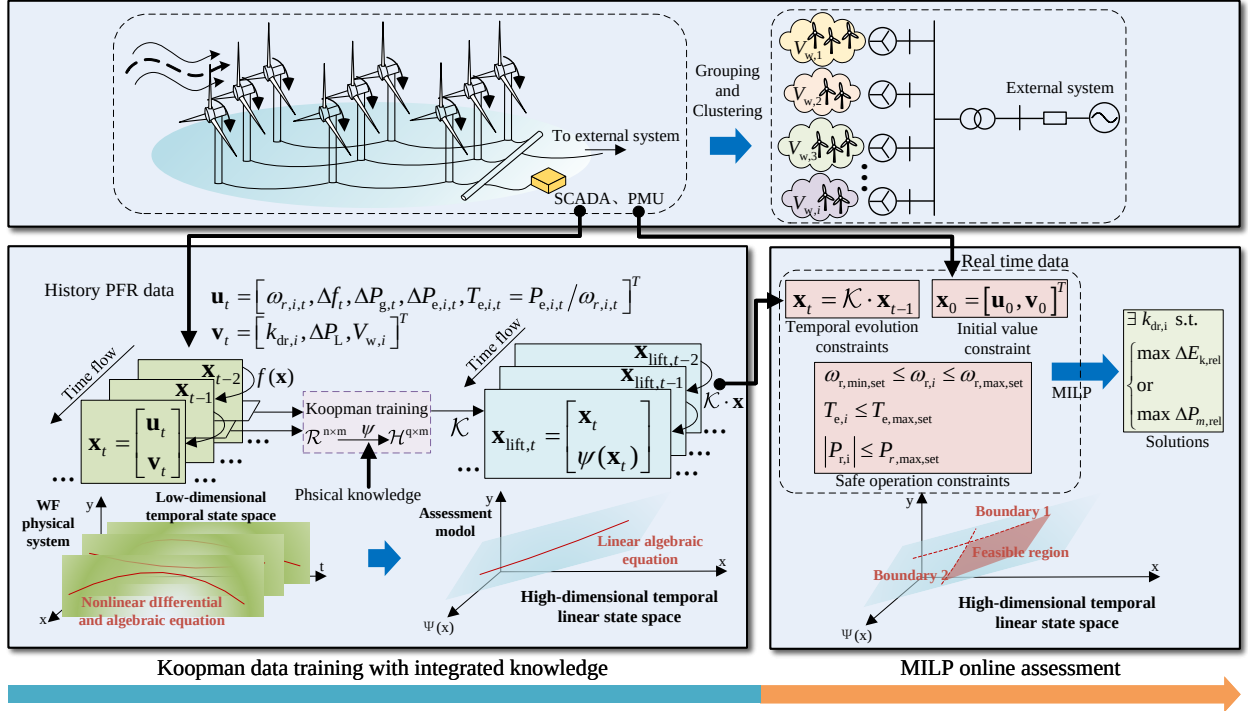


Figure 4: Summarized diagram for proposed Koopman-MILP assessment method

frequency support process and determines the evolution direction of each state variable at the next moment, as shown in Eq.(29).

$$\mathbf{u}_t = [\omega_{r,i}(t), \Delta f(t), \Delta P_g(t), \Delta P_{e,i}(t), T_{e,i}(t)]^T \quad (28)$$

where, $\omega_{r,i}(t)$ represents the rotor speed of the i th WT in the WF at time t after the start of frequency support. And it can be directly measured. $\Delta f(t)$ refers to the system frequency at time t . It can be collected from the PMU (phasor measurement unit) at the PCC (point of common coupling). $P_g(t)$ indicates the change in mechanical power output by the aggregated capacity of the synchronous machines at time t , which can be obtained through inter-station communication. $\Delta P_{e,i}(t)$ represents the change in power output by the i th WT at time t . It can also be directly measured. $T_{e,i}(t)$ denotes the electromagnetic torque of the i th WT at time t .

$$\mathbf{v}_t = [k_{dr,i}, \Delta P_L, V_{w,i}]^T \quad (29)$$

where, $k_{dr,i}$ represents the droop coefficient of the i th WT, which can be considered a constant. ΔP_L indicates the power disturbance in the system. $V_{w,i}$ denotes the wind speed at the location of the i th WT. It changes over a much longer time scale than that of a primary frequency response and can also be considered a constant.

Letting $\mathbf{x}_t = [\mathbf{u}_t, \mathbf{v}_t]^T$, the nonlinear system can be expressed as shown in Eq.(30):

$$\mathbf{x}_{t+1} = f(\mathbf{x}_t) \quad (30)$$

3.1.2. Construction of dictionary function using physical knowledge

The Koopman operator $\mathcal{K}$ is a linear operator acting on the observation function $g(\mathbf{x}_t)$, as illustrated in Fig.5. The original system evolves nonlinearly in $\mathcal{R}$ space. To linearize the system, an observation function $g(\mathbf{x}_t)$ maps the original system into an infinite-dimensional space $\mathcal{H}$. Under the action of the operator $\mathcal{K}$, the system then evolves linearly in this new space. The essence of Koopman operator theory is to globally linearize the nonlinear system through a coordinate transformation. $\mathcal{K}$ is an infinite-dimensional operator, satisfying:

$$\mathcal{K}g(\mathbf{x}_t) = g(f(\mathbf{x}_t)) = g(\mathbf{x}_{t+1}) \quad (31)$$

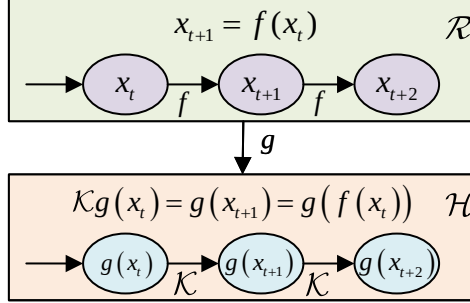


Figure 5: The linearization principle of the Koopman operator

However, selecting and utilizing an infinite-dimensional observation function and an infinite-dimensional Koopman operator $\mathcal{K}$ is challenging. Therefore, a common approach is to truncate the infinite-dimensional space to a finite-dimensional one, obtaining an approximate matrix for the Koopman operator $\mathcal{K}$. The observation function $g(\mathbf{x}_t)$ can be expressed as Eq.(32).

$$g(\mathbf{x}_t) = \begin{bmatrix} \mathbf{x}_t \\ \psi(\mathbf{x}_t) \end{bmatrix} \quad (32)$$

where, $\psi(\mathbf{x}_t)$ is the lifting function, also known as the dictionary function. The form of the dictionary function determines the fitting accuracy of the Koopman operator. To effectively reduce dimensionality and improve fitting accuracy, this paper proposes a dictionary function based on the physical knowledge of WF frequency regulation structure. After selecting the input variables as shown in Section 3.1.1, it is necessary to use the definition and derivative knowledge of each input variable to determine the corresponding lifting variables. Taking variable T_m as an example, the definition knowledge of T_m is based on the aerodynamic equation and torque formula:

$$T_m = \frac{P_m}{\omega_r} = \frac{0.5\rho C_p(\lambda, \beta)\pi R^2 V_w^3}{\omega_r} = a_1 \frac{V_w^3}{\omega_r} \cdot e^{\frac{-12.5V_w}{R\omega_r}} + a_2 \frac{V_w^4}{\omega_r^2} \cdot e^{\frac{-12.5V_w}{R\omega_r}} + a_3 \quad (33)$$

where, a_1, a_2, a_3 are constants. The nonlinear terms among them are selected as one of the lifting variables. To achieve higher fitting accuracy, the derivative knowledge can be further utilized to expand new lifting variables:

$$\left(\frac{V_w^3}{\omega_r} \cdot e^{\frac{-12.5V_w}{R\omega_r}} \right)' = a_1' \frac{V_w^3}{\omega_r^2} \cdot e^{\frac{-12.5V_w}{R\omega_r}} + a_2' \frac{V_w^4}{\omega_r^3} \cdot e^{\frac{-12.5V_w}{R\omega_r}} \quad (34)$$

where, a_1', a_2' are constants. The selection method for other lifting variables is similar and will not be further elaborated. The complete expression of the dictionary function for WF frequency regulation under a typical droop control structure is given in the appendix. For other forms of frequency support strategies that do not involve droop control, new dictionary functions can be rewritten accordingly. To achieve higher accuracy fitting effects, the dictionary functions can also be adjusted.

3.1.3. Data processing and Koopman operator approximation

Historical frequency regulation data are collected and formed into a sample matrix according to Eq.(35) and Eq.(36):

$$\mathbf{X}_0 = [\mathbf{x}_0, \mathbf{x}_1 \dots \mathbf{x}_{m-1}] \quad (35)$$

$$\mathbf{X}_1 = [\mathbf{x}_1, \mathbf{x}_2 \dots \mathbf{x}_m] \quad (36)$$

where, $\mathbf{X}_0, \mathbf{X}_1 \in \mathbb{R}^{n \times m}$, with n as the number of operational variables and m as the number of sampled data points. Following the observation function form in Eq.(32), $\mathbf{X}_0$ and $\mathbf{X}_1$ undergo a lifting transformation, resulting in:

$$\mathbf{X}_{0 \text{ lift}} = [g(\mathbf{x}_0), g(\mathbf{x}_1) \dots g(\mathbf{x}_{m-1})] \quad (37)$$

$$\mathbf{X}_{1 \text{ lift}} = [g(\mathbf{x}_1), g(\mathbf{x}_2) \dots g(\mathbf{x}_m)] \quad (38)$$

where, $\mathbf{X}_{0 \text{ lift}}, \mathbf{X}_{1 \text{ lift}} \in \mathbb{R}^{q \times m}$, with q as the number of variables in the high-dimensional space. By performing a least squares fit on the lifted samples, it is possible to obtain an approximate fitting matrix for $\mathcal{K}$, denoted as $\mathbf{K}$:

$$\mathbf{K} = \mathbf{X}_{1 \text{ lift}} \mathbf{X}_{0 \text{ lift}}^\dagger \quad (39)$$

where, $\mathbf{X}_{0 \text{ lift}}^\dagger$ denotes the Moore-Penrose pseudoinverse of $\mathbf{X}_{0 \text{ lift}}$, and $\mathbf{K} \in \mathbb{R}^{q \times q}$. Consequently, once the initial value $\mathbf{x}_0$ of the operational variable is known, the operational state at any subsequent moment t can be linearly calculated using Eq.(40).

$$g(\mathbf{x}_t) = \mathbf{K}^t \cdot g(\mathbf{x}_0) \quad (40)$$

3.2. MILP online assessment

After calculating $\mathbf{K}$, the original complex nonlinear system progresses linearly in high-dimensional space according to Eq.(40). This section introduces the principle of online solving for the practical potential of FSCB based on the fitting results.

In a quasi-steady state, to assess the FSCB of a WF, it is necessary to measure initial state data as initial values for the variables to be solved:

$$\mathbf{x}_0 = \left[\omega_{r,i,0}, 0, 0, 0, \frac{P_{e,i,0}}{\omega_{r,i,0}}, \sim, \Delta P_L, V_{w,i} \right]^T \quad (41)$$

where, the droop coefficient is a variable to be solved and does not have a set initial value. $\omega_{r,i,0}$, $P_{e,i,0}$, and $V_{w,i}$ represent the measured rotor speed, power, and wind speed data of each aggregated WT, respectively. ΔP_L represents the power disturbance in the system. It can be measured or set by the dispatcher as the maximum disturbance the system can handle.

Next, the initial value $\mathbf{x}_0$ is transformed into a higher dimension according to Eq.(32). Thus the initial value projection in high-dimensional space can be obtained. Since this step may involve nonlinear calculations, consider using a mixed integer approach to segment the linearization:

$$\begin{cases} \sum_{i=1}^{N_{pc}-1} z_{pc,i} = 1 \\ \sum_{j=1}^{N_{pc}} \mu_{pc,j} = 1 \\ \mu_{pc,i} \leq z_{pc,i-1} + z_{pc,i} \forall i = 2, 3, \dots, N_{pc} - 1 \\ \mu_{pc,i} \leq z_{pc,1} \\ \mu_{pc,N_{pc}} \leq z_{pc,N_{pc}-1} \\ k_{dr} = \sum_{j=1}^{N_{pc}} \mu_{pc,j} k_{dr,pc,j} \\ \varphi(C, k_{dr}) = \sum_{j=1}^{N_{pc}} \mu_{pc,j} \varphi(C, k_{dr,pc,j}) \end{cases} \quad (42)$$

where, $z_{pc,i}$ and $\mu_{pc,j}$ are integer variables. pc denotes the total number of segments. $k_{dr,pc,j}$ represents the values of the variables to be solved at each segment endpoint. φ refers to the nonlinear operations in the dictionary function.

The inequality constraints are determined by various safety operational conditions. They can be set according to Eq.(16) to Eq.(19).

Next, set the objective function using the discrete expressions in Eq.(23) and Eq.(24). Where, $\omega_{r,i}^2(t)$ can be obtained from the first element in Eq.(A.2), avoiding nonlinear operations.

Ultimately, by combining the objective functions in Eq.(23) and Eq.(24) with the safety operational inequality constraints in Eq.(16) to Eq.(19), as well as the linear temporal progression constraints expressed in Eq.(40) to Eq.(42),

a complete MILP formulation is obtained. This can be inputted into a large-scale linear programming solver such as GUROBI for online computation of the practical potential value indicators. Since the model is linear, it avoids complex nonlinear computations, significantly enhancing the solving speed and suitability for online assessment.

The overall process of the proposed knowledge and data-driven fusion Koopman-MILP online assessment method is illustrated in Fig.6.

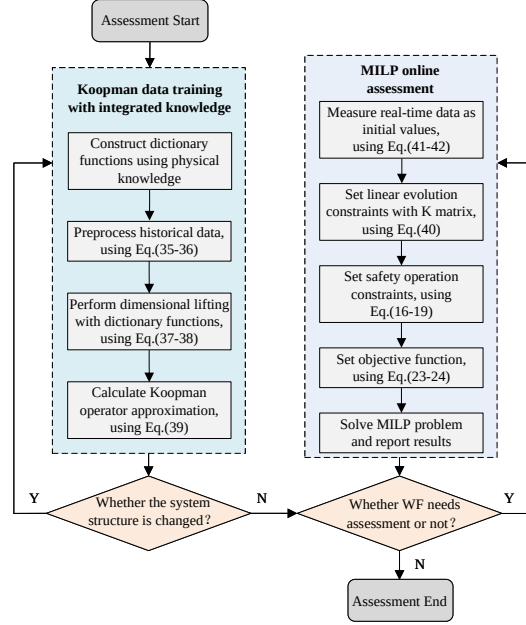


Figure 6: The overall process of proposed Koopman-MILP method

4. Case studies

A four-machine two-area system model including a DFIG-based WF was built using the MatPSST (Matlab/Simulink-based power system simulation toolbox)[41], as shown in Fig.7. The specific parameters were presented in previous work[9]. The WF is connected to the grid at node bus 12 and contains contains 250 DFIG WTs, each with a capacity of 2 MW and identical internal parameters. The WF uses a frequency regulation scheme combining overspeed de-loading and droop control[40]. Depending on operating conditions, the WF can be aggregated into a different number of WTs. At the initial moment of frequency response, a sudden load increase occurs at node 7, while the rest of the system remains in a quasi-steady state. Calculations were performed on a hardware environment with a CPU Intel(R) Core(TM) i7-9750H @2.60GHz and 32GB RAM.

4.1. Validation of assessment errors and indicator rationality

To observe the assessment errors and assessment time of the proposed method, different methods were used to assess the practical potential value of the RKE component in the FSCB of the DFIG-based WF. The assessment errors and computation times under various wind speed conditions are shown in Fig.8 and Tab.2. The nonlinear programming method uses a nonlinear solver to solve Eq.(25). The rotor inertia and blade radius are set to deviate by 10% from their accurate values to determine whether the results are influenced by the accuracy of the physical knowledge. The proposed Koopman-MILP method employs three dictionary functions to examine the effects of knowledge fusion. The first is the proposed one in Eq.(A.2). The second is the universal function of 100 dimensions from Ref.[32] without integrated knowledge. The third, sourced from Ref.[33], includes an integration of limited knowledge.

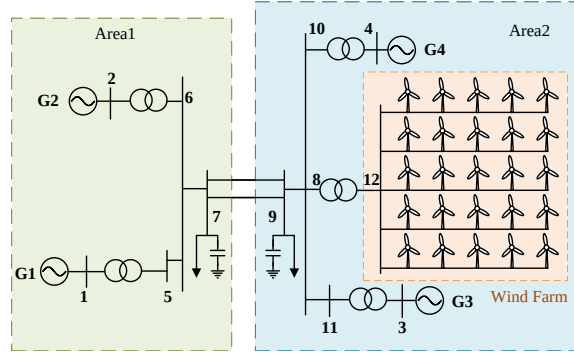


Figure 7: Schematic diagram of four-machine, two-area system including a DFIG-based WF

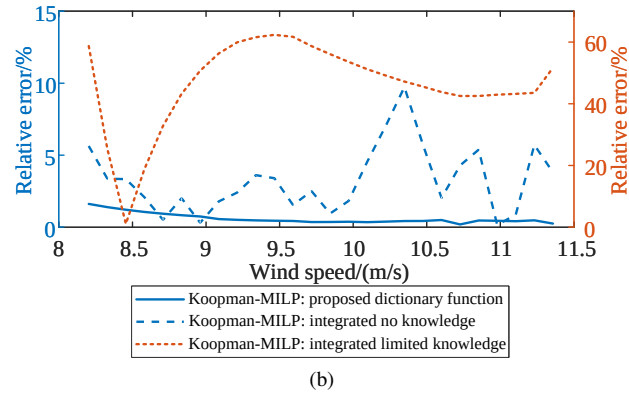
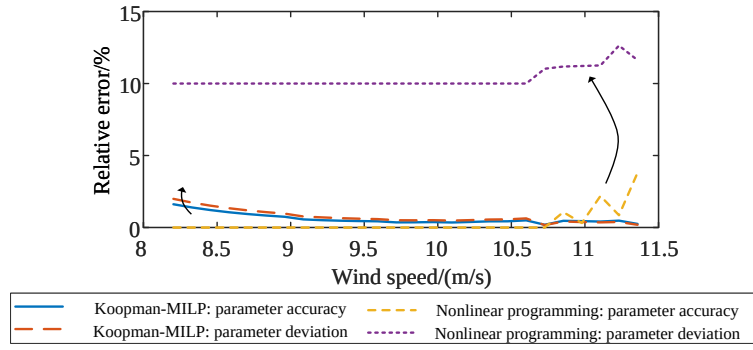


Figure 8: The assessment errors of RKE by different methods: (a) Errors under parameter deviation (b) Errors under different dictionary functions

Table 2: The assessment time of different methods

Wind speed conditions	Methods	Nonlinear programming method	Koopman-MILP method using universal dictionary function	Koopman-MILP method using proposed dictionary function
9.5m/s		2.4s	0.83s	0.18s
10.1m/s		3.4s	0.72s	0.13s
10.7m/s		2.9s	0.85s	0.14s
11.4m/s		2.5s	0.80s	0.13s

The accuracy of the nonlinear programming method depends on the precision of the knowledge model. Therefore, parameter accuracy greatly affects the results. Additionally, due to its nonlinear computational structure, the assessment time is lengthy. In contrast, the proposed method does not rely on knowledge model accuracy for assessment. With the dictionary function deviating by 10% from accurate values, the error remains small. The proposed method uses a linearized model, leading to faster computation. This meets the requirements for online assessment. Moreover, the proposed dictionary function achieves higher fitting accuracy and requires fewer dimensions than the universal function with no integrated knowledge, thereby reducing computation time.

The Koopman operator enables global linearization. It assesses and calculates global conditions using historical frequency regulation data from a subset of conditions. To verify the impact of training set range on accuracy, different sample training sets were configured. Training set 1 has a wind speed range of 10.1 m/s to 10.7 m/s. Training set 2 ranges from 8.2 m/s to 8.8 m/s. Training set 3 ranges from 8.2 m/s to 11.4 m/s. The range of other variables is the same: the droop coefficient range is 0 to 60, and the system power disturbance range is 200 MW to 500 MW. The assessment errors for the practical potential value of the RKE component are shown in Fig.9.

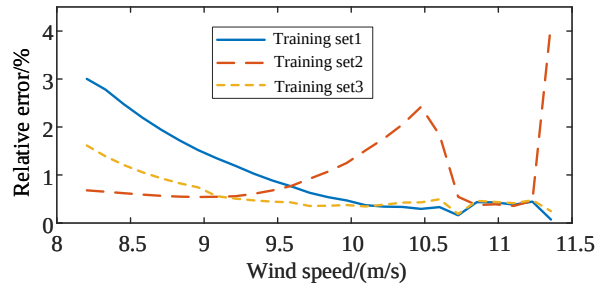


Figure 9: The assessment errors of RKE under different training sets

The assessment results show that partial condition data processed through Koopman global linearization can estimate the global condition range. This approach avoids the need for data collection under extreme conditions, thereby reducing the difficulty of obtaining assessment data. However, expanding the range of the training sample set appropriately can effectively reduce assessment errors. Therefore, it is essential to comprehensively consider both accuracy and data acquisition factors. The training sample set range should be selected reasonably to avoid significant errors and consider actual WF operation conditions.

During frequency events, if the disturbance power remains unchanged, the FSCB reflects its frequency support capability. The larger the FSCB, the smaller the frequency drop. To demonstrate the rationality of the defined indicators, the relationship between the proposed indicators and the lowest frequency point, steady-state frequency, and rate of change of frequency (ROCOF) is shown in Fig.10.

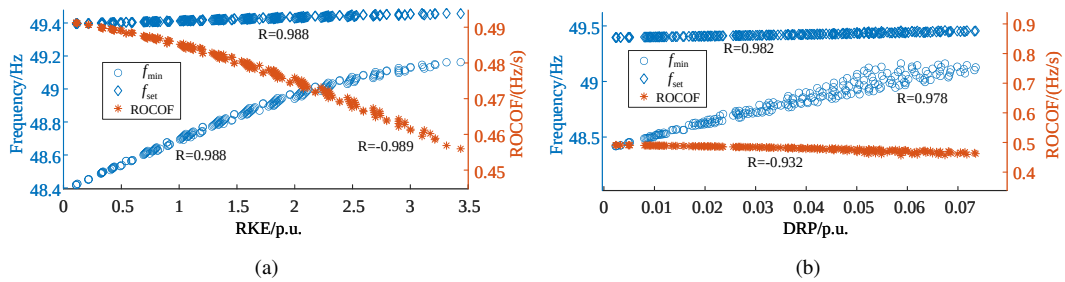


Figure 10: The relationship between the proposed indicators and frequency characteristics: (a) RKE component (b) DRP component

The results indicate a strong correlation between the defined indicators and the depth of frequency drop. There is a close relationship between the lowest frequency point and ROCOF with the FSCB in the inertia time scale. Similarly, the relationship between the steady-state frequency and FSCB in the PFR time scale is also close. Therefore, it is

reasonable to use RKE to measure FSCB in the initial inertia stage and DRP to measure it in the subsequent PFR stage.

4.2. Assessment under different safety operation constraints

Assuming the same wind speed for each WT in the WF, resulting in an aggregated single-machine model, the wind speed varies from 8 to 11.5 m/s with a system disturbance power of 400 MW. Other parameters remain unchanged. Three constraint scenarios are set: Scenario 1 considers only rotor speed constraint, Scenario 2 considers rotor speed and load constraint, and Scenario 3 considers rotor speed and capacity constraint. The assessment results of RKE at the inertia time scale are shown in Fig.11(a). The assessment results of DRP at the PFR time scale are shown in Fig.11(b). The potential utilization rates are shown in Fig.11(c).

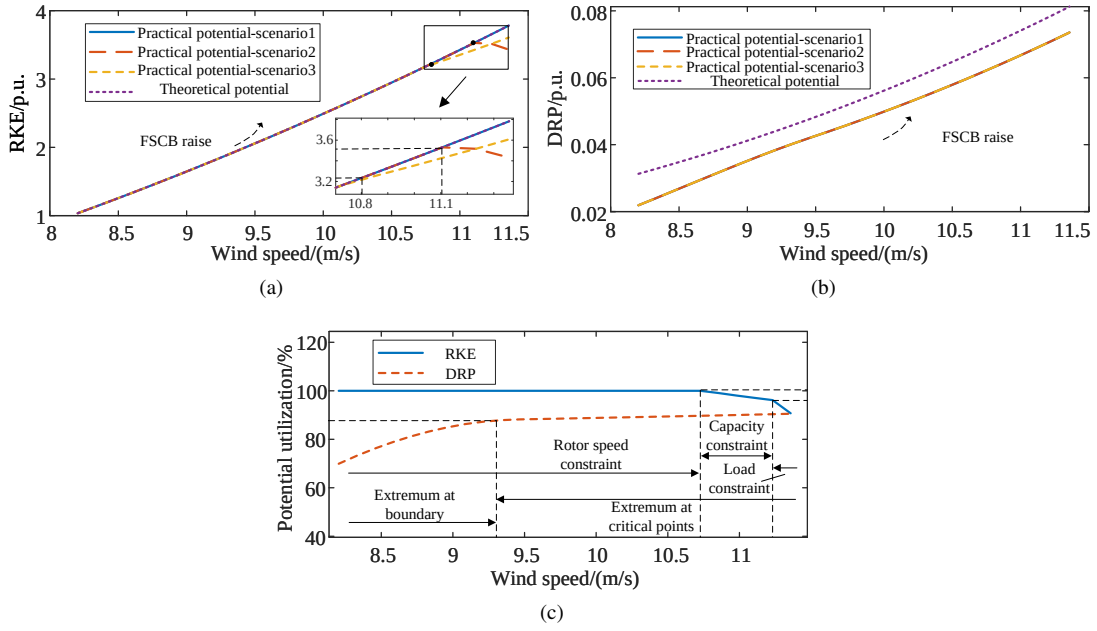


Figure 11: Assessment results with changes in safety operation constraints: (a) Curve of RKE variation with wind speed (b) Curve of DRP variation with wind speed (c) Curve of potential utilization variation with wind speed

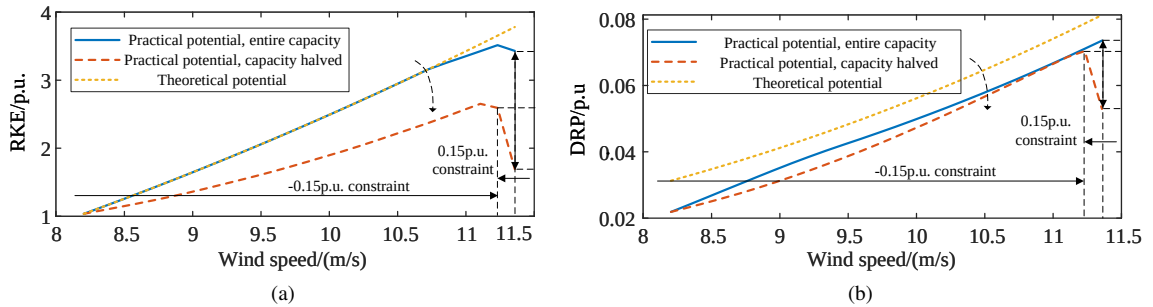


Figure 12: Assessment results with changes in converter capacity constraint: (a) Curve of RKE variation with wind speed (b) Curve of DRP variation with wind speed

The results in Fig.11(a) and Fig.11(b) show that in the low to medium wind speed range, rotor speed constraint is dominant. At high wind speeds, near the rotor speed upper limit, load constraint is dominant. When the reactive

power output is zero, the active power capacity is large, making capacity constraint less significant. The results in Fig.11(c) show that the RKE value is always achieved at the boundary formed by constraints. In contrast, the DRP value reaches the boundary only at low wind speeds. At medium to high wind speeds, its extreme values are within the boundary at critical points.

In specific scenarios, capacity constraint can also be dominant. During a disturbance, if the system needs to support both voltage and frequency, the WF needs to emit reactive power to support the voltage. If half of the rotor-side converter capacity is allocated to reactive power, the remaining active power capacity can be calculated to be 0.15 p.u.. The reassessment results are shown in Fig.12.

When the available capacity is halved compared to using the entire capacity for active power, capacity constraint becomes dominant for wind speeds over 8.25 m/s. At 11.4 m/s wind speed, the available RKE of the WF is reduced to half its original value. Therefore, increasing the converter capacity can enhance the FSCB of the DFIG-based WF.

4.3. Assessment under different frequency regulation schemes

The proposed assessment method evaluates the practical potential values of FSCB under different frequency regulation schemes. It allows comparative analysis of the potential utilization of FSCB by various schemes. The assessment results of RKE under droop control and synthetic inertia control for a 400 MW disturbance in different scenarios are shown in Fig.13.

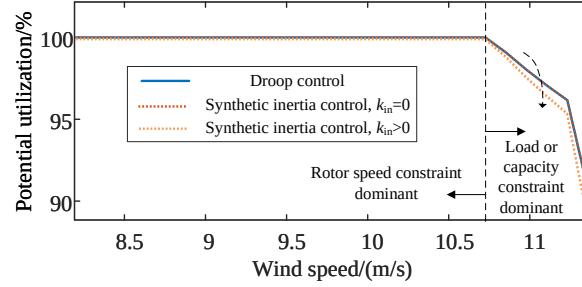


Figure 13: Comparison of potential utilization rates under different frequency regulation schemes

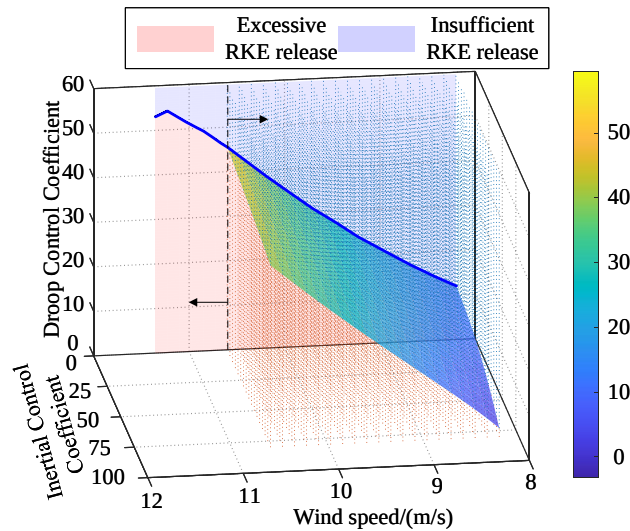


Figure 14: Calculation boundaries of control coefficients for synthetic inertia control

The maximum utilization rates of RKE under droop control and synthetic inertia control are the same for different wind speeds. The droop and inertia coefficients meet the boundary relationship shown by the blue line and surface

in Fig.14 to achieve the practical potential values of RKE. Notably, when rotor speed constraint dominates under low wind speeds, the inertia coefficient can be non-zero, and the maximum utilization rate of RKE can reach 100%. However, under high wind speeds, load or capacity constraint dominates. At this point, a non-zero inertia coefficient further increases the constraint limitations. Compared to droop control with a zero inertia coefficient, the potential utilization rate is further reduced.

4.4. Assessment under different wind speed scenarios

Keeping other conditions constant, FSCB of the DFIG-based WF is assessed sequentially under different wind speeds and power disturbance scenarios. The theoretical and practical potential values of RKE at the inertia time scale are shown in Fig.15(a). The theoretical and practical potential values of DRP at the PFR time scale are shown in Fig.15(b).

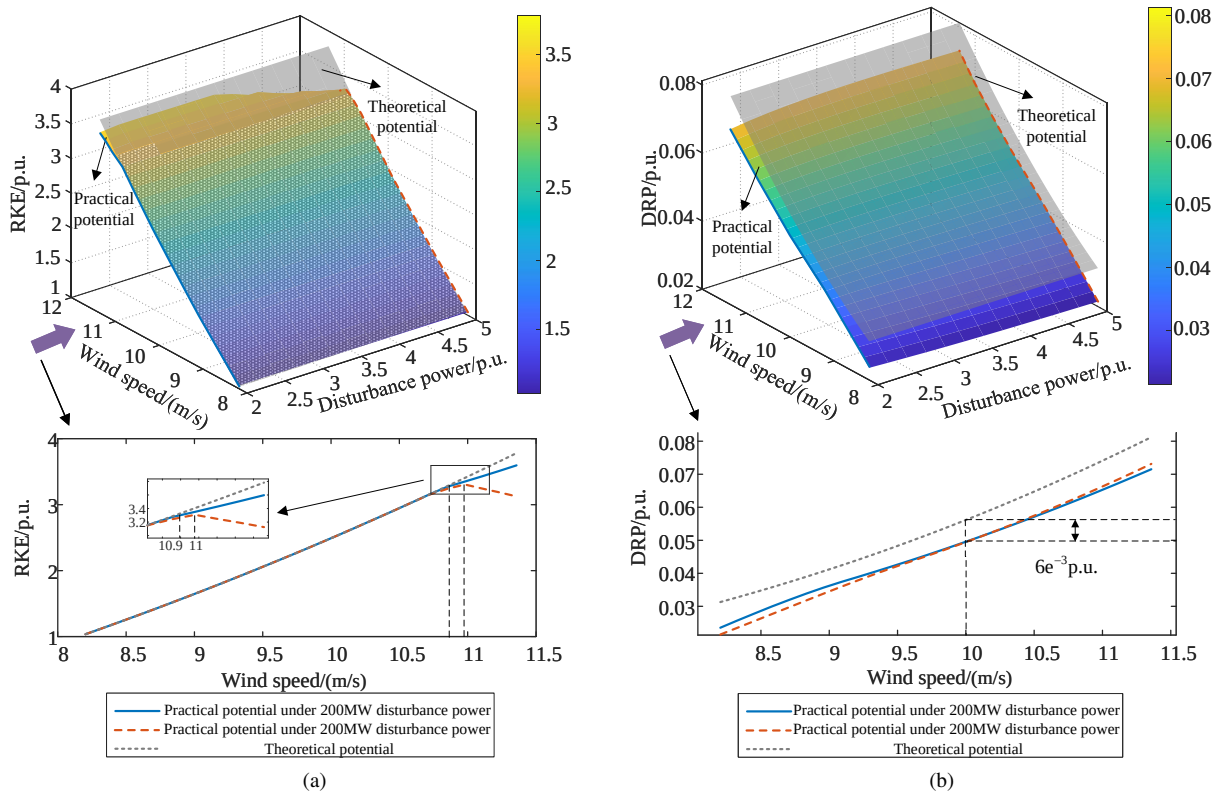


Figure 15: Assessment results with changes in wind speed and disturbance power: (a) The RKE released at the inertia time scale (b) The DRP at the PFR time scale

The results in Fig.15(a) and 15(b) show that the practical potential of FSCB is always less than or equal to its theoretical potential due to safe operation constraints. As wind speed increases, the FSCB of the WF gradually rises. On one hand, higher wind speeds increase rotor speed along the derating curve, raising available RKE. On the other hand, they also increase maximum output power at the MPP, resulting in more DRP for frequency support based on a fixed derating proportion. The impact of system power disturbances on FSCB is relatively small because FSCB is an inherent attribute of the WF and independent of power system parameters. However, as disturbance power decreases further, the power generation increase of the WF cannot exceed active power shortfall of the system. This leads to a reduction in practical potential of FSCB.

At the quasi-steady-state time scale, wind speed fluctuations in the WF are significant. The proposed Koopman-MILP method can assess FSCB online using real-time wind speed measurements. The real-time wind speed data from

measurements is shown in Fig.16(a). The online DRP assessment results are shown in Fig.16(b).

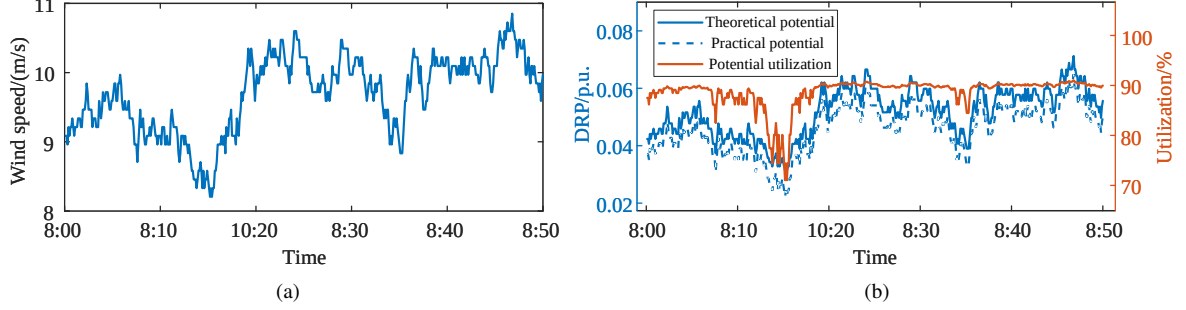


Figure 16: The real-time assessment results using proposed Koopman-MILP method: (a) The real-time wind speed data (b) The real-time assessment results of DRP

The assessment results show that the theoretical and practical potential values of DRP in the DFIG-based WF fluctuate with wind speed in real-time. This demonstrates that the proposed method can accurately assess the real-time FSCB of the WF online.

Due to the wake effect, wind speeds at different DFIG WT locations within the WF are not identical. This increases the dimensionality of variables in the solution process. To verify the proposed Koopman-MILP method in a multi-turbine aggregated model, a 5x5 multi-turbine aggregation model was established to assess FSCB under different wind direction angles. The wind speeds in the WF are shown in Fig.17, and the assessment results are shown in Fig.18.

The assessment results show that the proposed Koopman-MILP method can accurately assess WTs under multiple wind speed states within the WF. The dominant influencing factors of FSCB for each WT are consistent with the conclusions from single WT analysis.

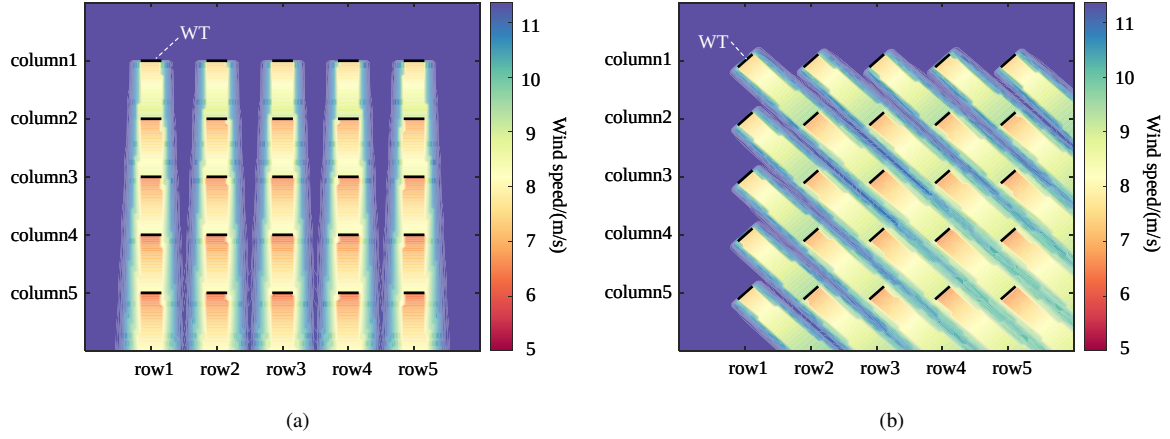


Figure 17: Wind speed distribution in the WF considering wake effect:(a) 90° wind direction angle (b) 45° wind direction angle

To further investigate the impact of coupling effects among multiple wind speed WTs on FSCB, two WTs (WT1 and WT2) from the 5x5 array are selected. The assessment results of the practical potential of RKE under various wind speed combinations are shown in the Fig.19, where Fig.19(b) is a projection of Fig.19(a) under typical wind speed conditions. Considering the symmetry of RKE between WT1 and WT2, only the assessment results of WT1 are plotted.

The assessment results show that for low wind speed WTs dominated by rotor speed constraint, the performance

of their FSCB is not affected by the wind speeds of other WTs. However, the FSCB of high wind speed WTs can be influenced by the wind speeds of other WTs. As the wind speeds of other WTs decrease, the practical potential RKE of high wind speed WTs decreases.

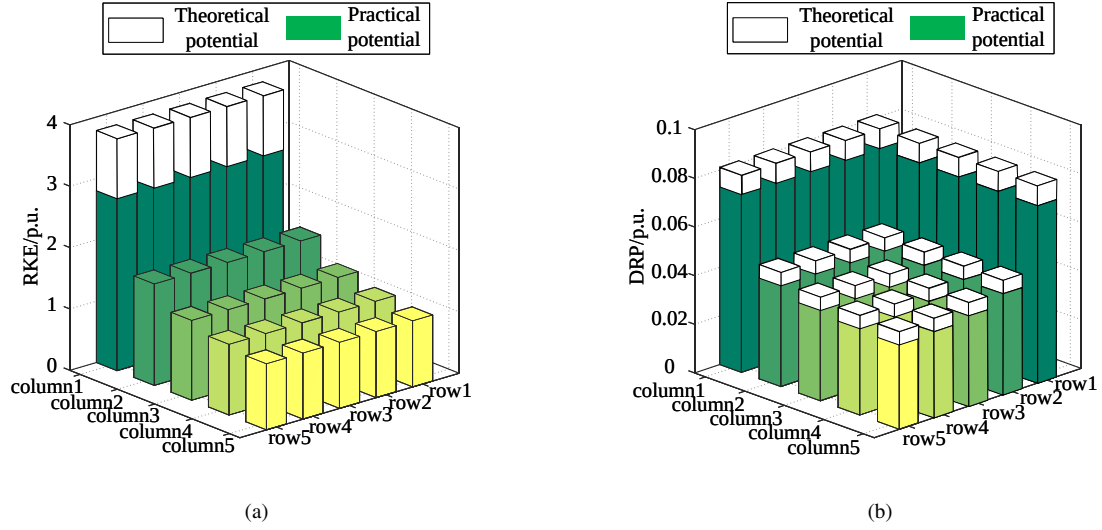


Figure 18: Assessment results of FSCB considering wake effect:(a) Assessment results of RKE at 90° wind direction angle (b) Assessment results of DRP at 45° wind direction angle

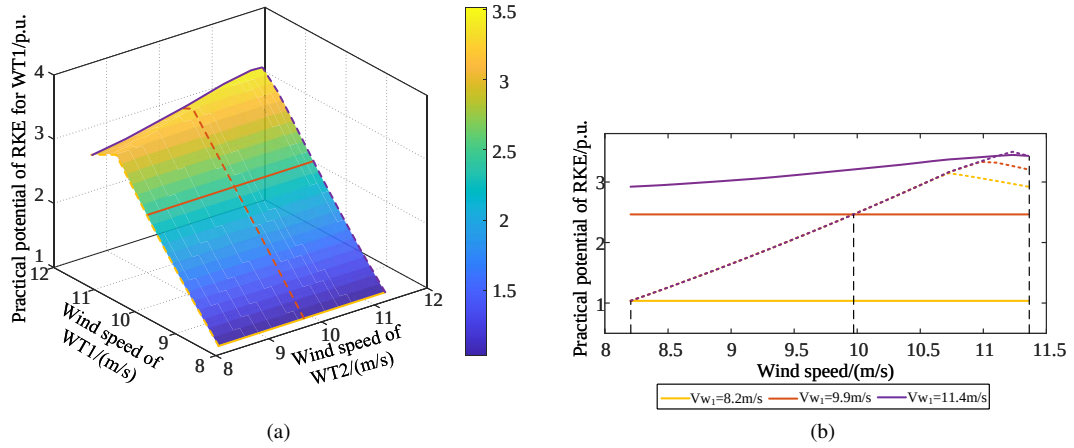


Figure 19: Illustration of the coupling effect on FSCB of WTs:(a) The impact of different WT wind speeds on RKE (b) Projection diagram under specific wind speed conditions

5. Discussion

5.1. Potential application scenarios for proposed FSCB assessment indicators

Based on above case study results, the proposed assessment indicators accurately characterize the FSCB of each WT within a DFIG-based WF. This enables power distribution based on frequency support capabilities of WTs during frequency regulation, instead of the traditional capacity-based distribution scheme. This method fully leverages the

frequency support capabilities of each WT, avoiding insufficient FSCB for low wind speed WTs and wasted capabilities for high wind speed WTs. Under a 400MW load surge, assuming the wind speed distribution in the WF is as shown in Fig.17(a). The system frequency variation curves and additional power generation curves of the WF under different distribution schemes are shown in Fig.20(a) and 20(b).

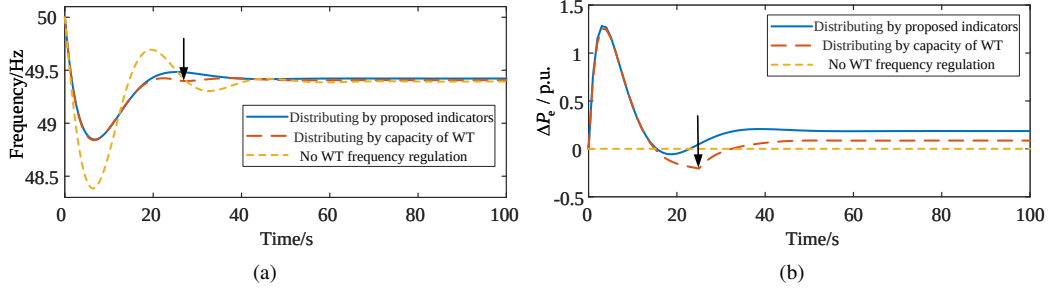


Figure 20: Frequency response and additional power generation of the WF under different distribution schemes: (a) Frequency response (b) Additional power generation

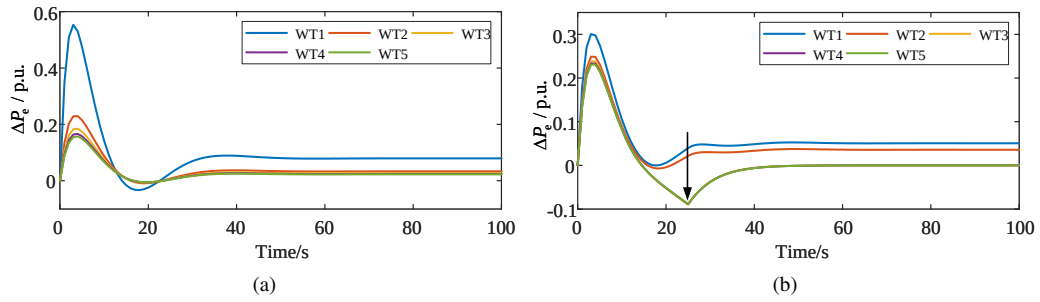


Figure 21: Additional power generation of each WT in the WF: (a) Distributing by proposed indicators (b) Distributing by capacity of WT

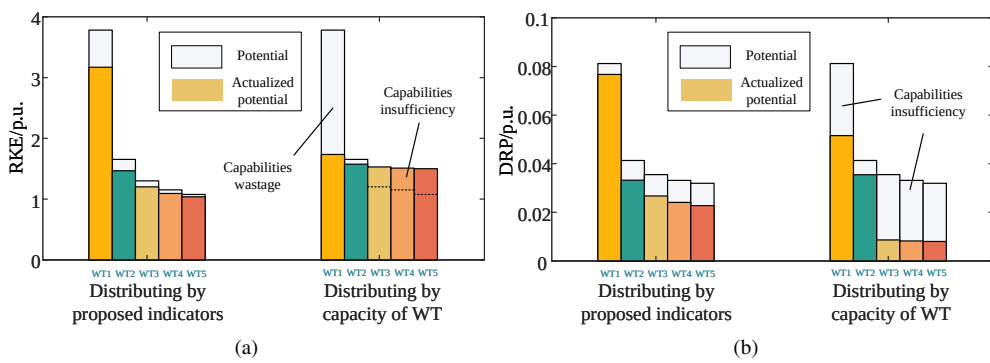


Figure 22: The theoretical potential and actualized potential of FSCB for each WT: (a) RKE (b) DRP

As shown in Fig.20, the participation of the WF in frequency support enhances grid frequency security. The total output power of both distribution schemes is similar in the initial stage of frequency support. In the mid-to-late stages of frequency support, low wind speed WTs under capacity-based distribution exit frequency regulation due to low rotor speed. They enter rotor speed recovery mode, and this results in lower WF output power. Consequently,

a secondary frequency drop occurs. In contrast, the output power under the proposed indicator-based distribution is higher and more stable, with a smaller frequency drop in the system.

Fig.17(a) shows the wind speed conditions of five types of WTs. For clarity, the WTs are aggregated into five units, represented as WT1 to WT5. The power response curves of the aggregated WTs under the proposed indicator-based distribution are shown in Fig.21(a). And those under capacity-based distribution are shown in Fig.21(b). The theoretical potential and actualized potential of FSCB for each aggregated WT are illustrated in Fig.22.

In the initial stage of frequency support at the inertia time scale, low wind speed WTs under capacity-based distribution release too much RKE. This causes rotor speed to drop below the safe limit, leading them to exit frequency regulation and enter rotor speed recovery mode. Correspondingly, high wind speed WTs release too little RKE, wasting capabilities. In the mid-to-late stages of frequency support at the PFR time scale, low wind speed WTs exit frequency regulation, leading to low DRP utilization. High wind speed WTs also release too little DRP, wasting capabilities. Under the proposed indicator-based distribution, each WT fully utilizes its FSCB, maintaining rotor speed within safe limits. This enhances the economic and safety performance of WF operations.

In addition to intra-station power distribution, the proposed indicators can also be used for power dispatching between stations and even across system regions. The distribution effects are similar to those within a station, so they are not elaborated further here.

5.2. Potential application scenarios for proposed Koopman-MILP assessment method

The proposed knowledge and data-driven fusion Koopman-MILP method can linearly optimize and calculate the boundary of control coefficients under actual frequency regulation schemes. This allows for the determination of the practical potential of FSCB under these schemes. The computation speed is within seconds, and the error is within 2%. Therefore, for some frequency regulation schemes, the method can calculate coefficient boundaries while meeting safety limits. This guides subsequent parameter settings to avoid insufficient or wasted FSCB. Taking the typical droop control as an example, the boundary ranges of droop coefficients under different wind speeds and disturbance power are shown in Fig.23.

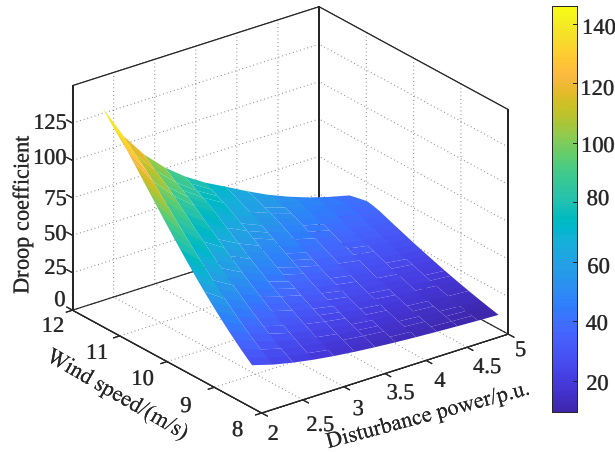


Figure 23: The boundary ranges of droop coefficients

For validation, wind speeds of 8.26 m/s and 11.36 m/s with a disturbance condition of 400 MW are selected. The droop coefficient boundaries calculated by the proposed method are 12.1 and 53.1, respectively. It is assumed that improper coefficient settings are due to not using the proposed method. Therefore, the settings deviate by 10% from the boundaries. The response curves during frequency support under each condition are shown in Fig.24 and Fig.25.

At a wind speed of 8.26 m/s, under the droop coefficient boundary assessed by the proposed method, the rotor speed reaches 0.7 p.u.. Compared to a condition with coefficients 10% larger, the proposed method addresses the rotor speed limit issue effectively. Compared to a condition with coefficients 10% smaller, the proposed method

fully utilizes the frequency support capability of WTs. For WTs with a wind speed of 11.36 m/s, the load constraint becomes dominant. The torque reaches 1.2 p.u. under the droop coefficient boundary calculated by the proposed method. The impact of parameter deviation on each constraint is more significant than at low wind speeds, leading to severe limit violations or capability underutilization.

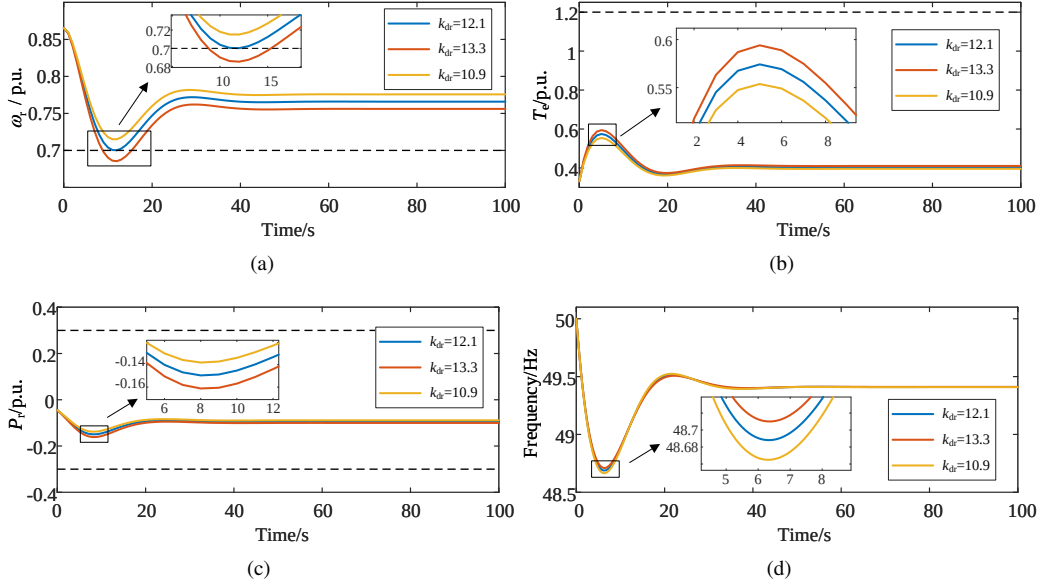


Figure 24: The constraint response curves during frequency support at 8.26 m/s wind speed: (a) Rotor speed (b) Electromagnetic torque (c) Rotor-side active power (d) Frequency

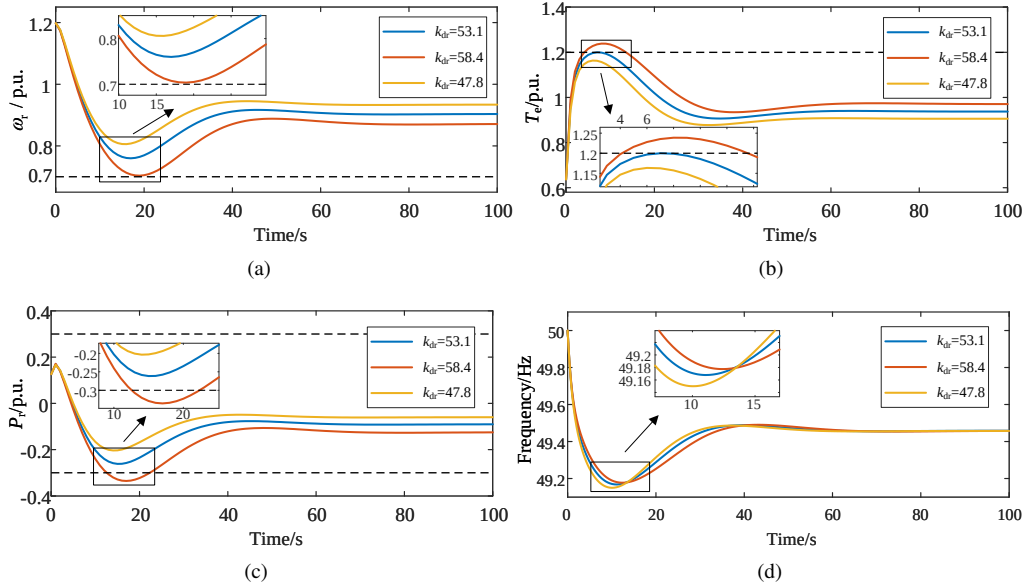


Figure 25: The response curves during frequency support at 11.36 m/s wind speed: (a) Rotor speed (b) Electromagnetic torque (c) Rotor-side active power (d) Frequency

For a DFIG-based WF with multiple wind speed states as shown in Fig.17(a), the proposed Koopman-MILP

method can also calculate the boundary values of the corresponding droop coefficients. The rotor speed, torque, and rotor-side active power response curves of each aggregated WT are shown in Fig.26.

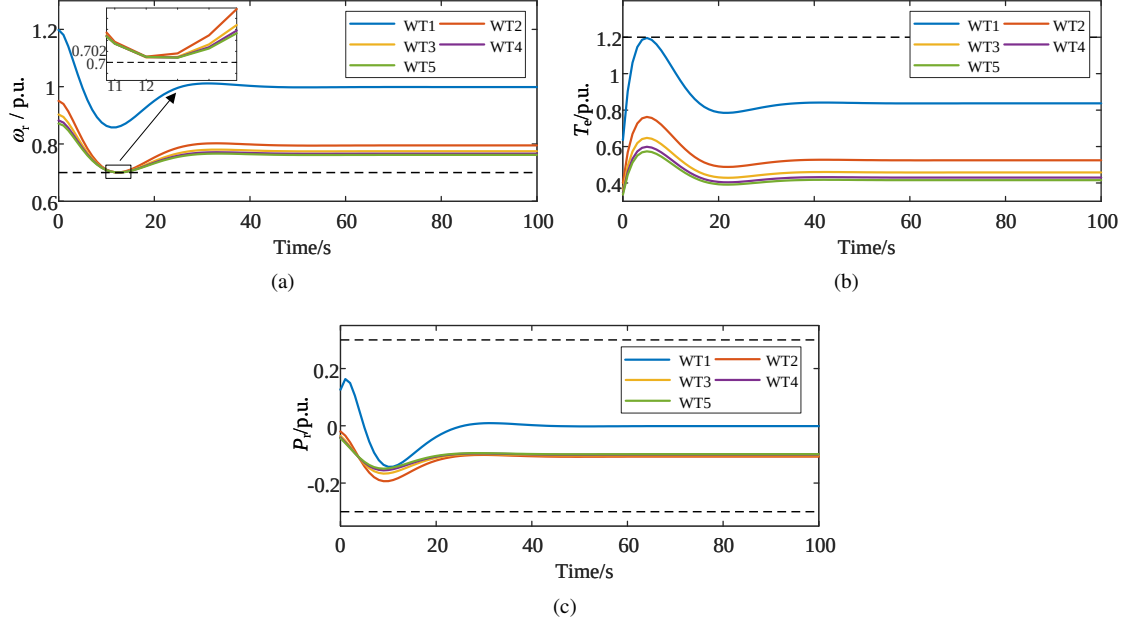


Figure 26: The response curves of each WT in the WF during frequency support: (a) Rotor speed (b) Electromagnetic torque (c) Rotor-side active power

The high wind speed WT1 reaches the load constraint boundary. The medium to low wind speed WT2-5 reach the rotor speed constraint boundary. And all other constraints are within their respective limits. The case study results demonstrate that the proposed Koopman-MILP method can accurately calculate the boundary values of control coefficients. This fully explores the boundary of their frequency support capability. Guidance are provided for coefficient configuration.

Additionally, the proposed Koopman-MILP assessment method can calculate the potential utilization of FSCB for each frequency regulation scheme. This allows for a performance comparison of different schemes in terms of potential utilization. Relevant case studies are presented in section 4.3 and are not elaborated further here.

6. Conclusion

Given the difficulty in quantifying the FSCB of the DFIG-based WF, this paper proposes a multi-dimensional indicator system based on the characteristics of FSCB to reasonably quantify them. On this basis, a knowledge and data-driven fusion Koopman-MILP online assessment method is proposed to quickly and accurately calculate the indicators. Finally, case studies analyze the proposed method, demonstrating its rationality, applicability, and practicality. The specific conclusions are as follows:

- The proposed multi-energy form and multi-level assessment indicator system can accurately quantify FSCB of the DFIG-based WF. The Koopman-MILP method can quickly and accurately calculate these indicators, with an error within 2% and a speed nearly 10 times faster than conventional nonlinear programming methods.
- The proposed FSCB assessment method has strong applicability and can be applied under different scenarios, including different operating constraints, control schemes, and wind speed scenarios. Analysis shows that rotor speed constraint mainly limits FSCB in low to medium wind speeds, while load and capacity constraints mainly limit FSCB in high wind speeds. Droop control and synthetic inertia control have consistent FSCB. Under the

wake effect, the FSCB of some medium to high wind speed WTs is further limited compared to uniform wind speeds within the WF.

- The proposed assessment indicators and method are highly practical. The method ensures higher economic efficiency and safety while maximizing the frequency support capability of the DFIG-based WF. It can be applied to various aspects such as power distribution and frequency regulation coefficient boundary calculation.

Future research will focus on applying the proposed method to voltage-reactive power resource assessment. It will also explore reactive power resources of the WF under the coupled effects of voltage and frequency in complex grid conditions.

Appendix A. Form of the proposed Koopman dictionary function for the DFIG-based WF

$$\mathbf{x}_t = [\omega_{r,i}(t), \Delta f(t), \Delta P_g(t), \Delta P_{e,i}(t), T_{e,i}(t), k_{dr,i}, \Delta P_L, V_{w,i}]^T \quad (\text{A.1})$$

$$\begin{aligned} \psi(\mathbf{x}_t) = & \left[\omega_{r,i}^2(t), \frac{V_{w,i}^3}{\omega_{r,i}(t)} \cdot e^{\frac{-12.5V_{w,i}}{R\omega_{r,i}(t)}}, \frac{V_{w,i}^4}{\omega_{r,i}^2(t)} \cdot e^{\frac{-12.5V_{w,i}}{R\omega_{r,i}(t)}}, \omega_{r,j}^3(t), \omega_{r,j}(t) \cdot \Delta f(t), k_{dr,j} \cdot \Delta f(t), \right. \\ & k_{dr,j} \cdot \Delta f(t) \cdot \omega_{r,j}(t), k_{dr,i} \cdot \Delta f(t) \cdot \omega_{r,i}^2(t), k_{dr,i} \cdot \omega_{r,i}(t) \cdot \Delta P_{e,i}(t), k_{dr,i} \cdot \omega_{r,i}(t) \cdot \Delta P_g(t), \\ & k_{dr,i} \cdot \Delta f(t) \cdot \frac{V_{w,i}^3}{\omega_{r,i}(t)} \cdot e^{\frac{-12.5V_{w,i}}{R\omega_{r,i}(t)}}, k_{dr,i}^2 \cdot \Delta f^2(t), \omega_{r,i}(t) \cdot \Delta P_g(t), \Delta f(t) \cdot \frac{V_{w,i}^3}{\omega_{r,i}(t)} \cdot e^{\frac{-12.5V_{w,i}}{R\omega_{r,i}(t)}}, \\ & \Delta f(t) \cdot \frac{V_{w,i}^4}{\omega_{r,i}^2(t)} \cdot e^{\frac{-12.5V_{w,i}}{R\omega_{r,i}(t)}}, \omega_{r,i}^2(t) \cdot \Delta f(t), k_{dr,i} \cdot \Delta f^2(t), \omega_{r,i}(t) \cdot \Delta P_{e,i}(t), k_{dr,i} \cdot \omega_{r,i}(t) \cdot \Delta P_L, \\ & \left. k_{dr,i} \cdot \Delta P_L, k_{dr,i} \cdot \Delta P_g(t), k_{dr,i} \cdot \Delta P_{e,i}(t), \omega_{r,i}(t) \cdot \Delta P_L, k_{dr,i} \cdot \omega_{r,i}(t) \cdot \Delta P_{e,i}(t), V_{w,i}^3 \right]^T \quad (\text{A.2}) \end{aligned}$$

In the equation, the subscripts i and j represent different WTs within the WF, each having distinct states. Expressions with the same subscript denote the state variable calculations for the same WT, while different subscripts indicate variable operations for WTs in different states. Currently, there is limited references on the selection of Koopman dictionary functions for DFIG-based WF frequency regulation, and this formula can serve as a reference.

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