Decentralized stability enhancement of DFIG-based wind farms in large power systems: Koopman theoretic approach

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ABSTRACT This paper proposes a data-centric model predictive control (MPC) for supplemental control of a DFIG-based wind farm (WF) to improve power system stability. The proposed method is designed to control active and reactive power injections via power converters to reduce the oscillations produced by the WF during disturbance conditions. Without prior knowledge of the system model, this approach utilizes the states measurements of the DFIG subsystem for control design. Therefore, a data-driven optimal controller with a decentralized feature is developed. The learning process is based on Koopman operator theory where the unknown nonlinear dynamics of the DFIG is reconstructed by lifting the nonlinear dynamics to a linear space with an approximate linear state evolution. Extended dynamic mode decomposition (EDMD) is then applied to determine the lifted-state space matrices for the proposed Koopman-based model predictive controller (KMPC) design. The effectiveness of the proposed scheme is tested on New England IEEE 68-bus 16-machine system under three-phase fault conditions. The results ascertain the effectiveness of the proposed scheme to enhance the system damping characteristics.

INDEX TERMS: Koopman operator, power system stabilizers, model predictive control, double-fed induction generator, decentralized control.
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I. INTRODUCTION

Extensive studies have been conducted to damp the oscillatory modes using power system stabilizers (PSSs) [1], [2] and Flexible AC transmission systems (FACTS) that have good performance under a wide range of network conditions [3], [4]. Nevertheless, PSS and FACTS are difficult to tune which may jeopardize their performance in damping the inter-area modes under varying network conditions induced by high penetration of intermittent renewable energy resources. More effective controllers can be derived utilizing modern control theory such as robust and optimal control [5] to enhance the PSS and FACTS efficacy in damping the inter-area modes. With the advent of new wide-area measurements (WAMs) technology, these devices can utilize remote signals and overcome the limitation of local measurements, which lack observing the interarea modes [6]–[8]. However, most of these controllers are model-based and no real-time knowledge of the system is utilized. In controller design and prediction of future system behavior, an accurate and thorough model of the system is required, which can sometimes lead to low performance due to model discrepancy or uncertainty.

For systems with significant wind penetration, the ability of wind generators to deliver ancillary services is vital. As such, transmission system operators (TSOs) have altered grid code criteria in response to the growing number of wind generation facilities around the world [9]. These grid regulations require wind farms to provide ancillary services such as inertial support, frequency regulation, and damping control. All these services are conventionally provided by synchronous generators.

This large-scale integration of wind farms, however, delivers an extreme challenge to handle the time-varying characteristics of such resources and is usually accompanied by modeling uncertainties [10]. Therefore, it is difficult to guarantee a sufficient deterministic model of wind-dominated power systems. Usually, the uncertainties are managed employing robust or adaptive approaches. The value set technique, for example, was utilized in [11] to undertake robust stability analysis and parameter design in large power systems. Ref [12] suggested a robust design of multimachine PSSs based on the simulated annealing optimization approach. These solutions, are
nevertheless analytical model-based, resulting in sophisticated designs and complex controls.
We emphasize that, whereas model-based design gives an appropriate solution for oscillation occurrences in principle, optimality and resilience are seldom attained in practice due to:

1) The real parameters of the devices (e.g., HVDC stations and SGs (synchronous generator)) are difficult to determine due to operating conditions dependence and parameter uncertainty.
2) Because of multiple operating modes, uncertainties, and relaying, the grid model is constantly evolving and hence difficult to generate.
3) The model-based design might not adapt to the operating condition changes and may not handle plant changes after some time due to the unceasing variations of load profiles and unpredicted faults. The difficulty of having a precise model without any parameter uncertainties would pose some limitations [13].

With the advent of synchronized phasor measurement units (PMU) along with the rapid progress in model identification theory, offline models may be replaced with measurement-based online models that can be used to construct damping controllers [14]–[16]. Data-driven methods are not widely discussed in the literature.

In [13], Xinze et al. proposed a two-stage control structure comprising adaptive linear quadratic gaussian control (LQGC). The model is estimated by N4SID algorithm (subspace identification method) to capture the electromechanical characteristics of the system. Ref [17] addressed a method to design a model-free adaptive wide-area PSS. The controller can modify its parameters only based on the input/output measurements without requiring any complex model. The methods discussed in [13], [17] can typically be used to mitigate the impact of model uncertainty. Generally, adaptive controllers are self-tuning and sensitive to incoming state data. The adaptive control scheme can handle system changes (system parameters that drift gradually over time) [18]. Nevertheless, the need for an explicit uncertainty model restricts its usefulness in general settings for adaptive and robust control strategies. Moreover, in [13], [17] the constraints of the system are not incorporated e.g., hard limits on the control signal. In [15] Liu et al proposed an autoregressive moving average exogenous (ARMAX) method to identify a low-order transfer function model for the power system using ambient and ring-down measurements. However, this work did not consider designing a coordinated damping control scheme.

Recently, Koopman operator theory has been introduced for robust identification, estimation, and control of electric power systems [19]. Koopman operator is an infinite-dimensional linear operator capable of reliably identifying the dynamic behavior of nonlinear systems. Koopman operator theory provides a general overview of the complex nonlinear dynamical systems in terms of the evolution of “observable-functions” in the state space. At the expense of operating in high-dimensional spaces, a reasonable approximation of the observables dynamics is given. By finding the observables, Koopman operator can be approximated in a finite-dimensional space in a data-driven fashion. In other words, a highly nonlinear power system can be represented as a linear dynamical system that contains all the nonlinear information (as opposed to a Taylor expansion of the dynamics centered at an equilibrium state) [20]. Koopman operator can provide a data-driven methodology for control and state estimation of nonlinear systems [19]. The controller is constructed based on [21], in which the system measured data is used to build a linear predictor that is embedded in a high-dimensional space. This predictor is mimicking the original system dynamics in the low-dimensional space. And thus, we can capture the nonlinear dynamics with a linear tool but in different space dimension.

By implementing this form of high-dimensional predictors, one can apply effective linear model predictive control (MPC) tools to control the power system. The MPC optimization problem is not affected by this high dimensionality, in terms of computational ability and complexity [21]. Thus, the control sequence can be obtained very fast, opening a gate for real-time control development.

MPC has been proven to be one of the most effective control strategies in numerous real-world control applications [22]. A mixture of prediction and regulation schemes are utilized by the MPC to maintain the system output at the required reference value by generating the optimal control sequence. The most notable element of the MPC compared with other control strategies such as LQG, is that it can produce the optimal control signal by minimizing a certain cost within a finite prediction horizon while considering explicitly the system constraints which are usually taken as a lower or upper limit of the control signal. Moreover, because of the time-varying gains acquired via online optimization, an MPC-based damping controller damps quicker than LQG-based damping controller.

Owing to the optimal characteristics and the ability to deal with system constraints, MPC has been utilized in various power system applications [23], [24]. Generally, MPC has the capability to consider the system requirements such as 1) frequency deviation can be constrained in a certain range via MPC; thus, generator removal because of protective relay action can be avoided; 2) to meet the generator physical limitations, the control action can be bounded, this can be important for practical considerations. In general, the plant operational points are designed to achieve economic targets and sit at the intersection of certain restrictions. The control mechanism usually works near the boundaries, so violations of constraints are possible. The control system, particularly for long-range predictive control, must foresee and correct violations of the constraints in an acceptable manner, MPC control could achieve this purpose efficiently.
A little effort has been done to implement Koopman theory in power system control problems. In [25] the first design application of data-driven MPC for power system control was introduced. The Koopman model was generated and used to design the MPC controller. The main downside of this work is that the model considered was a $2^{nd}$ order machine model. Furthermore, that work did not present any comparison between the identified model and the real one. In [26], Koopman-based PSS was presented where the $4^{th}$ order model was considered. The PSS was designed as a data-driven MPC controller and validated in a small-scale four-machine system. The measurements were collected in a decentralized manner to design a local Koopman-based model predictive controller (K MPC) for each generator. However, the generalization to a more complex and large-scale system is not considered. Furthermore, damping control via DERs has not been investigated up to now.

In this paper, we propose a novel data-driven scheme for supplemental damping based on Koopman operator theory. The main contributions of this paper can be summarized as follows:

1. The proposed damping control design of DFIG oscillations is a data-driven Koopman MPC, which is compared with existing tuned PSS-DFIG.

2. The proposed design scheme is decentralized in both identification and control stages and utilizes only the local measurements of the DFIG in the identification phase, therefore, no scalability issues are posed. At the learning phase, extended dynamic mode decomposition (EDMD) utilizes the local measurements and only computes the model associated with DFIG. At the control stage: the proposed controller receives only local feedback signals from the WF, and no states are hosted from the rest of the grid.

3. In the proposed design approach, neither the model nor the states of the rest of the grid are required for the design. Therefore, the MPC computes the optimal control sequence using the local model associated with the WF.

The remainder of this paper is organized as follows. In section II, an overview of the DFIG model is introduced, and the design problem is formulated. Section III presents the proposed scheme for prediction and control. The effectiveness of the proposed design is demonstrated by time-domain simulation in Section IV. Finally, Section IV concludes the paper with the major findings and remarks.

II. MODELING OF DFIG-WIND FARM

The power system adopted in this study mainly comprises synchronous generators, loads, and wind farms. The dynamic structure of each element is well discussed in the literature [26]. Each wind farm is represented by the combination of a single aggregate turbine and an aggregate DFIG. A large WF typically has tens to hundreds of wind turbines. According to earlier studies, if the wind turbine controllers are well-tuned, there would be no mutual coupling between the turbines on a wind farm [29]. Thus, in this paper, the wind farm connected to the $k_{th}$ bus is a collection of several wind generators aggregated inside the wind farm represented by one DFIG. The model of all the generators and turbines is similar [30]. The total power injected into the grid is the sum of the power output of each generator. The rated output of the aggregated wind turbine generator (WTG) is equal to the rated output of one WTG multiplied by the number of WTGs being aggregated.

The structure of the DFIG and the control system is given in Figure 1. This topology is sophisticated and relates mechanical, electrical, and aerodynamics. This paper, however, is concerned with the electromechanical dynamics in a time scale of oscillations damping, where a detailed model is considered to sufficiently reflect the nature of those dynamics. This detailed description maintains all the oscillatory modes to identify and characterize various frequency dynamics in the wind farm.

![Figure 1. DFIG structure including the MSC and GSC](image)

As shown in Figure 1, the stator is directly connected to the grid, whereas the rotor winding is fed through back-to-back converter and LCL filter. The control of DFIG is performed by active and reactive power modulation [31] as shown in Figure 2. The active and reactive power controls are decoupled via vector control technique.

![Figure 2. The proposed control scheme where the auxiliary signals are added to the power setpoints](image)

The model comprises back-to-back converter (B2Bc) which comprises three parts, rotor side converter (RSC), grid side converter (GSC), dc-link capacitor, generator electrical dynamics, turbine mechanical dynamics, turbine aerodynamics, and LCL filter dynamics. Below is a description of each component.
Turbine aero-dynamics: This component relates wind speed to mechanical torque. The following equations describe the turbine mechanical power considering the pitch angle, wind speed and rotor speed.

\[ P_t = 0.5 \rho \pi R^2 C_p(\lambda, \beta) v_w^3 \]  

(1)

\[ T_t = \frac{P_t}{\omega_t} \]  

(2)

\[ C_p(\lambda, \beta) = c_1 \left( \frac{c_2}{\lambda + c_3\beta} - \frac{c_9}{c_9 + c_4\beta} \right) \]  

(3)

where \( c_1, \ldots, c_9 \) are coefficients determined by the manufacturer [32].

Drive-train: The drive-train consists of low and high-speed shaft both coupled through a gearbox. To account for the torsional mode associated with the shaft, the wind turbine, and the DFIG rotational mass are represented by a two-mass model as follows:

\[ p\omega_r = 1/2 H_g (k\theta_{tw} + c_p\theta_{tw} - T_e) \]  

(5)

\[ p\theta_{tw} = \omega_{elB}(\omega_r - \omega_T) \]  

(6)

\[ p\omega_T = 1/2 H_l (T_k - k\theta_{tw} - c_p\theta_{tw}) \]  

(7)

where \( p = d/dt \).

Remark 1: Normally, more detailed models are needed when dealing with sub-synchronous resonance at wind-turbine torsional oscillations. However, since the focus of the paper is on systems dynamics and wind controls interactions with the synchronous generators we have determined that a simplified yet realistic two-mass model will be sufficiently accurate for studying inter-area oscillations. This assumption is even more justifiable for Type-3 wind generators used in this paper compared to type-4 generators which may be subjected to modal resonance under certain conditions (see [33], [34] for more clarification).

Representation of the generator: The DFIG is an induction machine which is described in d-q synchronous reference frame as follows:

\[ \begin{align*}
\left( \frac{L_s'}{\omega_{elB}} \right) p_i = & -R_1 i_{qs} + \omega_s e_{qs}' + \omega_s e_{qs}' \\
& - e_{ds}' - \omega_s e_{ds}' + K_{mrr} v_{qr} \\
\left( \frac{L_d'}{\omega_{elB}} \right) p_i = & -R_1 i_{ds} - \omega_s e_{ds}' + \omega_s e_{ds}' \\
& + e_{qs}' - \omega_s e_{qs}' + K_{mrr} v_{qr} \\
\left( \frac{L_q'}{\omega_{elB}} \right) p_e = & R_2 i_{qs} - e_{qs}' + \left( 1 - \frac{\omega_r}{\omega_s} \right) e_{ds}' \\
& - K_{mrr} v_{dr} \\
\left( \frac{L_d'}{\omega_{elB}} \right) p_e = & -R_2 i_{qs} - e_{ds}' - \left( 1 - \frac{\omega_r}{\omega_s} \right) e_{qs}' \\
& + K_{mrr} v_{qr}
\end{align*} \]

where

\[ R_1 = R_s + R_2, \]  

(12)

\[ R_2 = K_{mrr}^2 + R_r \]  

(13)

\[ K_{mrr}^2 = L_m/L_r \]  

(14)

The stator active power \( P_s \), rotor active power \( P_r \), stator reactive power \( Q_s \), rotor reactive power \( Q_r \), and electric torque \( T_g \) are given by (12)–(16) respectively

\[ p_i = v_{sq} i_{sq} + v_{sd} i_{sd} \]  

(15)

\[ P_r = v_r q_r + v_r d_r \]  

(16)

\[ Q_s = -v_s q_s + v_s d_q \]  

(17)

\[ Q_r = -v_r q_d + v_r d_r \]  

(18)

\[ T_g = L_m (i_{sq} d_r - i_{sd} q_r) \]  

(19)

The total active and reactive power is

\[ P_{dfig} = P_s + P_r \]  

(20)

\[ Q_{dfig} = Q_s + Q_r \]  

(21)

Rotor-side converter (RSC): This component modulates the active power by adjusting \( v_{qr} \) and modulates the grid terminal voltage by adjusting \( v_{rq} \). Both adjustments are carried out independently in two loops; the outer slow loop which creates the \( d, q \) current setpoints for the inner fast loop to achieve the prementioned purpose. Since we are concerned with the electro-mechanical dynamics, the converters switching dynamics are assumed to be fast, as such; we can represent the associated converter control loops only [32]. Figure 3 depicts the control scheme, while the control equations are described as follows:

\[ p x_1 = p_{ref} - p_s \]  

(22)

\[ i_{qr\_ref} = K_{p1} (p_{ref} - P_s) + K_{i1} x_1 \]  

(23)

\[ p x_2 = i_{qr\_ref} - i_{qr} \]  

(24)

\[ p x_3 = v_{ref} - v_s \]  

(25)

\[ i_{dr\_ref} = K_{p3} (v_{s\_ref} - v_s) + K_{i3} x_3 \]  

(26)

\[ p x_4 = i_{dr\_ref} - i_{dr} \]  

(27)

\[ v_{qr} = K_{p2} (K_{p1} \Delta p + K_{i1} x_1 - i_{qr}) + K_{i2} x_2 \]  

(28)

\[ v_{dr} = K_{p2} (K_{p3} \Delta v + K_{i3} x_3 - i_{dr}) + K_{i2} x_4 \]  

(29)
Grid-side converter (GSC): Figure 4 describes the GSC controller. Like RSC, the reactive power and the capacitor dc-link voltage are regulated by $i_{dq}$ and $i_{dq_r}$, respectively in a decoupled fashion. The control equations are given below:

\begin{align}
px_5 &= Q_{ref} - Q_s \\
i_{dq_{ref}} &= K_{p_{d1}}(Q_{ref} - Q_s) + K_{i_{d1}}x_5 \\
pv_x &= v_{DC_{ref}} - v_{DC} \\
i_{dq_{ref}} &= -K_{p_{d2}}\delta v_{DC} + K_{i_{d2}}x_6 \\
px_7 &= i_{dq_{ref}} - i_{dq} \\
pv_x &= K_{p_{d1}}\Delta v_{DC} + K_{i_{d1}}x_6 - i_{dq} \\
v_{dq} &= K_{p_{dq}}px_x + K_{i_{dq}}x_7 \\
px_8 &= v_{dq_{ref}} - v_{dq} \\
v_{dq} &= K_{p_{d1}}\Delta v_{DC} + K_{i_{d1}}x_6 - i_{dq} \\
v_{dq} &= K_{p_{dq}}px_x + K_{i_{dq}}x_7 \\
px_9 &= K_{p_{dq}}(i_{dq_{ref}} - i_{dq}) + K_{i_{dq}}x_7
\end{align}

$LCL$ Filter: which is used to filter out the components of switching frequency harmonics, described in d-q frame by the following:

\begin{align}
\left( \frac{L_s}{\omega_{elB}} \right) p_i &= v_i - v_{cf} - (R_i + R_cf)i_i + T\omega L_i i_i \\
R_{cf}i_g \\
\left( \frac{L_s}{\omega_{elB}} \right) p_i &= v_{cf} - v_g - (R_g + R_{cf})i_g + T\omega L_i i_g + R_{cf}i_i \\
C_f v_{cf} &= i_t - i_g - T\omega C_f v_{cf}
\end{align}

where

\begin{align}
i_i &= [i_{q1}, i_{d1}]^T; i_g = [i_{qg}, i_{dg}]^T \\
v_i &= [v_{q1}, v_{d1}]^T; v_g = [v_{qg}, v_{dg}]^T; v_{cf} \\
T &= [1, 0; 0, -1]
\end{align}

To this end, the equations representing DFIG shown above can be described compactly as:

\begin{equation}
\dot{x}(t) = F(x(t), u(t))
\end{equation}

where $x, u$ represents the state and control vectors of the DFIG, respectively. Those vectors are defined as follows:

\begin{equation}
x = \begin{bmatrix}
\omega_r, \omega_{\tau}, \omega_t, i_{q1}, i_{d1}, i_{q2}, i_{d2}, e_{q1}, e_{d1}
\end{bmatrix}^T \in \mathbb{R}^{2x1}
\end{equation}

\begin{equation}
u = \begin{bmatrix}
P_{ref}, Q_{ref}
\end{bmatrix}^T \in \mathbb{R}^{2x1}
\end{equation}

### III. THEORETICAL BACKGROUND ON KOOPMAN MODEL IDENTIFICATION

#### A. Koopman Operator theory: an overview

Consider the following autonomous system that evolves on n-dimensional finite manifold $X$:

\begin{equation}
\dot{x}(t) = F(x(t)), t \in \mathbb{R}, x(t) \in X \subset \mathbb{R}^n
\end{equation}

where $x$ is the system state and $F$ represents the nonlinear continuous function. The solution to (48) at time $t$ starting with the initial condition $x_0$ at time 0, is denoted by $\phi(t, x_0)$, which is known as the “flow map”. The represented system $F$ can be lifted to a higher dimensional space $\mathcal{F}$ that contains scalar-valued continuous functions, invariant under the Koopman operator action in the manifold $X \subset \mathbb{R}^n$. The flow in the lifted space is described by the action of Koopman operator $U_f: \mathcal{F} \to \mathcal{F}$, $\forall t \geq 0$. The Koopman operator for the continuous-time system which acts on the space of observables is defined by:

\begin{equation}
U_tf = f \circ \phi_t
\end{equation}

where $\circ$ denotes the composite function. $f: \mathbb{R}^n \to \mathbb{R}$ is a scalar-valued function known as the observable, which includes the information of the state $x$, i.e., the mapping $x \to x_1$ belong to $\mathcal{F}$, $\forall i \in \{1, ..., n\}$. $U_f$ is a linear space despite the nonlinearity of the system (21), since for $f_1, f_2 \in \mathcal{F}$ and $\lambda_1, \lambda_2 \in \mathbb{R}$, then

\begin{equation}
U_f(\lambda_1 f_1 + \lambda_2 f_2) = \lambda_1 f_1 \circ \phi_t + \lambda_2 f_2 \circ \phi_t = \lambda_1 U_f f_1 + \lambda_2 U_f f_2
\end{equation}
Figure 5. Depiction of Koopman mapping of the nonlinear system

B. Koopman operator approximation

The infinite-dimensionality of Koopman operator renders a difficulty of gaining an actual matrix representation of the operator, therefore, EDMD is utilized to compute a finite approximation of the operator [35] [16]. EDMD is a regression-based method used to find a finite-dimensional approximation of \( U_t \). It is a data-driven approach and relies upon the accessibility of the system states observations.

Consider \( \overline{\mathcal{F}} \subset \mathcal{F} \) to be a subspace of \( \mathcal{F} \). Linearly independent basis functions which span \( \overline{\mathcal{F}} \) are defined by \( \{ \psi_i = \mathbb{R}^n \to \mathbb{R} \}_{i=1}^N \); the image of \( \psi_i \) is denoted by \( \mathcal{R}_i \), which is equal to \( \{ \omega \in \mathbb{R} | \exists x \in \mathbb{R}^n, \psi_i(x) = \omega \} \). For the sake of simplicity, we suppose that the first \( n \) basis functions are defined as \( \psi_i(x) = x_i \), where \( x_i \) is the \( i \)-th element of \( x \). The observables \( \overline{\mathcal{F}} \subset \mathcal{F} \) is constructed by the linear combinations of \( \psi_i \):

\[
\overline{\mathcal{F}} = \theta_1 x_1 + \ldots + \theta_N x_N
\]

where \( \theta_j \in \mathbb{R} \). For neat display, let's set the vector \( \theta = [\theta_1 \ldots \theta_N]^T \) which provides a vector representation of \( \overline{\mathcal{F}} \in \mathcal{F} \), and the lifting functions \( \psi; \mathbb{R}^n \to \mathbb{R}^N \) as

\[
\psi(x) = [x_1 \ldots x_n \psi_{n+1}(x) \ldots \psi_N(x)]^T
\]

the image of \( \psi \) is defined as \( \mathcal{M} = \mathcal{R}_1 \times \ldots \times \mathcal{R}_N \subset \mathbb{R}^N \). At a sample \( x \), \( \overline{\mathcal{F}} \) is calculated by \( \overline{f}(x) = \theta^T \psi(x) \). We, in this manner, allude to \( \overline{\mathcal{F}} \) as the lifted state. Now we can express the operator in terms of a \( N \times N \) matrix as \( U_t \theta = \theta' \), where \( \theta, \theta' \) are vector portrayals in the space of observables.

Following the lifting step, we need to identify the Koopman operator that describes the lifted version of the space, with the existence of data snapshots \( (a[k] = x[k], b[k] = \phi_{T_s}(x[k]) + \sigma[k]), \forall k \in \{1, \ldots, K \} \) where \( K \) is the number of samples, \( T_s \) is the sampling time and \( \sigma \) is the process noise, then we have the following representation of the lifted measurements

\[
\Psi_s = [\psi(s[1]) \ldots \psi(s[K])]^T; s \in [a, b]
\]

where \( \Psi_a, \Psi_b \in \mathbb{R}^{K \times N} \) represents the lifted-state measurements. Using EDMD least-square we can get the best fit of the data observation by

\[
U_{T_s} = \Psi_a^T \Psi_b
\]

where \( \Psi_a^T \) denotes the pseudo-inverse of \( \Psi_b \)

C. Linear Predictors

For the dynamical systems with control inputs, the Koopman operator should satisfy the following discrete linear form

\[
x[j + 1] = Ax[j] + Bu[j],
\]

\[
x[j] = Cz[j]
\]

\( \forall j \in \mathbb{N} \), where \( x[0] \) is the initial condition in the original state-space, \( z[0] = \psi(x[0]) \) is the initial condition in the lifted-state space. \( u[j] \in U \subset \mathbb{R}^m \) represents the system input at the \( j \)-th sample and \( U \) is the space of control inputs. Above all, the control input is preserved in its original space (un-lifted), thus the control inputs appear linearly; linear constraints may be applied linearly and keep the predictor’s linear reliance on the original input, rendering the predictor form suited for real-time application. The Matrix \( A \in \mathbb{R}^{N \times N}, B \in \mathbb{R}^{N \times m} \) are a decomposition of \( U_{T_s} \), which is given in [21]. \( C \) is a projection factor that projects the lifted space into the original one and it is different from the state-space output matrix. The previous form is well known as a linear predictor form [21].

As explained in the previous section, the operator can be identified with EDMD considering the pair of lifted snapshots amended by the addition of the control sample

\[
\alpha[k] = [\psi(a[k]), u[k]]^T, \quad \beta[k] = [\psi(b[k]), u[k]]^T; \forall k \in \{1, \ldots, K\}
\]

where \( \alpha, \beta \) represents vectors of present and future samples, respectively. We can collectively define the pairs as

\[
\Gamma_a = [\alpha[1]^T, \ldots, \alpha[K]^T]^T, \quad \Gamma_b = [\beta[1]^T, \ldots, \beta[K]^T]^T
\]

In the same manner, the best fit of the measured data is offered by \( U_{T_s} \in \mathbb{R}^{(N+m) \times (N+m)} \)

\[
U_{T_s} = \Gamma_a^T \Gamma_b
\]

The previous equation can be written differently by realizing that the transpose of \( U_{T_s} \) is the minimizer of

\[
\min_{\theta'} \sum_{k=1}^{K} \| \theta^T \alpha[k] - \beta[k] \|^2_2
\]

\[
= \min_{\alpha, \beta} \sum_{k=1}^{K} \| A \psi(a[k]) + Bu[k] - \psi(b[k]) \|^2_2
\]

Provided that \( U_{T_s} = [A_{N \times N} B_{N \times m}] \), where \( I \) represents the identity matrix, \( O \) represents the zero matrix. Matrix \( C \) is given by \( C = [I_{n \times n} O_{n \times (N-n)}] \).

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D. Local Computation of Koopman Operator

As explained previously, we may need to add basis functions to stretch out the nonlinear system with \( \pi \) dimensional space into a linear system with \( N \)-dimensional space where \( N \gg \pi \). However, for large systems with thousands of states (especially when a detailed model of a large power grid is considered); the size of dictionary functions grows exponentially as the number of states grows. Considering memory constraints, we may end up with a difficulty learning a centralized Koopman model. In addition to the matter of basis function selection, which might be easy when handling small systems, but for large ones, we might need to use kernel methods for implicit expression of those functions [35]. However, the issue of memory limitation still poses a problem. Moreover, overfitting may occur because of enormous basis functions integration, and thus the generated model may provide an accurate prediction for the existing training data but do not adapt well to new data sets. This motivates us to learn only a local Koopman model for the subsystem of concern (DFIG-WF in our case) to avoid the aforementioned obstacles. The identification algorithm is summarized as follows:

Algorithm 1: Koopman operator identification

Input: \([a[k], b[k]]\) and \(u[k]\) for \(k = 1, ..., K\)
Step 1: Lift the combined states/inputs data according to (44)
Step 2: Compute Koopman operator according to (46)
Step 3: Extract the lifted-state space matrices A, B, C

E. Koopman MPC (KMPC)

A diagram describing the proposed control strategy is depicted in Figure 6. Where \( u \) is the control action, \( u_0^* \) is the first sample of the computed sequence \( \{u_0^*, u_1^*, ..., u_{Np-1}^*\} \) of the optimization problem that is solved by the optimizer within the prediction horizon window \( N_p \), we take only the first sample and cast the others. Note that the objective function \( f \) is a convex quadratic function. \( Z, U \) are the set of state and input constraints, respectively. This paper embraces discrete-time MPC since it is computationally less demanding as contrasted to the continuous-time MPC.

The optimization problem can be solved as a convex optimization problem in the lifted space owing to the linearity of the obtained predictor and the freedom of choice of the mapping functions, no matter how nonlinear it is in the original space [21].

\[
J(\omega_j, u_j) = (\omega_{N_p}^* - \omega_{r,N_p})^T Q_{N_p} (\omega_{N_p}^* - \omega_{r,N_p}) \\
+ \sum_{i=0}^{N_p-1} (\omega_i - \omega_{r,i})^T Q_i (\omega_i - \omega_{r,i}) + u_i^T R_i u_i
\]  

(60)

where, \( \omega_{r,i} \) is the rotor-speed reference at the sample \( i \). \( N_p \) is the prediction horizon, \( Q_i \in \mathbb{R}^{N \times N} \) and \( R_i \in \mathbb{R}^{m \times m} \) are tuning weighting matrices (positive semidefinite). The MPC controller aims at minimizing (60) at each prediction horizon window, considering the states and control signals constraints. Generally, linear MPC minimizes a convex quadratic cost function, in this way taking into consideration an incredibly quick generation of the control input sequence. Contrary to Nonlinear MPC, which solves a troublesome non-convex function [36], thus requiring a high computational effort.

IV. SIMULATION RESULTS

In the previous section, we have shown the mathematical model of the DFIG and presented an overview of Koopman theory that is used to establish the basis of the data-driven MPC. In this part, we show the simulations to demonstrate the ability of the proposed scheme to improve the dynamic stability of wind-integrated power systems.

A. Study System

The wind-integrated IEEE 68-bus/16-machine system is considered to verify the effectiveness of the proposed KMPC. The system is built in MATLAB/SIMULINK on a desktop PC with Intel Core i7-5500U CPU processor at 2.40 GHz with 16 GB RAM. Figure 7 shows the single-line diagram of the test system. Power system stabilizers have been added to enhance the damping of local modes of some SGs. The PSS setting is given in [37]. It should be noted that not all generators are equipped with PSSs; we just placed PSSs at a set number of SGs to ensure the system’s stability; in the meantime, we retain room to demonstrate the performance of our concept. Adding PSSs across the system may overpower our proposed controller, causing its performance to be shadowed.

The number of the connected WFs depends upon the concept to be illustrated, i.e., in the learning phase, we use only one WF, in the control phase we use two WFs. The intended DFIG-MPC will be equipped at the wind farm’s central control center, and the control signals will be relayed to each turbine via fiber-optic interconnections.
states is shown in Figure 8. The results demonstrate that the predicted model can capture the system dynamics and achieve a satisfactory prediction of the actual model. This allows us to use the predicted model to design an MPC controller for the actual plant, even though we have considered a black-box model.

**Remark 2:** By generating data matrices of proper dimensions, measurement noise may be viewed as part of the unknown system, and its influence is indirectly acknowledged in the proposed algorithm.

**Figure 8. The identification of some selected states of DFIG**

**C. Damping Control Design**

In general, the typical control architecture of DFIG-WF shown in Figure 1, does not provide enough control flexibility to accomplish oscillation damping functionality, necessitating the use of supplemental control. The auxiliary control signals can be actuated through different controllable subsystems such as FACTS and HVDC to provide a damping aid with the PSS. In this paper, the actuation is performed via DFIG to enhance weakly oscillatory modes. It should be noted that this controller must be installed in each wind generator that forms the aggregated WF. The controller is designed considering two WFs located at different areas replacing generators G7, G10 delivering an
active power of 560 MW and 700 MW, respectively. Each WF is identified using the method discussed earlier.
To mitigate system oscillations MPC supplementary controller is attached locally at each WF. The MPC computes the time-varying gain at each horizon by minimizing the objective function described in eq (50) using “qpOASES” optimization toolbox [38]. The controller is built in MATLAB “s-function” and linked with the Simulink platform. The local feedback signal is the DFIG rotor speed \( \omega_{\text{dfig}} \), the auxiliary control signals are added to the active and reactive powers references as shown in Figure 2. The auxiliary inputs \( P_{\text{aux}}, Q_{\text{aux}} \) are assumed to be zero when no controller is integrated.

The MPC settings are as follows:
1) The sampling time is 0.01 s.
2) The prediction horizon \( N_p = 10 \) samples.
3) The weighting factor of the cost function is \( R = I, Q = Q_{N_p} = 100 \times I \) (\( I \) is the identity matrix, the dimension of which can be deduced from the context).

**D. Modal Analysis:**
Since the closed-loop is nonlinear and the gain of the MPC varies every prediction horizon \( N_p = 10 \) samples, thus, rendering a time-varying gain. This inevitably means the transfer function of the closed-loop system changes at each operating condition; thus, we will get a different state-space representation at every new horizon. Therefore, linear analysis tools would not reflect the dynamic characteristics, it is not possible to apply linear tools to identify the linear modal traits i.e., eigenvalues and damping ratios. Therefore, a measurement-based technique is required, Prony method is used to capture the variable frequency components of the measured signals [39]. In this part two cases are considered, 1) the impact of replacing the conventional SGs with DFIG with a similar power delivery on the oscillatory modes, this case is a general study in which the proposed design is not introduced. 2) The second case addresses the effect of the proposed scheme on the oscillatory modes and damping enhancement.

**Replacing the SG with a DFIG**
In the first part of linear analysis, we evaluate the effect of substituting the conventional SGs (with their local control if any) with the WF-based DFIG (injecting the same amount of power) on the local and inter-area modes of oscillation. Table 1 provides the frequencies and the damping ratios of different modes. The system contains four interarea modes, which we refer to as M1 to M4. The range of the interarea oscillatory frequencies lies between 0.2 and 0.8 Hz. Furthermore, various local modes are also identified in the range between 1-2 Hz. denoted by L1 to L10.

| Scenario | Only SGs | DFIG at G7 |
|----------|----------|------------|
| Modes    | \( \xi (%) \) | \( f (Hz) \) | \( \xi (%) \) | \( f (Hz) \) |
| M1       | 0.87     | 0.36       | 0.87     | 0.36       |
| M2       | 1.66     | 0.67       | 1.59     | 0.68       |
| M3       | 3.33     | 0.37       | 3.33     | 0.37       |
| M4       | 1.22     | 0.72       | 1.22     | 0.72       |
| L1       | 6.34     | 1.022      | 6.34     | 1.022      |
| L2       | 5.56     | 1.056      | 5.56     | 1.055      |
| L3       | 7.978    | 1.273      | 7.978    | 1.272      |
| L4       | 3.435    | 1.324      | 3.433    | 1.324      |
| L5       | 4.324    | 1.176      | -        | -          |
| L6       | 9.954    | 1.433      | 9.954    | 1.433      |
| L7       | 2.354    | 1.768      | 2.354    | 1.767      |
| L8       | 3.985    | 1.583      | 3.985    | 1.582      |
| L9       | 6.587    | 1.884      | 6.586    | 1.883      |
| L10      | 1.234    | 1.764      | 1.233    | 1.764      |

As shown in Table 1, the second interarea mode M2 is weakened slightly by the substitution of G7, and the associated damping has reduced. L5 has disappeared because the DFIG does not contribute to local modes due to the decoupling impact of the power converter which split the machine mechanical mechanism from the legacy grid, that is why it doesn’t introduce a new electromechanical mode. However, the interarea mode can still be captured in the busbar frequency. The rest of the local modes were not subject to significant drifts. Because the DFIGs have lower shaft inertia than the SGs, the frequency in M2 rises a little bit when G7 is substituted due to the absence of WF inertial involvement.

Wind turbines do not contribute to low-frequency electromechanical oscillations since they are not simultaneously coupled to power networks due to the decoupling effect of the B2B convertor. Furthermore, because grid-connected wind turbine technologies do not engage in power system oscillations, wind turbines do not introduce additional oscillatory modes into power systems. [40].

**The inclusion of the proposed controller**
The modal analysis of the DFIG-integrated power system with and without auxiliary control is illustrated in Table 2. The interarea modes are poorly damped without a controller that why a disturbance may cause instability; however, the proposed scheme has shown a significant improvement compared to the baseline case. This has resulted in the WT operating steadily for both techniques, but better for the proposed methodology.

The system demonstrates a good performance without supplemental control. However, with the addition of the conventional PSS and the proposed control, we notice a superior damping performance.
Table 2. Oscillatory modes characteristics with all three control scenarios

| Cases | No auxiliary control | Baseline | Proposed |
|-------|----------------------|----------|----------|
| Mode index | ζ (%) | f(Hz) | ζ (%) | f(Hz) | ζ (%) | f(Hz) |
| M1 | 0.87 | 0.36 | 1.23 | 0.345 | 3.67 | 0.311 |
| M2 | 1.66 | 0.67 | 5.67 | 0.653 | 10.56 | 0.62 |
| M3 | 3.33 | 0.37 | 36.89 | 0.333 | 40.57 | 0.317 |
| M4 | 1.22 | 0.72 | 24.86 | 0.702 | 30.65 | 0.69 |

E. Time-domain simulation:
In addition to modal analysis, nonlinear time-domain simulation is performed. To assess the impact of the proposed design on transient behavior, the system has been subjected to two significant disturbances: three-phase bus and line faults. In contrast to the bus fault scenario, a change in network topology is considered in the line fault scenario.

Three-phase bus fault:
An instantaneous three-phase fault at bus 5 is applied and cleared soon after 0.1 sec. Figure 9 to Figure 13 shows the following quantities: DFIG rotor speed deviation, DFIG active power, DFIG reactive power, dc voltage of B2B capacitor, and the terminal voltage of the DFIG, in three cases: 1) conventional PSS-DFIG [41] which is used as a base-line method (red line), 2) proposed KMPC-DFIG (yellow line) 3) no additional damping controller (gray line). The results indicate that using conventional PSS improves the dynamics of DFIG, although with clear consequences for DFIG torsional dynamics in Figure 9. This is because the baseline method’s sole goal is to dampen inter-area oscillations according to its tuning objective without paying much attention to the WF internal dynamics [41]. It can be noticed that the torsional dynamics with MPC have much better damping than the poorly damped oscillations with PSS installed. It is obvious that the proposed technique can not only effectively dampen inter-area oscillations, but also ensure the optimal control of the WF dynamics.

Figure 9. DFIG rotor speed deviation under 100 ms fault.

Figure 10. The active power output of DFIG connected to bus 7 under 100 ms fault.

Figure 11. The reactive power output of DFIG connected to bus 7 under 100 ms fault.

Figure 12. The capacitor voltage of DFIG connected to bus 7 under 100 ms fault.

Figure 13. DFIG terminal voltage under 100 ms fault.
The interarea modes are represented by the relative speeds and rotor-angle deviations of G5 vs G15 and G1 vs G13 are shown in Figure 14 and Figure 15. With the proposed MPC design, the swings following a substantial system disturbance are damped much faster.

It must be noted that the proposed controller cannot guarantee the overall stability, nevertheless, it can only improve the local damping performance of WF. Therefore, local PSSs are added at different locations. For instance, G15 is not equipped with a PSS, unlike G1, which explains why oscillations of \( \omega_5 - \omega_{15} \) are extremely large in the no-control case compared to \( \omega_1 - \omega_{13} \). The results demonstrate that the damping has been enhanced successfully when KMPC for each WF is introduced. The controller gives satisfactory action when the fault takes place and improves the damping greatly. Furthermore, the oscillations settling time is reduced significantly, which perfectly achieves the system damping requirement.

For clarity, the speed deviation of all conventional synchronous generators in all three control scenarios is depicted in Figure 16.

**Three-phase line fault**

In this case, a three-phase fault is applied in the middle of the line connecting bus 62 and bus 63 at t=1 sec and cleared after 0.1 sec by opening the circuit breaker at both ends of the faulted line, thus a topological change has occurred. Figure 17 and Figure 18 depict the DFIG speed deviation and the SGs average speed, respectively. It’s shown the torsional dynamics has again improved and the inter-area oscillations settle well within an acceptable timespan of 8 s for the post-fault topology that was not included in the controller design. The proposed MPC can dampen oscillations significantly quicker than the standard PSS even though the network is different from the one that is initially used to gather the data and build the Koopman model due to the line tripping.
Note that the location of the fault impacts the performance of the decentralized MPC used, the closer a disturbance is to the WF bus, the greater the deviation from equilibrium in the WF initial states. Because of the poor observability of the WF states toward various system oscillation modes, the MPC only performs meaningful actions when the feedback signal has sufficient information about the modes of interest that are to be damped. However, in this paper, the selected local feedback signal is a mechanical state belonging to a mechanical part that is decoupled from the main grid via the converter. The fault that is electrically far will excite an insignificant oscillation in the mechanical-detached states, thus the cost function to be minimized by the MPC would have less weight compared to the cost function resulting from a close fault (Note that this function is dependent on the output feedback signal as shown in eq (60)). Therefore, any disturbance that occurs electrically far from the WF would have little influence on its internal dynamic states, and so the contribution of interarea oscillation damping would be minimal.

V. CONCLUSION

In this paper, the design of a data-driven KMPC is presented for a wind-integrated power system. The methodology is decentralized in both learning and control phases. The design scheme utilizes only the local measurements of the DFIG in the learning phase, thus no scalability issues are posed. The controller receives only a local feedback signal from the WF, and no extra states are hosted from the rest of the grid. As such, neither the model nor the states of the rest of the grid are required for the design. The learning process is based on Koopman operator theory where the unknown nonlinear dynamics of the DFIG is reconstructed by lifting the nonlinear dynamics to a linear space with an approximate linear state evolution. EDMD is then applied to determine the lifted-state space matrices which are used to design the KMPC. The effectiveness of the proposed scheme is tested on New England IEEE 68 bus, 16-machine system under three-phase faults. The result ascertain the effectiveness of the proposed scheme at enhancing the damping performance. The design is also validated by small-signal analysis by identifying the oscillatory modes associated with the DFIGs using Prony method and the findings coincide with the simulations results.

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