A Data-Driven Energy Storage System-Based Algorithm for Monitoring the Small-Signal Stability of Power Grids with Volatile Wind Power

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Abstract—In this paper, we propose a data-driven energy storage system (ESS)-based method to enhance the online small-signal stability monitoring of power networks with high penetration of intermittent wind power. To accurately estimate inter-area modes that are closely related to the system’s inherent stability characteristics, a novel algorithm that leverages on recent advances in wide-area measurement systems (WAMs) and ESS technologies is developed. It is shown that the proposed approach can smooth the wind power fluctuations in near real-time using a small additional ESS capacity and thus significantly enhance the monitoring of small-signal stability. Dynamic Monte Carlo simulations on the IEEE 68-bus system are used to illustrate the effectiveness of the proposed algorithm in smoothing wind power and estimating the inter-area mode statistical properties.

Index Terms—Data-driven methods, energy storage systems, small-signal stability monitoring, wind power

I. INTRODUCTION

Wind power is a rapidly evolving renewable energy technology worldwide because of its cleaness, abundance and cost-effectiveness. However, the volatile and stochastic nature of wind poses many challenges to the secure operation of modern grids. Concerning small-signal stability, the intermittency of wind energy may not only lead to instability [1] but also result in great obstacles regarding the power system stability monitoring and assessment [2]. Particularly, poorly-damped inter-area oscillations may become undetectable if small-signal stability monitoring is deteriorated. Such a phenomenon can cause major power outages [3]. Recent works have proposed probabilistic approaches to study and quantify the impact of wind power on small-signal stability analysis, which may nevertheless require large computational effort [4], [5].

The recent advances in energy storage systems (ESSs) have provided power engineers with an effective means to minimize the unwanted impacts of wind energy on power networks by smoothing wind power variations [6]. However, even with ESSs, additional challenges may arise as power grids are transforming into large-scale networks with increasing complexity, due to the continuous integration of power electronics-based devices, the transmission system expansion, etc. In fact, [7] has shown that the conventional model-based methods for small-signal stability monitoring may fail when the power system experiences unexpected disturbances or undetected topology changes. In this direction, measurement-based methods have been proposed in the recent literature to monitor and control small-signal stability considering load uncertainties [7]–[10]. These strategies mainly rely on the enormous growth of wide-area measurement systems (WAMs) and phasor measurement units (PMUs) over the last 10 – 20 years [11]. Despite of providing advancements, these works do not consider wind stochasticity.

To address these challenges, in this paper, a novel data-driven ESS-based algorithm for monitoring the small-signal stability of power grids with volatile wind power is proposed. Our method exploits two of the key emerging technologies—WAMS and ESS—that have already been massively installed in most power networks [6], [12], [13]. We then apply an online data-driven mode identification approach to estimate the dynamic system state matrix and the inter-area mode characteristics. Unlike probabilistic stability assessment approaches, the proposed method enables small-signal stability assessment online (within a 5 minutes window). In addition, it will be shown that the ESS capacity required for wind power smoothing can be determined based on the statistical properties of wind farm power output, whereas its size is not significant when compared with the large scale of power grids. To the best of authors’ knowledge, this work represents the first attempt to enhance the data-driven monitoring of small-signal stability considering the stochastic nature of renewable energy sources.

II. STOCHASTIC MODEL FOR POWER GRID DYNAMICS

Inter-area modes lie in the low-frequency portion of the electromechanical mode spectrum (i.e. 0.1 – 1 Hz) [14]. Thus, fast generator dynamics can be neglected and aggregated synchronous machines can be represented by the classical model [14]. By numbering generator buses as \( i = 1, ..., n \):

\[
\dot{\delta}_i = \omega_i \tag{1}
\]

\[
M_i \dot{\omega}_i = P_{mi} - P_{ei} - D_i \omega_i \tag{2}
\]
\[ P_{e_i} = E_i \sum_{j=1}^{n} E_j |Y_{i,j}| \cos(\delta_i - \delta_j - \phi_{i,j}) \]  

(3)

where \( \delta_i \) is the rotor angle, \( \omega_i \) the rotor speed deviation from synchronous speed, \( M_i \) the inertia coefficient, \( D_i \) the damping coefficient, \( P_m \) the mechanical power input, \( P_e \) the electrical power output, \( E_i \) the transient emf magnitude, and \( |Y_{i,j}|/\angle \phi_{i,j} \) the \((i,j)^{th}\) entry of the Kron-reduced admittance matrix \( Y \).

A. Stochastic Load Model

Generator dynamics prevail over load dynamics in the study of inter-area modes. Therefore, we model loads as constant impedances to simplify the computations and obtain the generator electromechanical dynamics from the network dynamics [14]. Considering a steady-state grid operation, we assume that inter-area modes are excited by Gaussian load fluctuations that translate into variations of the diagonal elements of \( Y \) [15]:

\[ Y_{i,i}' = |Y_{i,i}|(1 + \sigma_i \xi_i) / \angle \phi_{i,i}, \quad i = 1, ..., n \]  

(4)

where \( \xi_i \) are mutually independent standard Gaussian random variables, \( \sigma_i \) is the standard deviation of load variations and \( Y_{i,i}' \) is the \((i,i)^{th}\) element of \( Y \). Substituting (4) into (3), i.e. replacing \( Y_{i,i} \) with \( |Y_{i,i}|(1 + \sigma_i \xi_i) \) gives

\[ P_{e_i}' = P_{e_i} + E_i^2 G_{i,i} \sigma_i \xi_i \]  

(5)

B. Stochastic Wind Speed Model

In this work, wind farms associated to a wind speed model are integrated into the power network. Due to its intermittency, wind speed adds stochastic perturbations to the grid that can be described by various continuous probability distributions, such as the Weibull distribution, the beta distribution, etc [16]. Therefore, wind speed can be statistically represented by a generic vector stochastic process \( \mathbf{v}_{w} = [v_{w1}, ..., v_{wm}]^T \) where \( m \) is the number of wind farms installed in the grid. In the simulation study of this paper, wind speed is modeled as a Weibull distributed stochastic process by a set of stochastic differential algebraic equations, following [17]–[19].

The power captured by a variable speed wind farm is

\[ P_{w_j} = \frac{n_{ws} \rho \beta}{2} c_{p_j} A_{r_j} v_{w_j}^3, \quad j = 1, ..., m \]  

(6)

where \( n_{ws} \) is the number of wind turbines that compose the wind farm, \( \rho \) is the air density, \( c_{p_j} \) is the performance coefficient, and \( A_{r_j} \) is the rotor turbine swept area. Hence, wind farm power output is also a stochastic process. Wind power dynamics are closely coupled to the voltage phasors of the buses where wind farms are installed [20], which subsequently affect the electrical power output \( P_{v_i} \) of synchronous generators (see [5]). That being said, \( P_{v_i}, \quad i = 1, ..., n \) is a function of \( \mathbf{v}_{w} \). Thus, (6) can be re-written as:

\[ P_{v_i}' = P_{v_i}(\mathbf{v}_{w}) + E_i^2 G_{i,i} \sigma_i \xi_i \]  

(7)

C. Stochastic Dynamic Power System Model

Substituting (7) to (2), we obtain the power system dynamic model operating around steady state under the influence of small random load fluctuations and wind speed perturbations:

\[ \delta_i = \omega_i \]  

(8)

Linearization around the stationary point \((\delta_0, \omega_0)\) yields:

\[
\begin{bmatrix}
\Delta \delta \\
\Delta \omega
\end{bmatrix} =
\begin{bmatrix}
\frac{\partial P_{v_i}(\mathbf{v}_{w})}{\partial \delta_i}

\frac{\partial P_{v_i}(\mathbf{v}_{w})}{\partial \omega_i}
\end{bmatrix}_{\delta_i = \delta_0, \omega_i = \omega_0}
\begin{bmatrix}
0

1
\end{bmatrix}
\begin{bmatrix}
\Delta \delta \\
\Delta \omega
\end{bmatrix} +
\begin{bmatrix}
0

1
\end{bmatrix} \mathbf{B}_\xi
\]

(9)

where \( \delta = [\delta_1, ..., \delta_n]^T \), \( \omega = [\omega_1, ..., \omega_n]^T \), \( \Delta \delta = \delta - \delta_0 \), \( \Delta \omega = \omega - \omega_0 \), \( \xi = [\xi_1, ..., \xi_n]^T \), \( P_{v_i}(\mathbf{v}_{w}) = [P_{v_i}(\mathbf{v}_{w1}), ..., P_{v_i}(\mathbf{v}_{wm})]^T \), \( G_{i,i} = \text{diag}([G_{1,i}, ..., G_{n,i}]) \), \( M = \text{diag}([M_{1,i}, ..., M_{n,i}]) \), \( D = \text{diag}([D_{1,i}, ..., D_{n,i}]) \), \( E = \text{diag}([E_{1,i}, ..., E_{n,i}]) \), and \( \Sigma = \text{diag}([\sigma_1, ..., \sigma_n]) \). \( B_\xi \) expresses the effect of load variations. \( A \) is the state matrix whose eigenproperties provide all the modal information including frequencies, damping ratios, etc. Thus, the accurate knowledge of \( A \) plays a crucial role in identifying inter-area modes and performing online small-signal stability monitoring. Traditionally, the calculation of \( A \) requires the knowledge of \( \frac{\partial P_{v_i}(\mathbf{v}_{w})}{\partial \delta_i} \), \( M \) and \( D \). However, it may be hard to obtain the exact values of \( M \) and \( D \) in large-scale power grids [9]. Moreover, the computation of the Jacobian \( \frac{\partial P_{v_i}(\mathbf{v}_{w})}{\partial \delta_i} \) requires information about the network model and its parameters (e.g. \( Y \) and \( E \)), which may be unknown or corrupted in practice [8].

D. Data-Driven Inter-Area Mode Estimation

To overcome the aforementioned challenges, the purely data-driven strategy [7] can be exploited to estimate \( A \), and thus the inter-area mode properties, from PMU data. For simplicity, we assume that all generator terminal buses are equipped with PMUs that provide measurements of real-time phasors of voltages and currents. However, the method can also handle cases of missing PMUs [7]. Rotor angles \( \delta \) and speed deviations \( \omega \) can be estimated from synchrophasor data around steady state [21]. Hence, the state vector \( \mathbf{x} = [\Delta \delta, \Delta \omega]^T \) is obtained. The state covariance matrix \( C_{xx} \) and the \( \tau \)-lag time correlation matrix \( G_{xx}(\tau) \) of \( \mathbf{x} \) satisfy:

\[ C_{xx} = E[(\mathbf{x}(t) - \bar{x})(\mathbf{x}(t) - \bar{x})^T] \]  

(11)

\[ G_{xx}(\tau) = E[(\mathbf{x}(t + \tau) - \bar{x})(\mathbf{x}(t) - \bar{x})^T] \]  

(12)

According to the regression theorem for the Ornstein-Uhlenbeck process \( A \) can be estimated purely from the statistics of state variables that can be obtained from PMU data:

\[ A = \frac{1}{\tau} \log \left[ G_{xx}(\tau) C_{xx}^{-1} \right] \]  

(13)

which bypasses the knowledge of network topology and generator parameters. After estimating \( A \) purely from field measurements, we extract the inter-area mode information by modal analysis. Each inter-area mode is associated to an eigenpair \( \lambda_{i+} = \tau_i \pm j \omega_i, \quad i \in \{1, ..., n\} \) of \( A \) and has its own frequency \( f_i = \frac{\omega_i}{2\pi} \) and damping ratio \( \zeta_i = \frac{\omega_i}{2\lambda_{i+}} \).

When wind speed fluctuations are trivial (i.e. the variance of \( \mathbf{v}_{w} \) is negligible), \( P_{w_j} \) remains approximately constant and the normally distributed load randomness prevails over wind randomness. Since \( A \) is almost fixed, \( \mathbf{x} \) can be termed as a vector Ornstein-Uhlenbeck process in steady-state operation. Consequently, the data-driven method [13] is expected to
yield accurate inter-area mode estimation results that greatly enhance small-signal stability monitoring. On the other hand, if wind speed variations become more significant, the non-Gaussian distributed wind randomness dominates load uncertainty. Meanwhile, $P_w$ might be highly fluctuating. As a result, $A$ is no longer constant such that the data-driven method \cite{7} based on the property of the vector Ornstein-Uhlenbeck process may fail to provide accurate estimation for inter-area modes. Nonetheless, the recent advancement of ESSs can be used to smooth out the random wind power, thus improving the inter-area mode estimation accuracy. It will be shown in the next section that by installing a small extra capacity to the existing ESS infrastructure, only a negligible additional effort is required to achieve an accurate real-time small-signal stability monitoring of power grids with volatile wind power.

E. Energy Storage System (ESS) for Wind Power Smoothing

The randomness of wind power results in active wind power imbalance on the wind generator side:

$$P_{imj}(t_k) = P_{w_j}(t_k) - P_{ref_j}, \quad k = 1, \ldots, N \quad (14)$$

where $P_{w_j}(t_k)$ is the actual power output, $P_{ref_j}$ is the reference (rated) power output, and $P_{imj}(t_k)$ is the initial power imbalance of wind farm $j \in \{1, \ldots, m\}$ at time instant $t_k$. To smooth the wind power fluctuations, we assume that every wind farm is equipped with an ESS \cite{13}. Inspired by the single-bus multitemescale method introduced in \cite{22}, we model ESS discrete dynamics as follows:

$$S_j(t_{k+1}) = S_j(t_k) + \eta_{c j} C_j(t_k) - \frac{1}{\eta_{d j}} D_j(t_k) \quad (15)$$

where $S_j(t_k) \leq S_{max j}$, $C_j(t_k) \leq C_{max j}$, $D_j(t_k) \leq D_{max j}$ are the stored, charging and discharging power of ESS $j \in \{1, \ldots, m\}$ at time instant $t_k$, respectively; $\eta_{c j}$ is the charging efficiency (ratio of charged to input power); $\eta_{d j}$ is the discharging efficiency (ratio of output to discharged power). $S_{max j}$, $C_{max j}$, and $D_{max j}$ denote the ESS power capacity for smoothing purposes, the maximum ESS charging power and the maximum ESS discharging power, respectively, while $S_j(t_1)$ is known. If $P_{imj}(t_k) \geq 0$, there is a surplus of energy at wind farm $j$ and the ESS is charged with $0 \leq C_j(t_k) \leq \min\{P_{imj}(t_k), C_{max j}\}$ and $D_j(t_k) = 0$. If $P_{imj}(t_k) \leq 0$, there is a deficit of energy at wind farm $j$ and the ESS is discharged with $0 \leq D_j(t_k) \leq \min\{-P_{imj}(t_k), D_{max j}\}$ and $C_j(t_k) = 0$. The goal of ESS control \cite{15} is to minimize the expected average magnitude of the residual power imbalance

$$P_{resj}(t_k) = P_{imj}(t_k) - C_j(t_k) + D_j(t_k) \quad (16)$$

i.e. the wind power imbalance after ESS operation. In other words, $\mu_{P_{resj}} = E\left(\frac{1}{N} \sum_{k=1}^{N} |P_{resj}(t_k)|\right)$ needs to be as close to zero as possible so as to give a smoothed wind farm power output. It can be proved that a greedy policy (i.e. charging/discharging sequence) $\pi^* = \{(C_j^*(t_k), D_j^*(t_k)) : k = 1, \ldots, N\}$ solves the aforementioned minimization problem optimally \cite{22}. Particularly, if $P_{imj}(t_k) \geq 0$ then:

![Flowchart of the proposed ESS algorithm.](image)

**Step 1** Calculate $\text{Std}(P_{imj}(t_k)), j = 1, \ldots, m$

**Step 2** If $\text{Std}(P_{imj}(t_k)) > \gamma_p$ then $\text{ESS} j$ is ON else $\text{ESS} j$ is OFF

**Step 3** Set $C_{max j} = S_{max j}/\eta_{c j}$ and $D_{max j} = \eta_{d j} S_{max j}$

**Step 4** Apply optimal policy (17)–(18) to smooth $P_{imj}(t_k)$

**Step 5** Obtain $x = [\Delta \delta, \Delta \omega]^T$ from PMU data

**Step 6** Perform modal analysis on $A$ and obtain the inter-area mode properties $f_i, \xi_i, \epsilon_i \in \{1, \ldots, n\}$

**Step 7** Estimate state matrix $A$ by (13)

\[
C_j^*(t_k) = \begin{cases} 
C_{max j}, & \text{if } C_{max j} \leq \min\{P_{imj}(t_k), \frac{S_{max j} - S_j(t_k)}{\eta_{c j}}\} \\
D_{max j}, & \text{if } \max\{P_{imj}(t_k), -\eta_{d j} S_j(t_k)\} < -D_{max j} \\
D_{max j}, & \text{if } \max\{-\eta_{d j} S_j(t_k), -D_{max j}\} \leq P_{imj}(t_k) \\
S_{max j} - S_j(t_k), & \text{otherwise} \\
\end{cases} \
\]

\[
D_j^*(t_k) = \begin{cases} 
-D_{max j}, & \text{if } \max\{-P_{imj}(t_k), \eta_{d j} S_j(t_k)\} \leq P_{imj}(t_k) \\
D_{max j}, & \text{otherwise} \\
\end{cases} \
\]

This ESS policy allows the accurate online small-signal stability monitoring \cite{7} by smoothing the wind farm power output variations. Note that the considered generic ESS could be pumped hydro storage, battery energy storage, etc \cite{23}. Based on the above, we propose a data-driven ESS-based algorithm for monitoring the small-signal stability of power systems with intermittent wind power (see Fig. 1). Particularly:

- **In Step 1**, the standard deviation $\text{Std}(P_{imj}(t_k))$ can be either calculated using the CDF of $\omega_j$ and $\epsilon_j$ or directly obtained from wind power data or a probabilistic model \cite{22}.

- **In Step 2**, $\gamma_p$ is selected as a threshold for the acceptable deviations in the varying wind farm power output. In this paper, $\gamma_p = 0.1$ is chosen, the suitability of which is confirmed by the numerical experiments (see Section III).

- **In Step 3**, the value of $\alpha$ is determined based on the relevant ESS literature \cite{22} and our simulation experience. To reduce the expected average magnitude of the initial power imbalance, i.e. $\mu_{P_{imj}} = E\left(\frac{1}{N} \sum_{k=1}^{N} |P_{imj}(t_k)|\right)$, by 70%, $S_{max j}$ is set to
be only 7 \times \text{Std}(P_{imj}(t_k))$, i.e. $\alpha = 7$. The resulting $S_{\text{max}j}$ is only 1 per unit (p.u.).

- In Step 4, the efficiencies $\eta_{c,v}^2$ and $\eta_{d,w}^2$ typically lie in [50%, 95%] [22] and are considered as pre-known parameters.

### III. Numerical Results

In this section, the effectiveness of the proposed data-driven ESS strategy in enhancing online small-signal stability monitoring is validated. Simulations are conducted on the IEEE 68-bus system; see Fig. 2. Detailed modal analysis reported in the literature [9] reveals the presence of three inter-area modes with typical frequencies $f_1 = 0.42$ Hz (mode 1), $f_2 = 0.63$ Hz (mode 2) and $f_3 = 0.77$ Hz (mode 3). The classical model has been used to represent synchronous machines. Loads are modeled by constant impedances experiencing Gaussian variations with $\sigma_l = 20$ [9]. The rest of the power system is represented according to [24]. Wind power is integrated into the grid through the widely used doubly-fed induction generator (DFIG) [20]. The stochasticity of wind speed $v_{w}$ is modeled by the Weibull distribution with shape parameter $k_{v_w} = 1$ and scale parameter $\lambda_{v_w} = 0.02$ obtained from real-life applications [25]. Wind power fluctuations are smoothed using ESS with $\eta_{c,v}^2 = \eta_{d,w}^2 = 70\%$ and $S_{\text{max}j} = \eta_{c,v}^2/\eta_{d,w}^2 = 100$ MW (1 p.u.), $j = 1, \ldots, m$. Time-domain simulations are implemented in PSAT toolbox [26], while ESS operates every $1/3$ s [22].

#### A. Validation of the Data-Driven ESS Algorithm for Enhancing Inter-Area Mode Identification

In this case study, we install 500 MW DFIG-based wind farms to the zero-injection buses $\{19, 31, 32, 62\}$, reaching a wind penetration level of $11\%$. Buses 19, 31, 32, 62 correspond to $j = 1, 2, 3, 4$, respectively (see Fig. 14). Next, we conduct 100 Monte Carlo time-domain simulations (i.e. 100 different wind speed realizations $v_{w}$) to perform the probabilistic small-signal stability monitoring of the grid. Note that the proposed algorithm can work using a single scenario, yet Monte Carlo simulation results are more rigorous from a statistical sense.

Since $\text{Std}(P_{imj}(t_k)) > \gamma_0 = 0.1$ p.u., $\forall j$, ESS is activated (ON). Table I presents a comparison of the expected average magnitude of the power imbalance when the ESS is OFF (i.e. $\mu_{P_{imj}}$) and ON (i.e. $\mu_{P_{resj}}$). It can be observed that the ESS algorithm achieves a decrease of almost $70\%$ in the expected average magnitude of the power imbalance even though $S_{\text{max}j}, j = 1, \ldots, 4$ is very small given the system scale. This result is consistent with the findings of relevant works [22]. Furthermore, the per-unit value of $\mu_{P_{resj}}$, ($\approx 0.05$ p.u. = 5 MW) approaches zero and is less than $1\%$ of the reference wind farm power output (500 MW = 5 p.u.).

Next, we compute the statistical properties of $A$, $f_i$ and $\zeta_i$, $i = 1, 2, 3$. To this end, we use 200 s PMU data with a sampling frequency of 60 Hz. Simulation results show that wind stochasticity mostly affects the estimation of mode 3. Therefore, a comparison of the mean true and estimated frequency and damping ratio of inter-area mode 3 with and

![Fig. 2. 68-bus, 16-generator, 5-area benchmark system [24].](image)

**TABLE I**

| Bus | $\mu_{P_{imj}}$ (p.u.) | $\mu_{P_{resj}}$ (p.u.) | Decrease (%) |
|-----|----------------------|----------------------|-------------|
| 19  | 0.142                | 0.044                | 69.014      |
| 31  | 0.138                | 0.046                | 66.667      |
| 32  | 0.121                | 0.040                | 66.942      |
| 62  | 0.132                | 0.041                | 68.939      |

**TABLE II**

Mean True and Estimated Properties of Inter-Area Mode 3

| Bus | $\mathbf{E}(f_{imj})$ (Hz) | $\mathbf{E}(f_{resj})$ (Hz) | Error (%) | $\mathbf{E}(\zeta_{imj})$ (%) | $\mathbf{E}(\zeta_{resj})$ (%) | Error (%) |
|-----|---------------------------|---------------------------|-----------|-----------------------------|-----------------------------|-----------|
| OFF | 0.753                     | 0.760                     | 0.930     | 1.756                       | 1.378                       | 21.526    |
| ON  | 0.754                     | 0.758                     | 0.531     | 1.754                       | 1.660                       | 5.359     |

Note: "\*" stands for "True", "Estimated", and "Err." for "Error".

![Fig. 3. Initial power imbalance $P_{imj}(t_k)$ (displayed in blue) and residual power imbalance $P_{resj}(t_k)$ (displayed in red) for the wind farm of bus 62.](image)
inter-area mode can be potentially identified as well-damped. On implementing the proposed data-driven ESS in practice, demonstrate that the proposed technique achieves the inter-area mode properties by smoothing stochastic wind power penetration. Our method can accurately estimate the inter-area mode frequencies, damping ratios, which are the main focus of small-signal stability monitoring, exhibit large estimation errors when ESS is deactivated, especially for higher wind penetration levels (e.g. 23%). As a result, a poorly-damped inter-area mode can be potentially identified as well-damped. Clearly, our method promotes the accurate estimation of $\zeta_i$ by smoothing the unwanted wind power fluctuations.

### IV. CONCLUSION AND PERSPECTIVES

This paper proposed a novel data-driven ESS algorithm for small-signal stability monitoring of power systems with stochastic wind power penetration. Our method can accurately estimate the inter-area mode properties by smoothing the wind power variations, thus enhancing the small-signal stability assessment in near real-time. Numerical simulations demonstrate that the proposed technique achieves the inter-area mode identification and smoothing goals using only a small ESS capacity. Future endeavors will focus on developing methodologies for optimal ESS placement in wind farms and on implementing the proposed data-driven ESS in practice.

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