Impact Analysis of Intra-Interval Variation on Dynamic Security Assessment of Wind-Energy Power Systems

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***Abstract*—Dynamic security assessment (DSA) is to ensure the power system being operated under a secure condition that can withstand potential contingencies. DSA normally proceeds periodically on a 5 to 15 minutes basis, where the system security condition over a complete time interval is merely determined upon the system snapshot captured at the beginning of the interval. With high wind power penetration, the minute-to-minute variations of wind power can lead to more volatile power system states within a single DSA time interval. This paper investigates the intra-interval variation (IIV) phenomenon in power system online DSA and analyze whether the IIV problem is deserved attention in future DSA research and applications. An IIV-contaminated testing environment based on hierarchical Monte-Carlo simulation is developed to evaluate the practical IIV impacts on power system security and DSA performance. The testing results show increase in system insecurity risk and significant degradation in DSA accuracy in presence of IIV. This result draws attention to the IIV phenomenon in DSA of wind-energy power systems and calls for more robust DSA approach to mitigate the IIV impacts.**

***Index Terms*—Dynamic security assessment, intra-internal variation, Monte-Carlo simulation, power system security, wind power.**

I. Introduction

Wind energy, as a type of renewable energy, has experienced a dramatic increase in its share in global energy market over the last decade. Statistically, the world's wind power generating capacity has grown from 120 GW in 2008 to approaching 600GW by the end of 2018 [1]. The increasing penetration of wind power, as an intermittent energy source, injects significant uncertainties and poses great challenges to secure and reliable power system operation.

In recent years, with the advancement of power system monitoring infrastructure, the preventive analysis of power system ability to withstand potential contingencies, namely dynamic security assessment (DSA), can be implemented in an online manner where system operating states are captured in near real-time, tending to significantly reduce the dynamic insecurity risk incurred by the variation in renewable power generation. In online DSA environment, the conventional approaches based on time-domain simulations (TDS) suffer from massive computation burden in solving the complex system model, which calls for more efficient DSA solutions. Recently, DSA approaches based on artificial intelligence (AI) techniques have shown their efficacy, owing to their fast decision-making speed and minimal reliance on system modelling [2]. In the literature, the AI techniques contributing to online DSA include neural networks (ANN) [3], decision trees (DT) [4], support vector machine (SVM) [5], extreme learning machines (ELM) [6], and deep learning [7].

The objective of DSA is to ensure the system is from time to time operated under a secure condition that can withstand potential contingencies. In a typical online DSA scheme, the system's security condition is determined periodically (normally on a 5- to 15-minute basis) based on the received system state measurements and estimations [8]. If an insecure condition is detected, preventive control actions, such as re-dispatching the synchronous generation and/or curtailing the renewable generation, will be taken to redirect the system to its secure operating region. The length of the DSA time interval mainly depends on the size of power system, the number of contingencies to be screened, and the assessment speed. Once the assessment decision is made based on the initial system snapshot, this assessment results is recognized to be valid for the complete time interval. However, in today's power systems with higher penetration of wind power, the power outputs from wind farms are subject to stochastic minute-to-minute variations in the forms of wind die-out, wind rise, wind lull, wind gusts, and sudden loss of wind turbines [9]. Such wind power variations within a single DSA time interval, namely intra-interval variations (IIVs), may alter the power system security condition and reduce the reliability of the DSA result. The impact of renewable power IIVs have been recently emphasized in some areas, such as cascading overload failures [10], power market operation [11], automatic generation control [9], and power dispatch and scheduling [12]. Yet, how do wind power IIVs affect power system security and online DSA performance has not been investigated in the literature.

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The main contribution of this paper is as the first attempt to investigate the IIV phenomenon in online DSA, and analyzes whether the IIV problem is deserved attention in future DSA research and applications. To evaluate the IIV impact on power system security and online DSA performance in wind-energy power systems, we develop a probabilistic IIV model is built and propose an IIV-contaminated testing environment. To be practical, historical wind power data from a realistic wind farm is used to build the IIV model, and a hierarchical Monte Carlo simulation method is adopted to create the environment for IIV impact analysis. The analysis shows that the existence of IIV increases the insecurity risk between successive assessments, which necessitates the consideration of IIV in online DSA. Moreover, the testing results over a range of benchmark intelligent models show significant degradation in their DSA accuracy if IIVs are incorporated, which calls for more robust approaches to deal with IIVs in online DSA.

II. Modelling of Power System IIVs

A. Problem Description

The concept of IIV in online DSA is shown in Fig. 1. Within a DSA time interval that begins at t_k and ends at t_{k+1}, the system's security over a large set of credible contingencies will be screened based on the operating state s_k that is measured at t_k. This contingency screening result will serve as the anticipated system security condition over the complete $[t_k, t_{k+1})$ interval. Within this time interval, due to the intermittency of wind power, the operating state s_k is subject to continuous variations to maintain the balance between generation power and load demand. In this process, it is possible to experience unfavorable variations in operating state (e.g. Δs) that lead to system insecurity, especially when the system is operating close to its security boundary. Such insecurity risk induced by IIV, if not identified by DSA, could not be noticed by the operator, which may result in unexpected instability event if the corresponding contingency happens to occur. This will further trigger emergency control actions that lead to unnecessary load loss and economic loss.

Moreover, in a typical online DSA program, the DSA model uses the power system snapshot as the inputs and generate the estimation on power system security condition as outputs. In this process, the accuracy of the assessment highly relies on the input quality. At an arbitrary time, the DSA model can only perform the assessment based on the power system snapshot taken at the beginning of the assessment interval. This snapshot input received by the model at an earlier time would be deviated from the current operating state due to IIV, which could result in an inaccurate DSA result.

With above concerns, this paper develops a probabilistic IIV model and performs an impact analysis study to evaluate the practical significance of IIV problem in DSA programs.

B. Probabilistic IIV Model

The probabilistic IIV model describes the IIV phenomenon and is used to generate IIV input to the DSA model, from which we can analyze the practical IIV impact. Without an accurate IIV model, the impact of IIV can be over- or under-estimated, which could mislead the public research attention on the problem.

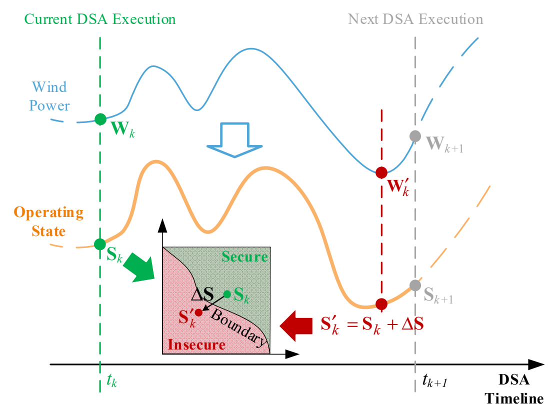

Fig. 1. Illustration of IIV phenomenon in online DSA.

In power systems with high wind power penetration, wind power minute-to-minute variation acts as the main source of IIVs, and the other operating quantities in the system adjust correspondingly to meet generation and load balance. Therefore, the IIVs of $\mathbf{S}_k$ can be described as follows

$$\Delta\mathbf{S} = \mathbf{S}'_k - \mathbf{S}_k = \mathrm{D}(\mathbf{W}_k + \Delta\mathbf{W}, \mathrm{X}) - \mathrm{D}(\mathbf{W}_k, \mathrm{X}) \tag{1}$$

where

$$\mathbf{W}_k = \begin{bmatrix} w_{1,k} \\ w_{2,k} \\ \vdots \\ w_{F,k} \end{bmatrix}, \Delta\mathbf{W} = \begin{bmatrix} \Delta W_1 \\ \Delta W_2 \\ \vdots \\ \Delta W_F \end{bmatrix}, \Delta W_{i=1\ldots F} \sim P(\Delta W_{i=1\ldots F}) \tag{2}$$

In (1) and (2), $\Delta\mathbf{S}$ represents the IIV of $\mathbf{S}_k$; $\mathrm{D}(\cdot)$ is the power system dispatch function based on optimal power flow (OPF); $\mathbf{W}_k$ is a vector containing the power output from each wind farm at time t_k; Ξ includes all other dependent variables for dispatch calculation, including network topology, load demand, operating limits, unit generation cost, etc; $\Delta\mathbf{W}$ includes the wind power IIVs from all wind farms; ΔW_i is a random variable following a probability distribution $P(\Delta W_i)$, which represents the practical IIV of the ith wind farm.

In above IIV model, the probability distribution $P(\Delta W_i)$ must be accurately modelled since it is the crucial term to quantify the IIVs $\Delta\mathbf{S}_k$. This $P(\Delta W_i)$ could be statistically fitted from the historical wind power data of each wind farm. The high frequency snapshots on the historical data show the IIV pattern in practical wind farm operation, allowing us to truly reflect the impact of IIV on power system security and DSA performance. For a historical wind power time-series $\Omega = \{w_t, w_{t+1}, \ldots, w_{t+H}\}$, the IIV information can be extracted via a data transformation process as follows. First, each available data point is regarded as the reference assessment point and the wind power within the incoming DSA interval is extracted as the intra-interval wind power series; Second, the wind power mismatch between each intra-interval time point and the corresponding reference assessment point is calculated to build the wind power IIV series. The data transformation from Ω to a wind power IIV series E is presented as follows

$$\mathrm{W} \Rightarrow \mathrm{E} = \{\varepsilon_t, \varepsilon_{t+1}, ..., \varepsilon_{t+H-T}\} \quad (3)$$

where

$$\varepsilon_i = \left\{\Delta w_{i,\Delta t} = w_{i+\Delta t} - w_i, \forall \Delta t \in \{1...T\}\right\}, \forall i \in \{t...t+H-T\} \quad (4)$$

where T is the time length of the assessment interval; ε_i denotes the wind power IIV at time i. After the data transformation, the IIV distribution of wind power is fitted by kernel density estimation which is a non-parametric method to model unknown distributions. The fitted distribution is

$$P(\Delta W) = \frac{1}{N\omega}\sum_{s=1}^{S} K(\frac{\Delta W - \Delta W_s}{\omega}) \quad (5)$$

where S is the population size; $K(\cdot)$ is the kernel function; and ω is the bandwidth. The following Epanechnikov kernel is adopted in this paper as it shows the lowest fitting error

$$K(u) = \frac{3}{4}(1-u^2) \quad (6)$$

III. IIV Impact Analysis

This section elaborates the proposed IIV-contaminated testing environment which includes the hierarchical Monte-Carlo simulation process and the procedures to evaluate IIV impact.

A. Hierarchical Monte-Carlo Simulation

The IIV-contaminated operating states are sampled via a hierarchical Monte-Carlo simulation method as shown in Fig. 2. The higher hierarchy generates the base case operating samples which represent the operating state snapshot observed at the beginning of each time interval. The lower hierarchy generates the potential IIV samples for each base case scenario based on the probabilistic IIV model. The wind power IIVs ΔW at each wind farm are randomly drawn from their fitted distribution, and the IIVs of operating state are calculated via power system re-dispatch. By doing so, a set of IIV samples are synthetically created for each base case scenario via a probabilistic sampling process. Suppose N base case samples are generated, and each of them is equipped with M IIV samples, the overall size of the IIV-contaminated dataset for IIV impact analysis will be $N \times (M+1)$.

B. IIV Impact Evaluation

The IIV impact evaluation can be divided into two parts. The 1st part is to evaluate the IIV impact on power system security. Contingency screening can be carried out on the operating states in both hierarchies via TDS, so as to obtain the system security condition with and without consideration of IIVs separately. The simulated security conditions of base case samples and the IIV-contaminated samples are then compared to evaluate the IIV impact on power system security. In this analysis, statistical results can be obtained to evaluate the probability of a secure operating state to become insecure due to the practical IIVs. Such evaluation can verify the intra-interval insecurity risk of power systems.

The 2nd part focuses on analyzing the IIV impact on online DSA performance. The intelligent models are trained by the base case samples. Through the training process, the intelligent models can map the inherent relationship between system state, contingency, and system security condition. The well-trained models are then tested on both the unknown base case samples and their associated IIV-contaminated samples. The DSA accuracy degradation of the intelligent models indicates the IIV impact on online DSA performance.

IV. Case Study

The proposed approach is applied on the New England 39-bus system in Fig. 3. The synchronous machines at bus 32 and 37 are replaced by wind farms. The capacities of the other generators are enlarged by 1.2 times to accommodate the wind energy. The TDS is performed in PSS/E 34.1.

A. IIV Distribution

In this study, a 1-year historical wind power data of a 100MW offshore wind farm in Shanghai, China is used as a benchmark to explore the IIV distribution of wind power. This wind farm consists of 34 3MW wind turbines whose power outputs are available at the SCADA system in a 1-minute resolution. The histogram and the fitted distribution of the wind power IIVs at this wind farm are shown in Fig. 4(a)-(c), respectively for DSA time intervals of 5, 10, and 15 minutes. The wind power IIVs tend to be more widely distributed (i.e. more significant) as the length of time interval increases. The kernel density estimation results in negligible residual, verifying the accuracy of the fitted distribution. To generalize the distribution to wind farms at bus 32 and 37, the sampled

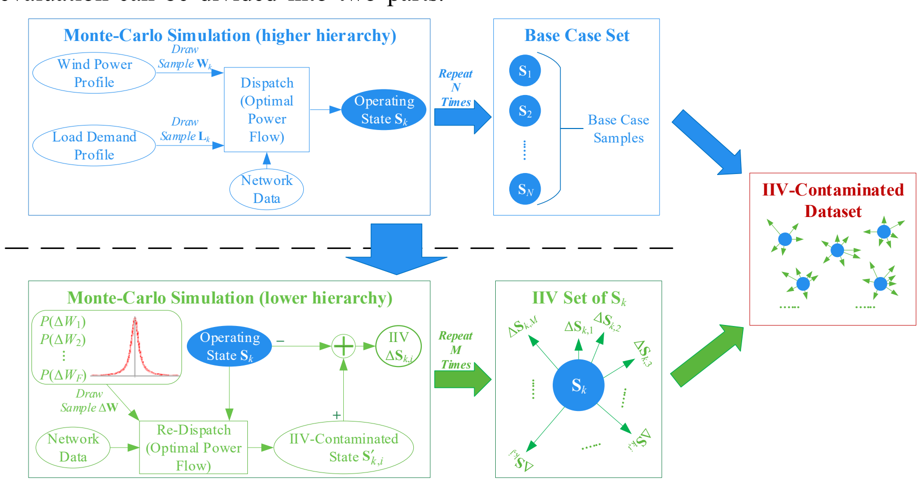

Fig. 2. Hierarchical Monte-Carlo simulation process.

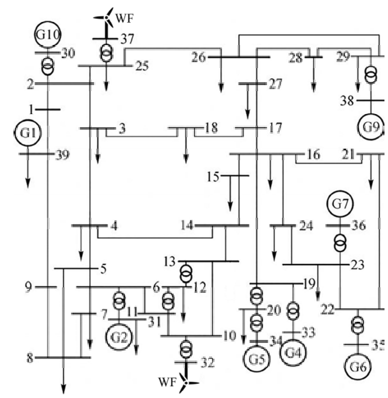

Fig. 3. The modified New England 39-bus system.

wind power IIVs are scaled up by $P_{max}/100$ where P_{max} is the MW capacity of the target wind farm.

B. Generation of IIV-Contaminated Dataset

The IIV-contaminated dataset is generated using hierarchical Monte-Carlo simulation following the process in Fig. 2. Totally 5000 base case samples are generated with the following settings. The wind power at each wind farm is randomly sampled between 0 and its capacity, and each load is randomly sampled between 0.8 and 1.2 of its nominal level. The other operating quantities, including machine outputs, bus voltages, and line flow, are calculated via OPF. 4500 and 500 out of the 5000 base case samples are respectively used for training and testing the intelligent model.

The 500 testing samples are also used as the reference points to generate IIV samples in the lower hierarchy. For each reference point, 100 IIV samples are drawn from their distributions in Fig. 4(a)-(c). The illustrate the structure of IIV-contaminated datasets, the wind power of 20 randomly selected samples are shown in Fig. 4(d)-(f), respectively for 5-, 10-, and 15-minute DSA time intervals. The base case samples are surrounded by their IIV-contaminated samples, which represents the noise brought by IIVs. Such noise may impact power system security and online DSA performance.

C. Contingency Selection

The candidate contingencies are three phase bus faults cleared by single line tripping. The fault duration is 0.2 second. A swing margin [13] η based on extended equal-area criterion (EEAC) is calculated via TDS and used to determine the security condition. A positive η means a secure condition. Based on the swing marge, 12 severe contingencies that result in a significant number of insecure samples are selected.

D. IIV Impacts on Power System Security

By comparing the security conditions of the base case samples and their associated IIV-contaminated samples, the ratio of the secure samples that become insecure is statistically evaluated to quantify the hidden insecurity risk induced by IIVs. As shown by the ratios in Table I, insecurity can be observed for all contingencies and DSA time intervals. Such insecure events are harmful because they are not detectable in conventional DSA program and no preventive control action will be taken. This testing result verifies the volatility of power system security due to the IIV impact.

To further investigate the IIV impacts on individual samples, the portion of secure IIV-contaminated samples is collected for each base case sample, which represents the probability of a base case sample being secure within the DSA time interval. The scatter between such probability and the swing margin η of each base case sample is shown in Fig. 5. As verified in [13], swing margin shows quasi-linear relationship with many key parameters such as generation output, fault clearing time, etc, thus the magnitude of η can approximately reflect the distance between the system operating state and the security boundary. $\eta = 100$ or $\eta = -100$ means the current operating state is extremely stable or unstable, whereas $\eta = 0$ means the system is operating close to the security boundary. In Fig. 5, the security conditions of IIV-contaminated samples are increasingly uncertain as η approaches to 0, meaning IIVs are more harmful when the

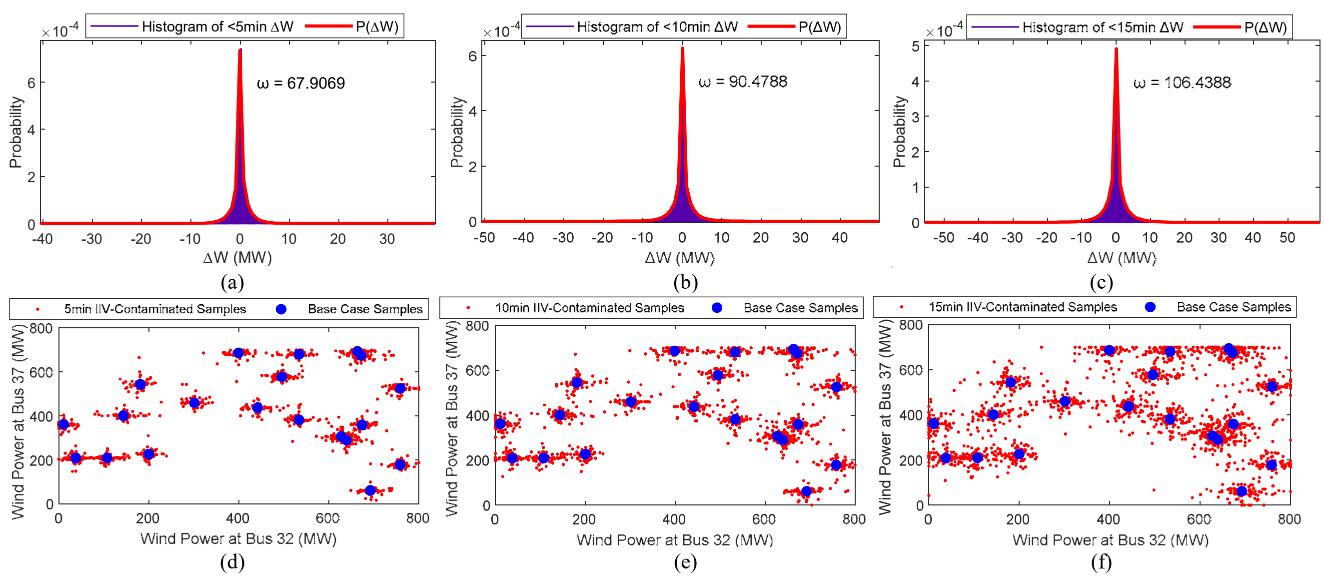

Fig. 4. Fitted wind power IIV distributions for DSA time intervals of (a) 5 minutes, (b) 10 minutes, and (c) 15 minutes, and illustration of the generated IIV-contaminated datasets for DSA time intervals of (d) 5 minutes, (e) 10 minutes, and (f) 15 minutes.

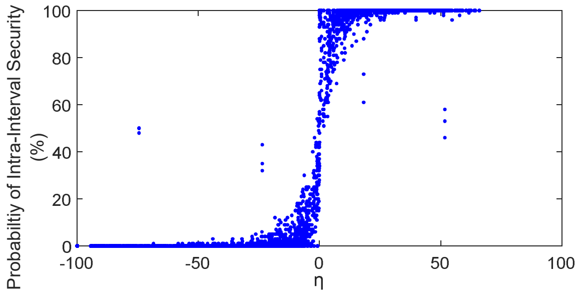

Fig. 5. Intra-interval security probability v.s. swing margin.

system is operating closer to its security boundary.

E. IIV Impacts on DSA Performance

The IIV impacts on typical intelligent DSA models, including ANN, DT, SVM, ELM, random forest (RF), ELM ensemble (ELME), and deep neural network (DNN), are also tested to demonstrate the IIV impact on DSA performance. In the test, the model's classification results on base case samples are directly used as the DSA results for the associated IIV-contaminated samples. This setup simulates the practical situation where the DSA results based on the snapshot at the beginning of the time interval will be used for the complete time interval. The classification accuracy of each classifier on base case samples and IIV-contaminated samples are listed in Table II where the results for 5-, 10-, and 15-minute DSA time intervals are shown separately. It shows that IIVs significantly degrade the DSA accuracy of all intelligent models for all time intervals. Such accuracy degradation is more significant for longer time intervals. All above results indicate that the IIV impacts should be taken in concern in future DSA research and applications, and there is a pressing need to improve the robustness of DSA models against IIV impacts.

V. Conclusion

This paper highlights on the IIV phenomenon in power system DSA and proposes a probabilistic IIV model and an IIV-contaminated testing environment to analyze the IIV impacts on power system security and DSA performance. In the proposed environment, operating states with and without IIVs are generated via hierarchical Monte-Carlo simulation and the impact of IIV is evaluated by comparing the DSA performance on based case samples and IIV-contaminated samples. The simulations show that IIV increases the risk of power system insecurity and significantly degrades the accuracy of DSA models. Such analysis result indicates that the impacts of IIV deserves attention in future DSA research and calls for more robust DSA approach to mitigate the detrimental IIV impacts.

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TABLE I
Power System Insecurity Risk Induced By IIVs

DSA Time Interval	Contingency ID											
	1	2	3	4	5	6	7	8	9	10	11	12
5 Mins	0.96%	1.05%	1.01%	1.12%	1.10%	0.78%	0.97%	1.04%	0.81%	0.87%	1.70%	1.18%
10 Mins	1.39%	1.52%	1.48%	1.57%	1.55%	1.17%	1.62%	1.49%	1.24%	1.29%	2.40%	1.71%
15 Mins	2.36%	2.54%	2.35%	2.43%	2.55%	2.13%	2.50%	2.48%	2.14%	2.18%	3.54%	2.63%

TABLE II
DSA Accuracy of Different Intelligent Models

	ANN	DT	SVM	ELM	RF	ELME	DNN
Base Case	97.93%	95.61%	97.83%	97.80%	98.28%	98.03%	98.61%
5-Min Time Interval	96.69%	94.41%	96.53%	96.76%	97.21%	96.98%	97.68%
10-Min Time Interval	96.34%	94.26%	96.15%	96.50%	96.91%	96.72%	97.37%
15-Min Time Interval	95.95%	94.11%	95.70%	95.87%	96.21%	96.11%	96.62%