Probabilistic Analysis of Small Signal Stability of Power System with Penetration of Distributed Generation: A Review

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Abstract:
The liberalization of electricity markets, continuous increase in power demand, shortage in conventional generating and transmission capacities and the environmental awareness of consumers contribute to the wide application of Distributed Generation (DG) into power systems. The presence of DG presents system operators with new challenges regarding DG availability, integration and impact on system security and stability. Therefore, analysis of renewable energy penetrated power system using probabilistic approaches is of utmost importance in other to ascertain the impact of intermittency of the renewable generation on the power network. This work firstly reviews the problem of instability of power systems with a considerable share of renewable generation and its significant demand for probabilistic analysis, then, provides a critical evaluation of the available probabilistic methods that have been used for the assessment of power system small signal stability. Overview of frequently used methods are presented stressing their advantages and disadvantages with the aim of highlighting their strength and weaknesses. This paper, then proposes a method known as Stochastic Collocation Method that promises to be an effective probabilistic tool for the analysis of renewable energy penetrated power system.

Keywords: Distributed generation, small signal stability, penetration, stochastic, probabilistic analysis

1. Introduction

Global environmental awareness, liberalization of electricity markets, continuous increase in power demand, shortage in conventional generating capacities and inadequate transmission facilities have made the concept of integrating small and medium size generating units into power distribution networks a reality worldwide. These small and medium size generating units are known as Distributed Generation (DG). However, the presence of Distributed Generation (DG) presents power system Engineers with new challenges regarding some DG sources intermittent nature, integration and impact on system security and stability, hence the need for probabilistic analysis of the power system. Distributed Generation can be defined as an electrical power source connected directly to the distribution network or on the consumer side of the meter[1], [2]. It refers to small power plants at or near the loads, operating in a stand-alone mode or connected to a grid at the distribution or sub-transmission level and geographically scattered throughout the service area. It includes small, modular technologies for electricity generation located close to the load[3], [4], [5].

IEEE defines the generation of electricity by facilities sufficiently smaller than central plants, usually 10 MW or less, so as to allow interconnection at nearly any point in the power system, as Distributed Resources.

Electric Power Research Institute (EPRI) defines distributed generation as generation from a few kilowatts up to 50 MW.

International Energy Agency (IEA) defines DG as ‘Power generation equipment and system used generally at distribution levels and where the power is mainly used locally on site’.

The International Council on Large Electricity Systems (CIGRE) defines DG as generation that is not centrally planned, centrally dispatched at present, usually connected to the distribution network, and smaller than 50-100 MW[6].While the term ‘Distributed Generation ’ has become very popular, there has been no consensus on its definition. Generally mentioned criteria are: not centrally planned and dispatched, usually connected to the distribution network with relatively small rating, from less than 100 kW up to several MW. Other characteristics mentioned in the literature to distinguish distributed generation from conventional generation are: fluctuations in its production and its production capacity in combination with the non-predictability of the production [7]. The utilization of DG sources offers a number of technical, environmental and economic benefits for utilities and consumers due to their location close to the customers. Some of the benefits that can be derived from the integration of DG into the distribution network are: reduced line losses,
This paper, therefore, reviews the problem of instability of power systems with a considerable share of renewable generation throughout the network with guaranteed system security and stability. As the electric power systems are riding the wave of decentralization through the deployment and use of ‘distributed power’ technologies, appropriate and efficient probabilistic analysis tools must be in place so that when fully deployed, distributed power technologies will create a decentralized power system within which distributed generators meet local power demand throughout the network with guaranteed system security and stability.

This paper is as follows: section 2 explores the technical issues associated with distributed generation. Section 3 captures the overview of power system small signal stability. Section 4 explains various computational techniques adopted for the analysis of probabilistic small signal stability. Section 5 presents the overview of the proposed stochastic collocation method while section 6 captures the conclusion.

2. Technical Issues Associated with Distributed Generation

The question of power quality and distributed generation is not straightforward. On one hand, as highlighted in the introduction, distributed generation contributes to the improvement of power quality. For instance, in the areas where voltage support is difficult, distributed generation offers significant benefits for the voltage profile and power factor corrections. On the other hand, large-scale introduction of decentralized power generating units may lead to instability of the power system. The bi-directional power flow and the complex reactive power management can be problematic and lead to voltage profile fluctuation. Additionally, short-circuits and overloads are supplied by multiple sources, each independently not detecting the anomaly[17], [18], [19], [20]. Some of the renewables are stochastic in nature fluctuating with changes in weather. Examples of such are solar PVs and wind turbines. The fluctuation poses serious stability challenges to the grid even at low penetration levels[21], [22], [23], [24], [25]In most countries at present, stability is hardly considered when assessing DGs. However, this is likely to change as DG penetration increases and their contribution to network security becomes greater[26], [27], [28]. As the penetration increases, the network will be stressed because it was not designed to transmit power in a bi-directional way. Hence, the integration of DG transforms the distribution network into an active system involved in generation as well as bi-directional transportation of power to the grid. As a result, the distribution system is further stressed [29], [30]. When more DG will be integrated into the grid, the problem of large rotor excursion, small signal stability and voltage collapse will be a serious concern. This is because increasing the integration of DG will increase the complexity of the system thereby making system stability cumbersome for analytical approach to solve in real time. Presently, the concern of system operators is shifting towards delivering the results of stability assessment in real time or near real time in other to present accurate result of the complex power system [31], [32], [33]. Lack of suitable control strategies for electrical networks with high penetration levels of DG units poses a problem for the future systems. For instance, DG units are likely to affect the system frequency. As they are often not equipped with a load-frequency control, they will free ride on the efforts of the transmission grid operator or the regulatory body to maintain system frequency. Also, the dynamic interaction between high-voltage parts of the network from one side and DG units from the other side is an essential subject that needs extensive research. In spite of the benefits of utilizing DG units within power systems, such as the increase of the system efficiency and the improvements in the power quality and reliability [34], many technical and operational challenges have to be resolved before DG becomes commonplace. In the light of the above, analysis of power systems with a significant share of renewable generation requires probabilistic approaches in order to ascertain the impact of intermittency of the renewable generation on the power network.

3. Overview of Power System Small Signal Stability

Small signal stability analysis is about power system stability when subjected to small disturbances. Refs [35]-[43] define small signal stability as the ability of the power system to maintain synchronism under small disturbances. Conventionally, small signal stability analysis of a power system is carried out in frequency domain using the eigenvalue analysis method. The usual steps are: deriving a linear model of the nonlinear power system around a certain operating condition, solving for the eigenvalues and eigenvectors of the linearized system, then calculating the mode shape, sensitivity and participation factor based on the eigenvalue and eigenvector information[44], [45]. Then, the power system can be represented by a state variable model after linearization as:

\[
\dot{x} = Ax + Bu \quad (1)
\]

\[
y = Cx + Du \quad (2)
\]

where A is the state matrix, x is vector of state variables, u is vector of control variables, and y is vector of output variables. The process of finding the state matrix's eigenvalues corresponds to finding nontrivial solutions of:

\[
AV = 
\begin{bmatrix}
V_1 \\
\vdots \\
V_n
\end{bmatrix} 
\Rightarrow \lambda_i V_i = \lambda_i V_i \quad (3)
\]

where, if A is an n x n matrix, V is an n x n matrix, whose columns are \(v_i, j = 1, \ldots, n\), and \(\Lambda = \text{diag}(\lambda_i)\) is an n x n diagonal matrix. A and V satisfying the equation are vector of eigenvalues and matrix of right eigenvectors of A respectively [46], [47]. The property of eigen values of the system is used to determine if the system is stable or not. For a system to be stable eigen values must be in left−hand side of the imaginary axis, otherwise, the system will be unstable. The indices of evaluating the
system's eigenvalues includes the polarity, controllability, observability, participation factor, mode shape and sensitivity. \[48\]. Meanwhile, the computation involved in the conventional small signal stability analysis is a time-consuming process for large networks which includes the load flow computation, the linearization at the operating point, and the eigenvalue computation. Now a days, an alternative method is to adopt model-free method such as neural networks (NN) which train the network using off-line historical data for different scenarios of critical eigenvalue prediction. By using NN, a fast computation of the eigenvalues is possible, provided that the network is properly designed and trained \[49\], \[50\]. Methods of Computational Intelligence (CI) can relieve the assessment of oscillatory stability rather than replace analytical tools and methods. Furthermore, they provide adaptability, fault tolerance and help to assist human reasoning. A very important step preparing the application of methods of computational intelligence to oscillatory stability assessment is the convenient selection of attributes for potential online use. It enables a fast assessment of the oscillatory stability within power system control \[51\]. When CI methods are implemented for a fast on-line oscillatory stability assessment, they always need feature extraction or feature selection based only on a small set of data. In general, results of CI methods are accurate enough for on-line oscillatory stability assessment \[52\]. Another method is the measurement-based analysis of small signal stability. This method is more popular for today’s power system analysis because it uses real-time synchrophasor has or measurement obtained from Phasor Measurement Units (PMUs) that are installed at various buses to estimate the mode of oscillations based on prony method \[48\]. Since small disturbances is inevitable in power system operation, analysis of small signal stability is critical to the reliable operation of power systems \[53\]. If power system oscillations caused by small disturbances can be suppressed, such that the deviations of system state variables remain small for a long time, the power system is stable. On the contrary, if the magnitude of oscillations continues to increase or sustain indefinitely, the power system is unstable. It must be noted that any power system that is unstable in terms of small signal stability cannot operate in practice. In other words, a power system that is able to operate normally must first be stable in terms of small signal stability. Hence, one of the principal tasks in power system analysis is to carry out small-signal stability analysis to assess the power system under the specified operating conditions \[54\].

4. Methods of Probabilistic Analysis of Small Signal Stability

The traditional deterministic approach of analyzing power system small signal stability which evaluates the performance of a system based on a specific scenario neglects the uncertainties in power system operation, models and variables. That is, the deterministic assessment is carried out based on a set of specified system operating conditions. The solution obtained with such approach is correct only for the particular conditions of the system but unable to properly reflect the uncertainties existing in the realistic power systems, such as the fluctuations and the random factors in the variations of loads and generations, intermittence of renewable energy generations, changes in network configuration and the parameters as well as the errors in the measurement and the forecast parameters. In order to increase the reliability of the results obtained, the most stressed operating conditions of the system are commonly used for the stability assessment. Consequently, conservative results will be obtained which may be impractical for the purpose of power system economic operation and planning \[55\]-\[58\]. Due to increased uncertainties associated with the operation of modern power systems, probabilistic approaches towards small-disturbance stability analysis have started to receive greater research attention. The benefits of the probabilistic approach are evident and result in more accurate depictions of the true modal variation \[59\]. Meanwhile, the accuracy of power system stability analysis depends on the accuracy of the models used. Using of more accurate models could result in increase in overall power system transfer capability and associated economic benefits. It is therefore important to attempt mathematical modeling and analysis of power system parameters probabilistically so that the system planners can gain a better understanding of the system stability margin \[60\]. Various probabilistic methodologies used for small signal stability analysis can be classified into three; numerical approach, analytical approach and combination of numerical and analytical approach. The numerical approach for determination of probabilistic small signal stability is the Monte Carlo simulation (MCS). Basically, Monte Carlo simulation takes the variable that has uncertainty and assigns it a random value. The model is then run and a result is provided. This process is repeated again and again while assigning the variable in question with many different values. Once the simulation is complete, the results are averaged together to provide an estimate. The process starts from the initial stage of random number generation, followed by a loop of random input variables generation, load flow and system eigenvalue calculation, and the final stage of eigen analysis \[61\]. Despite the fact that the Monte Carlo Simulation approach has high degree of accuracy, it requires high computational effort which is its main demerit. A conceptual framework for probabilistic power system stability analysis consists of the following three eigen analysis of uncertain input variables and operating conditions, applying probabilistic computational methods and calculation of probabilistic stability indices \[50\]. Over four decades ago, probabilistic analysis was introduced to load flow studies \[62\], power system dynamic stability studies \[63\] and later applied successfully to both load flow and stability studies \[64\] - \[76\]. Table 1 presents various applications of probabilistic computational techniques in power system small signal stability assessment. It shows the intensity of previous research in applying a probabilistic method in small signal stability analysis.
generalized for dependent random variables[144]. In the analysis of power system probabilistic small signal stability directly, calculating the central moments of the system output, and obtaining output standard moments and generating moments, establishing the system input-output sensitivity, calculating the cumulants of the change in system output. Cumulant-based methods require: calculating uncertain input cumulants based on input mean and input central moments, approximating probability density functions (pdfs). It is effective at obtaining the moments of output variables and rebuild the distributions of the same with asymptotic approximation between the uncertain parameters and the desired output of the system. It is a technique by which uncertainties in intensive power system computations can be related to parametric uncertainties using only a small number of simulations. It essentially creates polynomial models relating the uncertain parameters of the system to the outputs of interest. The power of the PCM method lies in its ability to select appropriate simulation points to create a polynomial model which has the same moments as a higher order model. It is computationally efficient and can significantly reduce the computation burden without compromising the result accuracy[136], [137], [138], [139].

The simulation requires the following steps: reducing the number of considered uncertainties based on a ranking algorithm (to due explosive computational burden with high numbers of uncertainties), establishing orthogonal polynomials to represent system uncertainties based on desired model and the input distributions, determining collocation points for each system uncertainty, where it considers the roots of higher order orthogonal polynomials and order based on the joint probability density associated with the operating point; completing a large number of deterministic studies to calculate all coefficients for the PCM model, selecting the most probable collocation points, and calculating output moments or produce a pdf based on the obtained data set [55].

| Probabilistic Computational Techniques | Modeled Variables |
|---------------------------------------|-------------------|
| Probabilistic Collocation Method       | Transmission system [77], Sparse grid points [78], [88], Wind and photovoltaic [79], Load [86], [106], parameter and operational uncertainties [87], Wind [117] |
| Point Estimate Method                  | N random parameter [58], Generator and load [59], Voltage source inverter [84], Wind [89], [93], [95], [102] |
| Cumulant-based method                  | Wind [94], [129],[130], [131], [133],[135], Generated power [98], [100], [101], [103], [105],[126], [132], [134], Voltage phasor measurements [104], Load [107] |
| Neural Networks/Clustering approaches  | VSC-HVDC [114], Load [119], Wind [120], [122],[125], Generated power and load [121] |
| Latin hypercube sampling              | Generation and demand [61], wind-hydro-thermal [90], Wind [96], [97], [115], [124], [127], [128], Load [108], [112], [116], [118], [123], Plug-in electric vehicles (PEVs) and wind [109], Wind and solar photovoltaic [110] |

Table 1: Probabilistic Computational Techniques

4.1. Probabilistic Collocation Method

The Probabilistic Collocation Method (PCM) is an approximate method that establishes a polynomial approximation between the uncertain parameters and the desired output of the system. It is a technique by which uncertainties in intensive power system computations can be related to parametric uncertainties using only a small number of simulations. It essentially creates polynomial models relating the uncertain parameters of the system to the outputs of interest. The power of the PCM method lies in its ability to select appropriate simulation points to create a polynomial model which has the same moments as a higher order model. It is computationally efficient and can significantly reduce the computation burden without compromising the result accuracy[136], [137], [138], [139].

The simulation requires the following steps: reducing the number of considered uncertainties based on a ranking algorithm (to due explosive computational burden with high numbers of uncertainties), establishing orthogonal polynomials to represent system uncertainties based on desired model and the input distributions, determining collocation points for each system uncertainty, where it considers the roots of higher order orthogonal polynomials and order based on the joint probability density associated with the operating point; completing a large number of deterministic studies to calculate all coefficients for the PCM model, selecting the most probable collocation points, and calculating output moments or produce a pdf based on the obtained data set [55]. The application of PCM was illustrated on small disturbance stability studies in [77-79, 86-88, 106, 117] to determine the effects of a supplementary power oscillation damping controller installed on a VSC-HVDC line in the presence of parameter and operational uncertainties, to evaluate the uncertainty in state estimation of power systems, to investigate the power system small signal stability of a power system consisting of wind and PV power generation. The simulation outputs show that the method is computationally efficient for small numbers of uncertainties and requires reduced computational time.

4.2. Point Estimate Method

The point-estimate method (PEM) is a simple but effective technique for evaluating the moments of functions of random variables. That is, it requires calculating input concentrations for each uncertainty, performing deterministic studies at each concentration, calculating the output raw moments; based on the deterministic simulation outputs and weights, calculating output central moments and standard moments to generate the required pdfs. Despite its simplicity, it can be accurate in many practical situations[140], [141]. It has a good balance of accuracy and computational burden. PEMs are superior to the simulation methods because it only needs few deterministic power flow runs [142]. It was applied to small signal stability analysis in [58, 59, 84, 89, 93, 95, 99, 102]. The outputs show that the tradeoff between the simulation precision and the computing speed can be implemented effectively while the stability probabilistic assessment and the probabilistic indices analysis can be carried out with less computational efforts to determine the small signal stability of a renewable energy penetrated power network.

4.3. Cumulant-based Method

Cumulant-based methods require: calculating uncertain input cumulants based on input mean and input central moments, establishing the system input-output sensitivity, calculating the cumulants of the change in system output directly, calculating the central moments of the system output, and obtaining output standard moments and generating pdfs. It is effective at obtaining the moments of output variables and rebuild the distributions of the same with asymptotic expansion theory such as Gram–Charlier expansion, Edgeworth expansion and Cornish–Fisher expansion [55], [143]. It has interesting properties and is computationally inexpensive. For large transmission networks, it is very adequate because of its low computational requirements. It has the disadvantage of the necessary linearization but it may be generalized for dependent random variables[144]. In the analysis of power system probabilistic small signal stability.
analysis, cumulant-based methods were applied in [80-83, 85, 91, 92, 111, 113] and the results show that this method gives a satisfactory result and can be used for further eigenvalues studies.

4.4. Neural Networks/Clustering Approaches

Neural Networks/Clustering approaches involve training of Neural Networks (NN) such as multilayer feed-forward, Fuzzy Logic, Self-Organizing Map by a set of training patterns and store the input-output relationships in weights. Once a NN is properly trained, it is able to approximate highly non-linear functions. Some of the advantages of the method are good interpolation behavior, improved speed of operation and usage of a small set of system data. This technique was used for the analysis of small signal stability of renewable resources penetrated power networks in [94, 98, 100, 101, 103-105, 107, 126, 129, 130-135] and the results demonstrate high efficiency, accuracy and less computation time.

4.5. Latin Hypercube Sampling

Latin hypercube sampling (LHS) was inspired by the concept of ‘Latin square’ from combinatorial mathematics, where an n-by-n matrix is filled with n different objects [145]. The basic idea of LHS is similar to the generation of random numbers via the inverse probabilistic transformation. The difference is that LHS creates the values of $F$ not by generating random numbers dispersed in chaotic way in the interval $(0; 1)$, but by assigning them certain fix values. The interval $(0; 1)$ is divided into several layers of the same width, and the $x$ values are calculated via the inverse transformation $(F^{-1})$ for the $F$ values corresponding to the center of each layer. With reasonably high number of layers (tens or hundreds), the created quantity $x$ will have the proper probability distribution. This approach is called stratified sampling [146], [147], [148]. Meanwhile, Latin Hypercube Sampling is typically used to save computer processing time when running Monte Carlo simulations. Studies have shown that a well-performed LHS can cut down on processing time by up to 50 percent (versus a standard Monte Carlo importance sampling) [149]. Analysis of renewables integrated power system small signal stability in [114, 119, 120-122, 125] was carried out using Latin Hypercube Sampling and effectiveness came to the forefront in terms of high speed and accuracy.

4.6. Monte Carlo Based Simulation

One of the most common and accurate stochastic methods is Monte Carlo Simulation (MCS). It is recognized to be a system-size independent approach and is used when the system is highly nonlinear, complicated or has many uncertain variables [150]. Monte Carlo simulation involves repeated random sampling of system uncertainties in order to obtain a large dataset from which the distribution of an unknown probabilistic entity, that is, output probability density function (PDF) can be determined. The method is very flexible and virtually limitless for analysis and the algorithms can be easily extended and developed [56]. Though Monte Carlo Simulation method handles uncertainty variables very accurately, the method is computationally complex [151], nevertheless, since MCS impose no limitations on the number or statistical properties of input parameters, they usually serve as a yardstick against which the performance of other approaches is compared [152]. Application of Monte Carlo based Simulation was illustrated on power system small disturbance stability studies in [61, 90, 96, 97, 108-110, 112, 115, 116, 118, 123, 124, 127, 128]. The uncertainties considered include; generation, demand, Plug-in electric vehicles (PEVs), wind, small hydro and solar photovoltaic. The results were characterized with high degree of accuracy and shows that power system small signal stability may either be enhanced or deteriorated depending on the penetration of renewable energy resources. Strengths and weaknesses of the reviewed probabilistic computational methods is presented in Table 2.
Probabilistic Computational Techniques | Advantages | Disadvantages
--- | --- | ---
Probabilistic Collocation Method | It reduces the computational burden without compromising the result accuracy | Not suitable for a system with large number of uncertainties. |
Point Estimate Method | Quick convergence hence low computational effort is required. Provides accurate results | Not suitable for the analysis of large power systems. |
Cumulant-based method | Accurate results are attainable. Low computational effort required. Finds application in the analysis of large-scale power systems. | Accuracy may be low in some situations due to inaccurate first order approximations. |
Neural Networks/Clustering approaches | Fast and accurate. Good interpolation behavior. Requires small set of system data. | High variation in objective function values affect accuracy |
Latin hypercube sampling | It is computationally efficient. | High computational burden |
Monte Carlo based Simulation | High degree of accuracy. Suitable for large-scale power systems. | Time consuming |

Table 2: Summary of Probabilistic Computational Techniques

5. Overview of Stochastic Collocation Method

Stochastic collocation (SC) method offers a computationally feasible alternative to traditional Monte Carlo approaches for assessing the impact of model and parameter variability [153]. It has been successfully used in computational electromagnetics [154], in medicine to quantify the effects of heart position in Electrocardiographic (ECG) forward simulation [155] and in modeling uncertainty in diffusion simulation due to microstructure variability [156]. The method can be seen as a ‘sampling’ extension to generalized polynomial chaos, which represents the stochastic process as a linear combination of orthogonal polynomials of random variables, that is, it approximates N-dimensional integrals using quadrature rules with a properly chosen set of collocation points or nodes and a corresponding set of collocation weights.

Since stochastic collocation builds statistics based on deterministic solutions for sampled stochastic parameter values, it only requires a standard discrete solver for the problem of interest. This makes for easy implementation and allows its use on problems with complicated governing equations for which a non-sampling generalized polynomial chaos formulation would be difficult or impossible. [153].

6. Conclusion

This paper reviews the problem of instability of power systems with a considerable share of renewable generation and its significant demand for probabilistic analysis, then, provides a critical evaluation of the available probabilistic methods that have been used for the assessment of power system small signal stability. Merits and demerits of the existing probabilistic methods were brought to the forefront because application of the appropriate methods of probabilistic analysis of power system small signal stability is critical to ensuring the stability and efficient operation of future power system. Meanwhile, the growth of grid integrated distributed generation which has changed the operation dynamics of power system necessitates more accurate probabilistic analysis, therefore, this paper proposes a method known as Stochastic Collocation Method that promises to be an effective probabilistic tool for the analysis of the small signal stability of renewable energy penetrated power systems.

7. References

i. V. S. Kumar, ‘An Integration of Distributed Generation into A Weak Distribution Network,’ vol. 3, no. 11, pp. 1177–1180, 2014.

ii. Š Bunda, ‘Specific Issues of Distributed Generation in Power Systems,’ vol. 7, no. 2, pp. 58–61, 2016.
iii. P. Dalwadi, V. Shrinet, C. R. Mehta, and P. Shah, 'Optimization of solar-wind hybrid system for distributed generation,' 2011 Nirma Univ. Int. Conf. Eng. Curri. Trends Technol. NUCONE 2011 - Conf. Proc., pp. 8–10, 2011, doi: 10.1109/NUICONE.2011.6153300.

iv. A. Rezaazadeh, M. Sedighizadeh, and A. Alavian, 'Optimal Sizing and Sitting of Distributed Generation for Power System Transient Stability Enhancement Using Genetic Algorithm,' Int. J. Eng. Technol., vol. 1, no. 5, pp. 387–390, 2009, doi: 10.7763/ijet.2009.v1.73.

v. A. M. Azmy and I. Erlitch, 'Impact of distributed generation on the stability of electrical power systems,' 2005 IEEE Power Eng. Soc. Gen. Meet., vol. 2, no. July, pp. 1056–1063, 2005, doi: 10.1109/pes.2005.1489354.

vi. V. Van Thong and J. Driesen, 'Distributed Generation and Power Quality,' Handb. Power Qual., pp. 521–528, 2008, doi: 10.1002/9780470754245.ch16.

vii. Y. Yang and M. Bollen, 'Power quality and reliability in distribution networks with increased levels of distributed generation,' 2008.

viii. P. Oluole and K. Folly, 'Impact of Stochastic Load and Hybrid Distributed Generation Penetration Level on Transient Stability of Power Systems,' Br. J. Appl. Sci. Technol., vol. 18, no. 3, pp. 1–14, 2016, doi: 10.9734/bjast/2016/28163.

ix. I. E. Davidson, 'A methodology for evaluating and integrating DG services into a restructured electrical power grid,' Proc. Inaug. IEEE PES 2005 Conf. Expo. Africa, vol. 2005, no. July, pp. 66–71, 2005, doi: 10.1109/pesaf.2005.1611787.

x. D. C. Chandra Shekhar Chandrakar, Bharti Dewani, 'An Assessment of Distributed Generation Islanding Detection Methods,' Int. J. Adv. Eng. Technol., vol. 5, no. 1, pp. 218–226, 2012.

xi. T. Ackermann, G. Andersson, and L. Soder, 'Electricity market regulations and their impact on distributed generation,' no. April, pp. 608–613, 2002, doi: 10.1109/drpt.2000.855735.

xii. A. A. Abou El-Ela, S. M. Allam, and M. M. Shatla, 'Maximal optimal benefits of distributed generation using genetic algorithms,' Electr. Power Syst. Res., vol. 80, no. 7, pp. 869–877, 2010, doi: 10.1016/j.epsr.2009.12.021.

xiii. M. Carreras-Sospedra, S. Vutukuru, J. Brouwer, and D. Dabdub, 'Central power generation versus distributed generation - An air quality assessment in the South Coast Air Basin of California,' Atmos. Environ., vol. 44, no. 26, pp. 3215–3223, 2010, doi: 10.1016/j.atmosenv.2010.05.017.

xiv. A. M. Guseynov and B. S. Akhundov, 'Defining Impact of Distributed Generation on Power System Stability,' pp. 122–125, 2012.

xv. G. V. K. Murthy, S. Sivanagaraju, S. Satyanarayana, and B. H. Rao, 'Voltage stability analysis of radial distribution networks with distributed generation,' Int. J. Electr. Eng. Informatics, vol. 6, no. 1, pp. 195–204, 2014, doi: 10.15676/ijjejii.2014.6.1.13.

xvi. M. Y. Wei, 'Impact of distributed generation on power system,' Appl. Mech. Mater., vol. 543–547, pp. 681–684, 2014, doi: 10.4028/www.scientific.net/AMM.543-547.681.

xvii. R. S. Al Abri, 'Voltage stability analysis with high distributed generation penetration,' A thesis presented to the University of Waterloo in fulfillment of the thesis requirement for the degree of Doctor of Philosophy in Electrical and Computer Engineering Waterloo, Ontario, Canada, p. 134, 2012.

xviii. P. Dondi, D. Bayouni, C. Haederli, D. Julian, and M. Suter, 'Network integration of distributed power generation,' Power Sources, vol. 106, no. 1–2, pp. 1–9, 2002, doi: 10.1016/S0378-7753(01)01031-X.

xix. J. A. P. Lopes, N. Hatzigiargyriou, J. Mutale, P. Djapic, and N. Jenkins, 'Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities,' Electr. Power Syst. Res., vol. 77, no. 9, pp. 1189–1203, 2007, doi: 10.1016/j.epsr.2006.08.016.

xx. K. Purchala, R. Belmans, KU Leuven L. Xarchakos and A. D. Hawkes, 'Distributed Generation and the GridIntegration Issues,' Imperial College London, 2006.

xxi. [21] Y. Xu, F. Wen, H. Zhao, M. Chen, Z. Yang, and H. Shang, 'Stochastic Small Signal Stability of a Power System with Uncertainties,' Energies, pp. 1–16, 2018, doi: 10.3390/en11112980.

xxii. H. Ahmad, H. Ghasemi, and H. Lesani, 'A Comparative Small Signal Stability Analysis of PMSG and SCIG-Based Wind Farms,' Proc. 25th Int. Power Syst. Conf. (PSC 2018), May, 2018.

xxiii. L. Yan and K. Wang, 'A summary of impacts of wind power integration on power system small-signal stability,' JOP Conf. Ser. Earth Environ. Sci., vol. 64, no. 1, 2017, doi: 10.1088/1755-1315/64/1/012085.

xxiv. S. B. Barot, M. V. Jain, C. R. Mehta, and S. C. Vora, 'Small Signal Stability Analysis of DFIG Penetrated Multi-machine Power System with Synthetic Inertia Control,' 2018 20th Natl. Power Syst. Conf. NPSC 2018, 2018, doi: 10.1109/NPSC.2018.8771765.

xxv. S. Q. Bu, X. Zhang, S. W. Xia, Y. Xu, B. Zhou, and X. Lu, 'Reducing model complexity of DFIG-based wind turbines to improve the efficiency of power system stability analysis,' Energy Procedia, vol. 142, pp. 971–976, 2017, doi: 10.1016/j.egypro.2017.12.155.

xxvi. N. D. Hatzigiargyriou and A. P. Sakis Meliopoulos, 'Distributed energy sources: Technical challenges,' Proc. IEEE Power Eng. Soc. Transm. Distrib. Conf., vol. 2, no. c, pp. 1017–1022, 2002, doi: 10.1109/pesw.2002.985163.

xxvii. F. Blaabjerg, Y. Yang, D. Yang, and X. Wang, 'Distributed Power-Generation Systems and Protection,' Proc. IEEE, vol. 105, no. 7, pp. 1311–1331, 2017, doi: 10.1109/JPROC.2017.2696878.

xxviii. S. Bakshi, T. Thakur, and R. Khanna, 'Exploration of Distributed Generation for Future Distribution Networks,' International Journal of Advanced Research in Computer Engineering & Technology, vol. 3, no. 11, pp. 3658–3666, 2014.
V. Sujatha and M. Umarani, ‘Impact of Hybrid Distributed Generator on Transient Stability of Power System’, International Journal for Modern Trends in Science and Technology, Vol. 2, Special Issue 01, 2016.

M. El Chehaly, ‘Power System Stability Analysis with a High Penetration of Distributed Generation’, Unpublished M.Sc. Thesis, McGill University, Montréal, Québec, Canada, February 2010.

J. G. Slootweg and W. L. Kling, ‘Impacts of distributed generation on power system transient stability’, Power Engineering Society Summer Meeting, ieee, Vol. 2, pp. 862 – 867, July 2002.

M. K. Donnelly, J. E. Dagle, D. J. Trudnowski and G. J. Rogers, ‘Impacts of the Distributed Utility on Transmission System Stability’, IEEE Transactions on Power Systems, Vol. 11, No. 2, May 1996.

Z. Zhengyi, Z. Xiangjun, T. Shunato and G. Zigan, ‘A Novel Scheme of Stability Control for Distributed Generation Systems’, International Conference on Power System Technology-POWERCON, Singapore, November 21-24, 2004.

M. R. A. Ahmed, ‘Simulation and Management of Distributed Generating Units using Intelligent Techniques’, PhD Thesis submitted to the Department of Electrical Engineering, University of Duisburg-Essen, 2005.

P. Kundur, ‘Power System Stability and Control’, New York: McGraw-Hill, Inc, 1994.

M. K. Donnelly, J. E. Dagle, D. J. Trudnowski and G. J. Rogers, ‘Impacts of the Distributed Utility on Transmission System Stability’, Power Engineering Society Summer Meeting, ieee, Vol. 2, pp. 862 – 867, July 2002.

S. Izumi, Y. Karakawa, and X. Xin, ‘Analysis of small-signal stability of power systems with photovoltaic generators’, Electr. Eng., vol. 101, no. 2, pp. 321–331, 2019, doi: 10.1007/s00202-019-07770-w.

K. Prasertwong, N. Mithulananthan, and D. Thakur, ‘Understanding low-frequency oscillation in power systems’, Int. J. Electr. Eng. Educ., vol. 47, no. 3, pp. 248–262, 2010, doi: 10.7227/IEEE.47.3.2.

S. L. Z. Aun, M. B. Marsadek, and A. K. Ramasamy, ‘Small signal stability analysis of grid connected photovoltaic’, Indones. J. Electr. Eng. Comput. Sci., vol. 6, no. 3, pp. 553–562, 2017.

R. Krishan, A. Verma, and B. Prasad, ‘Small signal stability analysis of grid connected distributed PV and wind energy system’, Proc. 6th IEEE Power India Int. Conf. PICON 2014, 2014, doi: 10.1109/34084POWER1.2014.7117730.

Z. Xu, W. Shao, and C. Zhou, ‘Power System Small Signal Stability Analysis Based on Test Signal’, 14th PSCC, Sevilla, pp. 24–28, 2002.

S. Eftekhamejad, V. Vittal, G. T. Heydt, B. Keel, and J. Loehr, ‘Small signal stability assessment of power systems with increased penetration of photovoltaic generation: A case study’, IEEE Trans. Sustain. Energy, vol. 4, no. 4, pp. 960–967, 2013, doi: 10.1109/TSTE.2013.2259602.

Z. Y. Dong, ‘Advanced methods for small signal stability analysis and control in modern power systems’, A thesis submitted in partial fulfillment of the requirements for the degree of Master of Philosophy, Faculty of Engineering and Applied Science, Memorial University of Newfoundland, 2015.

S. P. Teeuwsen, I. Erlich, and M. A. El-Sharkawi, ‘Neural network based classification method for small-signal stability assessment’, 2003 IEEE Bol. PowerTech - Conf. Proc., vol. 3, pp. 6–11, 2003, doi: 10.1109/PTC.2003.1304415.

J. Cao and Z. Fan, ‘Deep learning-based online small signal stability assessment of power systems with renewable generation’, Proc. - 2018 IEEE SmartWorld, Ubiquitous Comput. Adv. Trust. Comput. Scalable Comput. Commun. Cloud Big Data Comput. Internet People Smart City Innov. SmartWorld/UIUC/ATC/ScalCom/CBDCo, pp. 216–221, 2018, doi: 10.1109/SmartWorld.2018.00072.

I. Erlich and A. Fischer, ‘Fast Assessment of Small-Signal Oscillatory Stability in Large Interconnected Power Systems’, Balk. Power Conf. BPC, vol. 2, pp. 343–348, 2002.

S. P. Teeuwsen, ‘Oscillatory Stability Assessment of Power System using Computational Intelligence’, PhD Dissertation, University Duisburg-Essen, March 2005.

M. Ghorbaniparvar, ‘Survey on forced oscillations in power system’, J. Mod. Power Syst. Clean Energy, vol. 5, no. 5, pp. 671–682, 2017, doi: 10.1007/s40565-017-0273-4.

Xi-fan Wang, Y. Song and M. Irving, ‘Small Signal Stability Analysis of Power Systems in: Modern Power Systems Analysis’, Springer, Boston, MA, 2008.

K. N. Hasan, R. Preece, and J. V. Milanovi, ‘Existing approaches and trends in uncertainty modelling and probabilistic stability analysis of power systems with renewable generation’, Renew. Sustain. Energy Rev., vol. 101, no. 1, December 2017, pp. 168–180, 2019, doi: 10.1016/j.rser.2018.10.027.
lvi. J. V. Milanović, ‘Probabilistic stability analysis: The way forward for stability analysis of sustainable power systems,’ Philos. Trans. R. Soc. A Math. Phys. Eng. Sci., vol. 375, no. 2100, 2017, doi: 10.1098/rsta.2016.0296.

lvii. M. Aien, M. Rashidnejad, and M. Fotuhi-firuzabad, ‘On possibilistic and probabilistic uncertainty assessment of power flow problem: A review and a new approach,’ Renew. Sustain. Energy Rev., vol. 37, pp. 883–895, 2014, doi: 10.1016/j.rser.2014.05.063.

lviii. H. Yi, Y. Hou, S. Cheng, H. Zhou, and G. Chen, ‘Power system probabilistic small signal stability analysis using two point estimation method,’ Proc. Univ. Power Eng. Conf., no. 1, pp. 402–407, 2007, doi: 10.1109/UPPEC.2007.4468981.

lix. R. Preece, K. Huang, and J. V. Milanović, ‘Probabilistic small-disturbance stability assessment of uncertain power systems using efficient estimation methods,’ IEEE Trans. Power Syst., vol. 29, no. 5, pp. 2509–2517, 2014, doi: 10.1109/TPWRS.2014.2308577.

lx. Z. Y. Dong, C. K. Pang, and P. Zhang, ‘Power System Sensitivity Analysis for Probabilistic Small Signal Stability Assessment in a Deregulated Environment,’ Int. J. Control. Autom. Syst., vol. 3, no. 2, pp. 355–362, 2005.

lxi. Z. Xu, Z. Y. Dong, and P. Zhang, ‘Probabilistic small signal analysis using Monte Carlo simulation,’ 2005 IEEE Power Eng. Soc. Gen. Meet., vol. 2, no. 1, pp. 1658–1664, 2005, doi: 10.1109/pec.2005.1489425.

lxii. B. Borkowska, ‘Probabilistic Load Flow,’ IEEE Trans. on Power Apparatus and Systems, vol. PAS-93, pp. 752–759, 1974.

lxiii. R. C. Burchett and G. T. Heydt, ‘Probabilistic Methods for Power System Dynamic Stability Studies,’ IEEE Trans. on Power Apparatus and Systems, vol. PAS-97, pp. 695–702, 1978.

lxiv. R. N. Allan, B. Borkowska and C. H. Grigg, ‘Probabilistic analysis of power flows,’ Proceedings of the Institution of Electrical Engineers (London), vol. 121, no. 12, pp. 1551-1556, Dec. 1974.

lxv. P. Jørgensen, J. S. Christensen and J. O. Tande, ‘Probabilistic load flow calculation using Monte Carlo techniques for distribution network with wind turbines,’ 8th International Conference on Harmonics and Quality of Power, vol. 2, pp.1146-1151, 1998.

lxvi. R. N. Allan, M. R. G. Al-Shakarchi, ‘Probabilistic techniques in a.c. load-flow analysis,’ Proc. Inst. Electr. Eng., vol. 124, no. 2, pp. 154–160, 1977.

lxvii. P. Chen, Z. Chen and B. Bak-Jensen, ‘Probabilistic Load Flow: A Review,’ DRPT2008 6-9 April 2008 Nanjing China, pp. 1586–1591, 2008.

lxviii. P. Caramia, G. Carpinelli, M. Pagano and P. Varilone, ‘Probabilistic three-phase load flow for unbalanced electrical distribution systems with wind farms,’ IET Renewable Power Generation, vol.1, no.2, pp.115–122, Jun. 2007.

lxix. N. D. Hatziargyriou, T. S. Karakatsanis and M. Papadopoulos, ‘Probabilistic load flow in distribution systems containing dispersed wind power generation,’ IEEE Trans. Power Systems, vol.8, no.1, pp.159-165, Feb. 1993.

lxx. M. Madrigal, K. Pomambalam, V. H. Quintana, ‘Probabilistic optimal power flow,’ IEEE Canadian Conference on Electrical and Computer Engineering, 1998, vol.1, pp.385-388, May 1998.

lxxi. N. L. A. Method, H. Sheng, and X. Wang, ‘Probabilistic Power Flow Calculation using Non-intrusive Low-rank Approximation Method,’ IEEE Trans. POWER Syst., pp. 1–12, 2019.

lxxii. G. Carpinelli, T. Esposito, P. Varilone and P. Verde, ‘First-order probabilistic harmonic power flow,’ IEE Proc. Generation, Transmission and Distribution, vol.148, no.6, pp.541-548, Nov. 2001.

lxxiii. C. Su, ‘Probabilistic Load-Flow Computation Using Point Estimate Method,’ IEEE Trans. Power Syst., vol. 20, no. 4, pp. 1843–1851, 2005.

lxxiv. A. M. Leite da Silva and V. L. Arienti, ‘Probabilistic load flow by a multilinear simulation algorithm,’ IEEE Proc. C Gener. Transm. Distrib., vol. 137, no. 4, pp. 276–282, 1990, doi: 10.1049/ip-c.1990.0037.

lxxv. G. Verbič, A. Schellenberg, W. Rosehart, and C. A. Cañizares, ‘Probabilistic optimal power flow applications to electricity markets,’ 9th Int. Conf. Probabilistic Methods Appl. to Power Syst. PMAPS, pp. 1–6, 2006, doi: 10.1109/PMAPS.2006.360245.

lxxvi. A. P. S. Meliopoulos, G. J. Kokkinides and X. Y. Chao, ‘A new probabilistic power flow analysis method,’ IEEE Trans. Power Systems, vol.5, no.1, pp.182-190, Feb. 1990.

lxxvii. R. Preece and J. V. Milanovic, ‘The Probabilistic Collocation Method for dealing with uncertainties in power system small disturbance studies,’ IEEE Power Energy Soc. Gen. Meet., pp. 1-7, 2012, doi: 10.1109/PEGSYM.2012.6344707.

lxxviii. G. Lin, N. Zhou, T. Ferryman, and F. Tuffner, ‘Uncertainty quantification in state estimation using the probabilistic collocation method,’ 2011 IEEE/PES Power Syst. Conf. Exp. PSCE 2011, pp. 1–8, 2011, doi: 10.1109/PSCE.2011.5772599.

lxxix. C. Yan, L. Zhou, W. Yao, J. Wen, and S. Cheng, ‘Probabilistic small signal stability analysis of power system with wind power and photovoltaic power based on probability collocation method,’ Glob. Energy Interconnect., vol. 2, no. 1, pp. 19–28, 2019, doi: 10.1016/j.egoi.2019.06.003.

lxx. S. Gurung, S. Naetiladdanon, and A. Sangswang, ‘Probabilistic small-signal stability analysis of power system with solar farm integration,’ Turkish J. Electr. Eng. Comput. Sci., vol. 27, no. 2, pp. 1276–1289, 2019, doi: 10.3906/elk-1804-228.

lxxi. S. Liu, P. X. Liu, and X. Wang, ‘Stochastic Small-Signal Stability Analysis of Grid-Connected Photovoltaic Systems,’ IEEE Trans. Ind. Electron., vol. 63, no. 2, pp. 1027–1038, 2016, doi: 10.1109/TIE.2015.2481359.
S. Gurung, S. Naetiladdanon, and A. Sangswang, 'Impact of photovoltaic penetration on small signal stability considering uncertainties,' 2017 IEEE Innov. Smart Grid Technol. - Asia Smart Grid Smart Community, ISGT-Asia 2017, no. December, pp. 1–6, 2018, doi: 10.1109/ISGT-Asia.2017.8378404.

G. Wang, H. Xin, D. Wu, and P. Ju, 'Data-driven probabilistic small signal stability analysis for grid-connected PV systems,' Int. J. Electr. Power Energy Syst., vol. 113, no. July 2018, pp. 824–831, 2019, doi: 10.1016/j.ijepes.2019.06.004.

X. Xu, T. Lin, and X. Zha, 'Probabilistic analysis of small signal stability of microgrid using point estimate method,' 1st Int. Conf. Sustain. Power Gener. Supply, SUPERGEN '09, pp. 1–6, 2009, doi: 10.1109/SUPERGEN.2009.5348227.

K. W. Wang, C. Y. Chung, C. T. Tse, and K. M. Tsang, 'Improved probabilistic method for power system dynamic stability studies,' IEEE Proc. Gener. Transm. Distrib., vol. 147, no. 1, pp. 37–42, 2000, doi: 10.1049/ip-gtd:20000025.

M. Li, J. Ma, and Z. Y. Dong, 'Uncertainty analysis of load models in small signal stability,' 1st Int. Conf. Sustain. Power Gener. Supply, SUPERGEN '09, pp. 1–6, 2009, doi: 10.1109/SUPERGEN.2009.5348369.

R. Preece, N. C. Woolley, and J. V. Milanovic, 'The probabilistic collocation method for power-system damping and voltage collapse studies in the presence of uncertainties,' IEEE Trans. Power Syst., vol. 28, no. 3, pp. 2253–2262, 2013, doi: 10.1109/TPWRS.2012.2227837.

B. Mehta, P. Bhatt, and V. Pandya, 'Small signal stability analysis of power systems with DFIG based wind power penetration,' Int. J. Electr. Power Energy Syst., vol. 58, pp. 64–74, 2014, doi: 10.1016/j.ijepes.2014.01.005.

P. Kanyingi, K. Wang, G. Li, and W. Wu, 'A Robust Pair Copula-Point Estimation Method for Probabilistic Small Signal Stability Analysis with Large Scale Integration of Wind Power,' J. Clean Energy Technol., vol. 5, no. 2, pp. 85–94, 2017, doi: 10.18178/jocet.2017.5.2.350.

J. L. Rueda and D. G. Colomé, 'Probabilistic performance indexes for small signal stability enhancement in weak wind-hydro-thermal power systems,' IET Trans. Gener. Transm. Distrib., vol. 3, no. 8, pp. 733–747, 2009, doi: 10.1049/iet-gtd:2008.0574.

S. Q. Bu, W. Du, H. F. Wang, Z. Chen, L. Y. Xiao, and H. F. Li, 'Probabilistic analysis of small-signal stability of large-scale power systems as affected by penetration of wind generation,' IEEE Trans. Power Syst., vol. 27, no. 2, pp. 762–770, 2012, doi: 10.1109/TPWRS.2011.2170183.

Z. W. Wang, C. Shen, and F. Liu, 'Probabilistic Analysis of Small Signal Stability for Power Systems with High Penetration of Wind Generation,' IEEE Trans. Sustain. Energy, vol. 7, no. 3, pp. 1182–1193, 2016, doi: 10.1109/TSTE.2015.2432359.

Z. Wei, D. Wei, S. M. Liu, M. L. Yang, S. B. Pan, X. W. Zhu, and Z. G. Pan, 'Probabilistic Small Signal Stability Analysis of Power System with Large Scale Wind Power,' College of Electric Engineering, Shanghai Dian Ji University, Shanghai 200240, China, IETC Asia-Pacific 2014.

S. Madadi, B. Mohammadi-Ivatloo, and S. Tohid, 'Probabilistic Small Signal Stability Evaluation of Power Systems with High Penetration of Wind Farms,' Comput. Electr. Eng., vol. 85, 2020, doi: 10.1016/j.compeleceng.2020.106683.

H. Yue, G. Li, and M. Zhou, 'A probabilistic approach to small signal stability analysis of power systems with correlated wind sources,' J. Electr. Eng. Technol., vol. 8, no. 6, pp. 1605–1614, 2013, doi: 10.5370/JEET.2013.8.6.1605.

C. Wang, L. Shi, L. Yao, L. Wang, Y. Ni, and M. Bazargan, 'Modelling analysis in power system small signal stability considering uncertainty of wind generation,' IEEE PES Gen. Meet. PES 2010, 2010, doi: 10.1109/PES.2010.5589646.

W. C. B. Vicente, R. Caire, and N. Hadjsaid, 'Stochastic simulations and stability to determine maximum wind power penetration of an island network,' IEEE Power Energy Soc. Gen. Meet., vol. 2018-Janua, pp. 1–5, 2018, doi: 10.1109/PESGM.2017.8273855.

[98] R. LIU, 'Power system stability scanning and security assessment using machine learning,' A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy in the The Centre for Future Energy Networks, Electrical & Information Engineering, University of Sydney, 2018.

A. Soroudi, M. Aien, and M. Ehsan, 'A probabilistic modeling of photovoltaic modules and wind power generation impact on distribution networks,' IEEE Syst. J., vol. 6, no. 2, pp. 254–259, 2012, doi: 10.1109/JYST.2011.2162994.

S. P. Teeuwsen, I. Erlich, A. Fischer, and M. A. El-Sharkawi, 'Assessment of the small signal stability of the European interconnected electric power system using neural networks,' LESCOPE 2001 - 2001 Large Eng. Syst. Conf. Power Eng. Powering Beyond 2001, Conf. Proc., no. February 2001, pp. 158–161, 2001, doi: 10.1109/LESCEPE.2001.941643.

S. P. Teeuwsen, I. Erlich, and M. A. El-Sharkawi, 'Small-signal stability assessment for large power systems using computational intelligence,' 2005 IEEE Power Eng. Soc. Gen. Meet., vol. 3, pp. 2661–2668, 2005, doi: 10.1109/PELS.2005.1499375.

N. Soleimanpour and M. Mohammadi, 'Probabilistic small signal stability analysis considering wind energy,' Iranian Conference on Smart Grids, pp. 1-6, Tehran, 2012.
A. Hammoudeh, M. I. Al Saaideh, E. A. Felat, and H. Mubarak, 'Estimation of synchronizing and damping torque coefficients using deep learning,' 2019 IEEE Jordan Int. Conf. Electr. Eng. Inf. Technol. IEEE 2019, Proc., pp. 488–493, 2019, doi: 10.1109/JEEIT.2019.8717432.

civ. S. K. Azman, Y. J. Isbeih, M. S. El Moursi, and K. Elbassioni, 'A Unified Online Deep Learning Prediction Model for Small Signal and Transient Stability,' IEEE Trans. Power Syst., vol. 35, no. 6, pp. 4585–4598, 2020, doi: 10.1109/TPWRS.2020.2999102.

c. Fabio, M. M. de Lima and R. T. H. Alden, 'Neural Network Assessment of Small Signal Stability', Power Research Laboratory. McMaster University Hamilton, Ontario L8S 4K1.

cvi. D. Han, J. Ma and R. He, 'Uncertainty analysis of load models in dynamic stability,' 2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, Pittsburgh, PA, 2008, pp. 1-6, doi: 10.1109/PES.2008.4596440.

cvii. A. Hoballah, 'Power System Stability Assessment and Enhancement using Computational Intelligence,' A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy, Universität Duisburg-Essen, 2011.

cvi. P. N. Papadopoulos and J. V. Milanovic, 'Impact of penetration of non-synchronous generators on power system dynamics,' 2015 IEEE Eindhoven PowerTech, PowerTech 2015, 2015, doi: 10.1109/PTC.2015.7232308.

cxi. H. Huang, C. Y. Chung, K. W. Chan, and H. Chen, 'Quasi-monte carlo based probabilistic small signal stability analysis for power systems with plug-in electric vehicle and wind power integration,' IEEE Trans. Power Syst., vol. 28, no. 3, pp. 3335–3343, 2013, doi: 10.1109/TPWRS.2013.2254505.

cxii. P. Sivakumar and C. Birindha, 'Stability enhancement of DG sourced power system with modified AVR and PSS,' Proc. Int. Conf. Comput. Power, Energy, Inf. Commun. ICCPEIC 2013, pp. 105–109, 2013, doi: 10.1109/ICCPEIC.2013.6778508.

cxiii. S. Q. Bu, W. Du, and H. F. Wang, 'Investigation on Probabilistic Small-Signal Stability of Power Systems as Affected by Offshore Wind Generation,' IEEE Trans. Power Syst., vol. 30, no. 5, pp. 2479–2486, 2015, doi: 10.1109/TPWRS.2014.2367019.

cxiv. R. Arrieta, M. A. Ríos, and A. Torres, 'Contingency analysis and risk assessment of small signal instability,' 2007 IEEE Lausanne POWERTECH, Proc., vol. 2, no. 1, pp. 1741–1746, 2007, doi: 10.1109/PCT.2007.4538579.

cxv. S. Q. Bu, W. Du, and H. F. Wang, 'Probabilistic analysis of small-signal rotor angle/voltage stability of large-scale AC/DC power systems as affected by grid-connected offshore wind generation,' IEEE Trans. Power Syst., vol. 28, no. 4, pp. 3712–3719, 2013, doi: 10.1109/TPWRS.2013.2265712.

cxvi. R. Preece and J. V. Milanovic, 'Efficient Estimation of the Probability of Small-Disturbance Instability of Large Uncertain Power Systems,' IEEE Trans. Power Syst., vol. 31, no. 2, pp. 1063–1072, 2016, doi: 10.1109/TPWRS.2015.2417204.

S. Q. Bu, W. Du, H. F. Wang, 'Investigation on Probabilistic Small-Signal Stability of Power Systems as Affected by Offshore Wind Generation,' 2016 IEEE Power Engineering Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, Pittsburgh, PA, 2016, pp. 1-6, doi: 10.1109/PES.2016.7796467.

cxvii. H. Yin and R. Zivanovic, 'An application of probabilistic collocation method in wind farms modelling and power system simulation,' IEEE PES Innov. Smart Grid Technol. Conf. Eur., pp. 681–686, 2016, doi: 10.1109/ISGT-Asia.2016.7796467.

S. Ayasun and C. O. Nwankpa, 'Probability of small-signal stability of power systems in the presence of communication delays,' ELECO 2009 - 6th Int. Conf. Electr. Electron. Eng., pp. 70–74, 2009.

cxix. J. Zuo, Y. Li, D. Cai, and D. Shi, 'Latin hypercube sampling based probabilistic small signal stability analysis considering load correlation,' IEEE Trans. Power Syst., vol. 9, no. 6, pp. 1832–1842, 2014, doi: 10.1109/TPWRS.2014.2367019.

cxx. T. R. Ayodele, A. A. Jimoh, J. L. Munda, and J. T. Agee, 'The impacts of intermittent wind generation on network small signal stability considering load variation,' IEEE Power Energy Soc. Conf. Expo. Africa Intell. Grid Integr. Renew. Energy Resour. PowerAfrica 2012, no. July, pp. 9–13, 2012, doi: 10.1109/PowerAfrica.2012.6498607.

X. Li, Y. Li, L. Liu, W. Wang, Y. Li, and Y. Cao, 'Latin hypercube sampling method for location selection of multi-infeed HVDC system terminal,' Energies, vol. 13, no. 7, 2020, doi: 10.3390/en13071646.

cxxii. T. R. Ayodele, A. A. Jimoh, J. L. Munda, and J. T. Agee, 'Impacts of tie-lines and wind generator location on small signal stability of a power system,' Int. J. Renew. Energy Res., vol. 3, no. 1, pp. 51–59, 2013, doi: 10.20508/ijjre.61427.

cxxiii. Y. Chabane, A. A. Ladiji, A. Hella, and K. Dookhitram, 'Cooperative coevolutionary algorithms for optimal PSS tuning based on Monte-Carlo probabilistic small-signal stability assessment,' Int. Trans. Electr. Energ. Syst., vol. 30, no. 11, pp. 1–16, 2020, doi: 10.1002/2050-7038.12618.

cxxiv. A. U. Krisman and N. Mithulananthan, 'Probabilistic small signal stability analysis of autonomous wind-diesel microgrid,' 2017 IEEE Innov. Smart Grid Technol. - Asia Smart Grid Smart Community, ISGT-Asia 2017, pp. 1–6, 2018, doi: 10.1109/ISGT-Asia.2017.8378359.

cxxv. T. R. Ayodele, 'Comparative Assessment of SVC and TCSC Controllers on the Small Signal Stability Margin of a Power System Incorporating Intermittent Wind Power Generation,' J. Wind Energy, vol. 2014, pp. 1–12, 2014, doi: 10.1155/2014/570234.
cli. K. P. Kumar and B. Saravanan, ‘Recent techniques to model uncertainties in power generation from renewable energy sources and loads in microgrids – A review,’ Renew. Sustain. Energy Rev., vol. 71, no. December, pp. 348–358, 2017, doi: 10.1016/j.rser.2016.12.063.

clii. D. A. Barajas-Solano and D. M. Tartakovsky, ‘Stochastic collocation methods for nonlinear parabolic equations with random coefficients,’ SIAM-ASA J. Uncertain. Quantif., vol. 4, no. 1, pp. 475–494, 2016, doi: 10.1137/130930108.

cliii. J. S. Preston, T. Tasdizen, C. M. Terry, A. K. Cheung, and R. M. Kirby, ‘Using the stochastic collocation method for the uncertainty quantification of drug concentration due to depot shape variability,’ IEEE Trans. Biomed. Eng., vol. 56, no. 3, pp. 609–620, 2009, doi: 10.1109/TBME.2008.2009882.

cliv. D. Poljak et al., ‘Stochastic Collocation Applications in Computational Electromagnetics,’ Math. Probl. Eng., vol. 2018, 2018, doi: 10.1155/2018/1917439.

clv. D. A. J. S. Wenson, S. A. E. G. Eneser, J. E. G. S. Tinstra, R. O. M. K. Irby, and R. O. B. S. M. A. C. L. Eod, ‘Cardiac Position Sensitivity Study in the Electrocardiographic Forward Problem Using Stochastic Collocation and Boundary Element Methods,’ vol. 39, no. 12, pp. 2900–2910, 2011, doi: 10.1007/s10439-011-0391-5.

clvi. B. Ganapathysubramanian and N. Zabaras, ‘Modeling diffusion in random heterogeneous media: Data-driven models, stochastic collocation and the variational multiscale method,’ vol. 226, pp. 326–353, 2007, doi: 10.1016/j.jcp.2007.04.009.