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# Probabilistic Ranking of Critical Parameters Affecting Voltage Stability in Network with Renewable Generation

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**Abstract**— This paper introduces a probabilistic method for the ranking of influential uncertain parameters for the accurate assessment of power system voltage stability. Future power systems will be highly interconnected and complex with a variety of uncertain parameters such as the injection of intermittent renewable energy resources, the adoption of flexible hierarchical control structures and the appearance of new types of loads. Identifying and ranking the uncertain parameters are important in future power system operations since they can provide referable indexes for system operators to achieve better system management with less monitoring. This paper presents the probabilistic method for the identification and ranking of critical uncertain parameters. A modified version of the 68 bus NETS-NYPS test system is used in this study for simulation studies. The effects of uncertain parameters are modelled with Monte-Carlo method in the environments of MATLAB and DiGSILENT PowerFactory. The performances of the ‘nose-point area’ of P-V Curves for system load buses are used as indexes when evaluating their sensibility for specific uncertainties.

**Index Terms**-- power system dynamic analysis, probability distribution, sensitivity analysis, uncertain parameters, voltage stability.

## I. INTRODUCTION

The key characteristics of future power systems are considered to be an unprecedented mix of a wide range of electricity generating technologies and new types of loads. The stochastic and intermittent nature of Distributed Energy Resources (DERs) and loads can lead to uncertainty in generation and loading [1]. These uncertain parameters within power systems will affect the related system stability analysis results [2]. Since increasing loading demands force the power systems to operate closer to their stability margins these days, an accurate assessment for the effect of uncertain parameters on power system stability becomes critical. Many research efforts have been focused in the area of voltage stability due to the power system failures caused by voltage instability [3-6]. Power systems nowadays are developed into highly interconnected and complex dynamic systems. The malfunction of a power system can cause great loss to society.

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Therefore, for future power system designs and operations, an accurate evaluation of the effect of uncertain parameters on power system voltage stability is considered to be important.

Power systems voltage stability depends on the relationship between the load bus voltage (V), the reactive power (Q) and the power supplied to the load (P) [7]. PV curve plots bus voltage (V) against total loading (P), and can be obtained from the load flow solutions of voltage stability simulation. The nose point of a PV curve is defined as the last solution for power flow equations when the system has reached its voltage stability limit. It can be seen as the last point on a PV curve. On the other hand, the reactive power (Q) a generator can produce or absorb to compensate system dynamics also sets a limit on the voltage stability margin. An important index for voltage stability analysis is the voltage sensitivity factor, which is defined as  $VSF_i = \frac{\Delta V_i}{\Delta Q_i}$ . The stability criterion is  $VSF_i > 0$  [8].

Generating PV curves requires real solutions for system power flow equations. However, accurate operating conditions can be difficult to obtain due to the stochastic and intermittent nature of system uncertain parameters. For example, the wind power generator output can be varied in a day following the variance of wind speed. In this case, the deterministic assessment might make an overly conservative estimate of the scenario since it always considers the ‘worst-case’ scenario [8]. The probabilistic method, on the other hand, can provide a prediction of the system behaviour over a wide range while obtaining computational efficiency and higher accuracy [8-11].

Much research related to voltage stability assessment was done in the past. A Monte-Carlo based approach with probabilistic distributed generation scenarios and active/reactive load margin uncertainty have been applied in [7]. Maximum entropy method with Gaussian/Normal distributed system loads were implemented in [12]. Contingency enumeration based approaches with normal distributed load uncertainty have been introduced in [13]. Probabilistic eigenvalue analysis (through normal parametric distribution) has been used in [2]. Probabilistic collocation method has been proposed in [1].

However, as the number of uncertain parameters increases with the size of the power system, it becomes extremely costly to consider all uncertain parameters in the assessment of

power system stability [14]. The fact is that the uncertain parameters in a power system can have different levels of influence on the system operation. Ranking the uncertain parameters based on their level of influence can help system operators to achieve better system management with less monitoring.

This paper presents a probabilistic method for the identification and ranking of critical uncertain parameters affecting power system voltage stability. Monte-Carlo method is applied first to generate system behaviours under the implementation of different uncertain parameters. The influence of uncertainties with load demand, renewable generation and load models are investigated separately. The critical and stiff buses can be selected by ranking the load buses based on their loadability by increasing the total loading of the system until the first bus collapses. Finally by comparing ‘nose-area’, the effect of proposed uncertain parameters on system voltage stability can be evaluated.

## II. TEST SYSTEM AND MODELLED UNCERTAINTY

### A. Test System

The simulation network used in this paper is a modified version of a reduced order equivalent model of NETS-NYPS (New England Test System – New York Power System) as shown in Fig. 1. The network consists of 16 machines, 68 buses, and 5 distinct areas. NETS includes generators G1-G9, NYPS consists of G10-G13 and the three neighbouring areas are represented by generators G14, G15, and G16. The synchronous generators are represented by sixth order models. Transmission lines are modelled with the standard  $\pi$  circuit. Two types of RES model are introduced in the network; Type 3 doubly fed induction generators (DFIGs) and Type 4 Full converter Connected (FCC) units. In NETS, RES are connected to buses 26, 57 and 68, in NYPS at buses 33 and 37 and in the surrounding areas at buses 18, 41 and 42. The network is modelled in DIgSILENT PowerFactory 15.2. The reactive power limits for synchronous generators within this test network are set to be between the limits 0.85 Power Factor lagging and 0.95 Power Factor leading based on Grid Code requirement [15] and are imported to generators as capability curves. 30% of the generation in each of the five areas is replaced by renewables (RES). TABLE I presents system loading scenarios for this study. Peak loading has been considered as *base case* scenario. However, since the system load cannot be varied at peak loading, high and low loading scenarios have been analysed in Section III.

### B. Modelling of Uncertain Parameters

The probabilistic uncertain variables modelled in this paper are load demand, wind speed and solar irradiation, Which follows normal [2, 16, 17], Weibull [18-20] and Beta [21, 22] distributions, respectively. The Normal, Weibull and Beta distributions are represented through [mean ( $\mu$ ), standard deviation ( $\sigma$ )], [scale parameter ( $\alpha$ ), shape parameter ( $\beta$ )] and [shape parameter 1 ( $\alpha$ ), shape parameter 2 ( $\beta$ )], respectively. The model parameters of the variables are presented in TABLE II. A total of 49 uncertain parameters including 35 loads, 7 wind farms and 7 solar farms have been modelled probabilistically. The level of uncertainty is set to be at a High Level of Uncertainty scenario.

### C. Load Models

The static exponential load models are used in this paper to investigate their effect on power system voltage stability. This is based on an international survey on load modelling among WG members between 2010 to 2012 which revealed that the constant real and reactive power load model (constant P/Q) is the most widely used load model for steady state power system studies [23]. A simplified version of the exponential load model with neglected load dependence on frequency is used in this paper:

$$P = P_n \left( \frac{U}{U_n} \right)^{k_{pu}} \quad (1)$$

$$Q = Q_n \left( \frac{U}{U_n} \right)^{k_{qu}} \quad (2)$$

where  $P$  and  $Q$  are the real and reactive power drawn by the load at voltage  $U$  and frequency  $f$ ,  $P_n$  and  $Q_n$  are the real and reactive power drawn under rated voltage ( $U_n$ ). The exponents  $k_{pu}$  and  $k_{qu}$  describe the change in load demand in response to variations in the supply voltage. If the voltage exponents in (1) and (2) are set at 0 and 2, the load exhibits constant power or constant impedance characteristics, respectively.

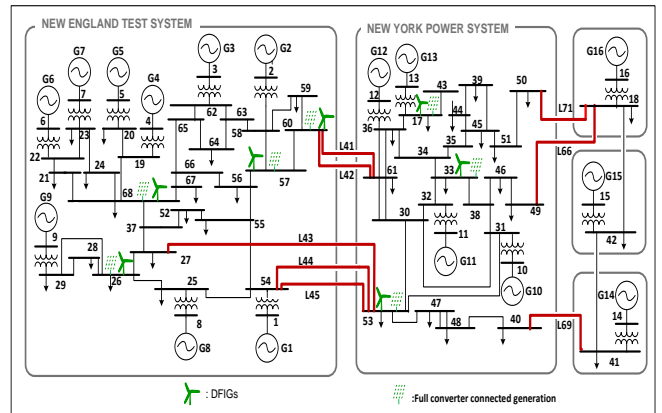


Figure 1. The modified NETS-NYPS test system

TABLE I LOADING SCENARIOS OF THE POWER SYSTEM NETWORK

| Loading Scenarios | System Loading | Proportion of Renewables |
|-------------------|----------------|--------------------------|
| Peak Load         | 100%           | 30%                      |
| High Load         | 75%            | 30%                      |
| Low Load          | 40%            | 30%                      |

TABLE II PROBABILISTIC MODEL PARAMETERS OF UNCERTAIN INPUT VARIABLES

| Level of Uncertainty | Load Demand ( <i>Normal</i> ) | Wind Speed ( <i>Weibull</i> ) | Solar Radiation ( <i>Beta</i> ) |
|----------------------|-------------------------------|-------------------------------|---------------------------------|
| High                 | $3\sigma=10\%$ of $\mu$       | $\alpha=2.2, \beta=11.1$      | $a=13.7, b=1.3$                 |

TABLE III CASE STUDIES AND UNCERTAINTIES CONSIDERED

| Case Study          | 1                          | 2        | 3        |
|---------------------|----------------------------|----------|----------|
| Operating condition | Loading level = 1 p.u.     |          |          |
| Loading Factor      | Variable                   | Constant |          |
| Wind Speed          | Constant                   | Variable | Constant |
| Solar Irradiation   | Constant                   |          | Variable |
| Load Model          | Constant<br>Power          |          |          |
| Case Study          | 4                          | 5        | 6        |
| Operating condition | Loading level = 0.568 p.u. |          |          |
| Loading Factor      | Variable                   | Constant |          |
| Wind Speed          | Constant                   | Variable | Constant |
| Solar Irradiation   | Constant                   |          | Variable |
| Load Model          | Constant<br>Power          |          |          |
| Case Study          | 7                          | 8        | 9        |
| Operating condition | Loading level = 0.568 p.u. |          |          |
| Loading Factor      | Variable                   | Constant |          |
| Wind Speed          | Constant                   | Variable | Constant |
| Solar Irradiation   | Constant                   |          | Variable |
| Load Model          | Constant<br>Impedance      |          |          |

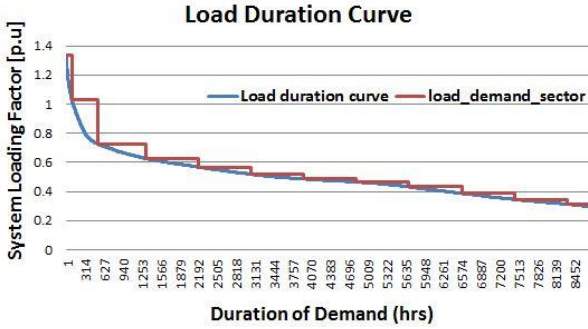


Figure 2. Annual loading curve

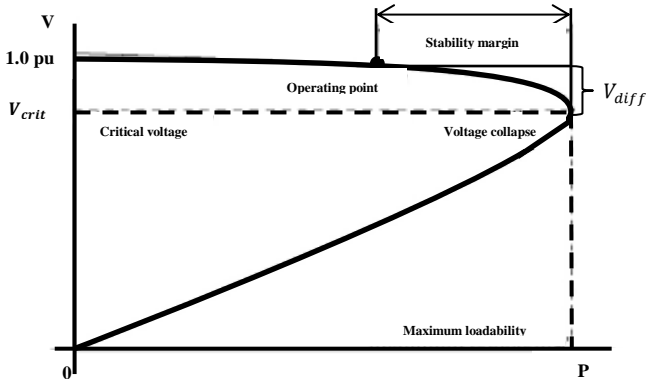


Figure 3. Typical P-V curve for voltage stability analysis [24]

### III. METHODOLOGY

The proposed methodology in this paper can be set out in the following steps:

- Ranking of the load buses based on their loadability against one uncertain parameter at one time.
- Selecting three weak and three strong buses from the ranking above, and checking that the ranking remains the same under various conditions. The effect of uncertain parameters on voltage stability can then be observed by investigating the distributions of nose points.
- Changing load models to see their influence on system voltage stability.

It should be noticed the parameter 'loadability' in this paper referred to the average voltage difference of a load bus between the nose point and initial operating point.

#### A. Case Studies

In reality, the loading demand for a power system is not constant. This can lead to a variation in system operation points. To ensure the study cases cover most of the system operation conditions, the annual loading curve of NETS-NYPS is introduced as shown in Fig. 2. The test system is able to withstand a maximum loading demand of 1.339p.u (base case), operating beyond that limit would result in OPF calculation not converged (system rated operation point is treated as 1p.u, 17.26GW). Two points on the curve, rated system operation point (second sector) and minimum system demand (fifth sector, without generator disconnection), are selected based on TABLE I with system loading factors 1p.u and 0.568p.u, respectively.

The study cases are then decided as shown in TABLE III.

#### B. Ranking of load buses

For each of the case studies stated above, the loading of all the system load buses are increased simultaneously until one bus collapses 1000 times. The average values of the voltage difference between  $V_{initial}$  and  $V_{nose}$  for each system load buses can then be obtained ( $V_{diff} = V_{initial} - V_{nose}$ ). The load bus with the largest or smallest  $V_{diff}$  is considered as the weakest or strongest bus, respectively. A typical P-V curve for voltage stability analysis is shown as Fig 3 [24].

The step size for system load increases is set to be adaptive. It will decrease before reaching the voltage stability limit. The initial step size is set at 0.5%, the maximum step size is set at 5% while the minimum step size is 0.01%. The Monte-Carlo simulation is repeated 1000 times within each study case to ensure 99% confidence that the difference between the true and sampled mean values is less than 1% of the true mean value, according to equation (5) [25].

$$\varepsilon_{\bar{x}_N} = \frac{\Phi^{-1}\left(1 - \frac{\delta}{2}\right) \sqrt{\frac{\sigma^2(X_N)}{N}}}{\bar{x}_N} \quad (5)$$

where  $\Phi^{-1}$  represents the inverse Gaussian conditional probability distribution with a mean of zero and standard

deviation of one;  $\sigma^2$  is the variance of a sample,  $\delta$  refers to the desired confidence level, and  $X_N$  represents a sample of measured outputs containing N samples.

### C. Distribution of nose points

With the identification of critical and stiff buses in different case studies, the data of total system load and voltage at collapse points can be obtained and considered as nose-points. The nose points for 1000 Monte-Carlo simulations can then be plotted into one scatter plot to see the effect of different uncertain parameters on system voltage stability. The probabilistic distribution functions of the voltage and active power of the scatter plot can also be obtained.

### D. Change of Load models

The effect of load models on system voltage stability behaviour can be investigated by employing different load models. This study uses constant power and constant impedance load models. The comparisons are set between study cases 4, 5, and 6 and study cases 7, 8, and 9.

## IV. ILLUSTRATIVE RESULTS AND DISCUSSION

In this paper, all simulations are performed on a PC with Intel(R) Core™ i7-4770 CPU @3.40GHz and 16.0 GB of RAM. The Monte-Carlo Probabilistic Simulation is done with MATLAB R2015a and the Optimal Power Flow (OPF) for different study cases are exported into text files. These files are then imported to DIGSILENT POWERFACTORY 15.2 software package as the initial conditions to perform P-V curve calculations. The calculation results are exported to MATLAB to find nose point distributions and these are investigated further.

### A. Finding Critical/Stiff Buses

TABLE IV below indicates the critical and stiff buses found for nine study cases.

TABLE IV CRITICAL AND STIFF BUSES

| Case Study   | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  |
|--------------|----|----|----|----|----|----|----|----|----|
| Critical Bus | 46 | 46 | 46 | 48 | 48 | 48 | 48 | 48 | 40 |
|              | 47 | 47 | 47 | 47 | 40 | 40 | 40 | 40 | 48 |
|              | 48 | 48 | 48 | 40 | 47 | 47 | 47 | 47 | 47 |
| Stiff Bus    | 21 | 21 | 21 | 24 | 24 | 24 | 24 | 24 | 24 |
|              | 28 | 28 | 28 | 21 | 21 | 21 | 21 | 21 | 21 |
|              | 50 | 50 | 50 | 28 | 28 | 28 | 28 | 28 | 28 |

From TABLE IV it can be observed that the group of the most-probable critical buses and the most-probable stiff buses remains almost the same under various conditions. The values of  $V_{diff}$  among the identified buses within their related groups are quite small. The fact that the buses remain unchanged is favourable for the following analysis, i.e. B and C Sections. Since the buses in TABLE IV have been identified as critical, they can now be located in Fig. 1. This indicates that the buses in NYPS area of the network are more susceptible to voltage collapse compared to buses in other parts of the system.

### B. Nose Points Distribution

In this part of the study, the critical buses from the previous section are investigated. As shown in Fig 4, 5 and 6, the nose areas for the most-probable critical buses related to different uncertainties are plotted.

From Fig 4 it can be observed that the clusters of nose points present different behaviour in terms of intensity. Since the nose points are obtained when the system stability limit is reached, a wider spread nose-area represents a larger variance in the voltage stability margin. In other words, the uncertain parameter with a wider spread nose-area can have a greater effect on system voltage stability. Therefore, it can be said that among the three uncertain parameters considered in this study, when the system operation point is at a higher value (1p.u, 75% of system peak loading), the uncertainty in the variance of loading factor is the most critical one, followed by uncertainty caused by wind speed and solar irradiation. However, the influence of wind speed on system voltage stability can increase rapidly and overtake the loading factor as the most important parameter when the system is operating at a lower demand (0.568p.u, 40% of system peak loading), as can be seen by comparing Fig. 4 and Fig. 5.

Another interesting finding from Fig 4, Fig 5 and Fig 6 is the similarity of nose-point areas in shape between the most critical uncertain parameter and the combination of all uncertain parameters.

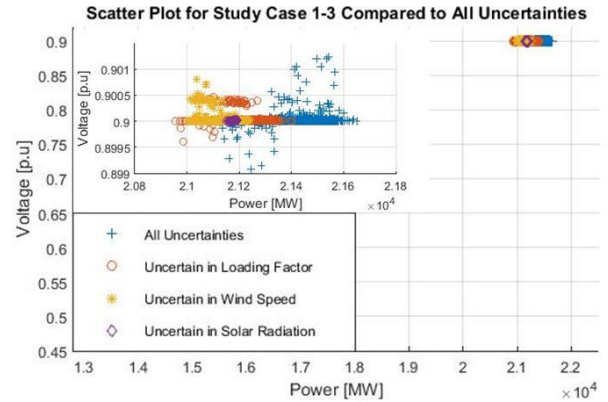


Figure 4. Scatter Plot for Study Cases 1-3

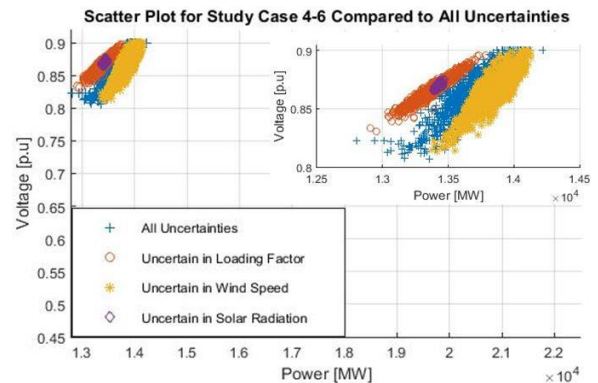


Figure 5. Scatter Plot for Study Cases 4-6

### C. Changing of Load Models

By investigating Fig. 5 and Fig. 6, it can be seen that the constant impedance load model can cause the system to collapse at a much higher Total Power and at a much lower voltage compared to the constant power load model, which represents a better performance in terms of power system voltage stability. In the wider context of uncertainties considered, it has been found though that load models have no influence on the ranking of uncertain parameters, nor on the ranking of critical buses.

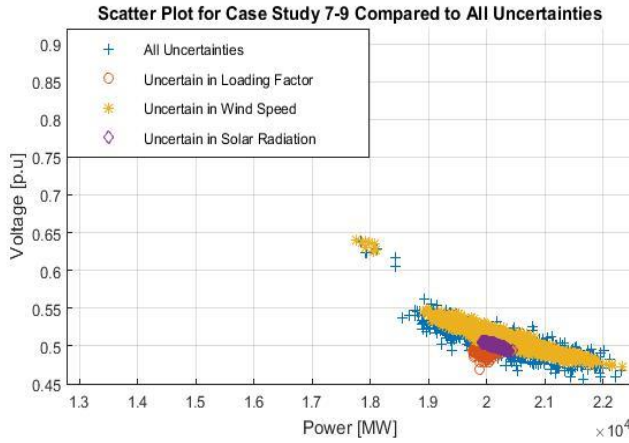


Figure 6. Scatter Plot for Study Cases 7-9

TABLE V QUANTITATIVE ANALYSIS RESULTS

| PDF parameters |   | $\mu_P [GW]$ | $\sigma_P [GW]$ | $\mu_V [p.u.]$ | $\sigma_V [p.u.]$ |
|----------------|---|--------------|-----------------|----------------|-------------------|
| Study Cases    | 1 | 21.20        | 0.07            | 0.90           | 0.00              |
|                | 2 | 21.12        | 0.05            | 0.90           | 0.00              |
|                | 3 | 21.17        | 0.01            | 0.90           | 0.00              |
|                | 4 | 13.39        | 0.13            | 0.87           | 0.01              |
|                | 5 | 13.85        | 0.14            | 0.87           | 0.02              |
|                | 6 | 13.42        | 0.01            | 0.87           | 0.00              |
|                | 7 | 20.04        | 0.11            | 0.50           | 0.01              |
|                | 8 | 20.30        | 0.70            | 0.51           | 0.02              |
|                | 9 | 20.08        | 0.09            | 0.50           | 0.00              |

### D. Quantitative Analysis

The quantitative analysis results for the above shown case studies can be produced by generating probabilistic density functions (PDFs) based on nose-point distributions. Normal Distribution PDFs have been applied to nine case studies on two dimensions, Voltage and Power. The obtained PDF parameters are listed in TABLE V. Parameters  $\mu_P [GW]$  and  $\mu_V [p.u.]$  represent the most-probable collapse Power and Voltage, respectively. Parameters  $\sigma_P [GW]$  and  $\sigma_V [p.u.]$  represent the discrete degree of the PDFs on Power and Voltage axis, respectively. The ranking of critical uncertain parameters can be easily concluded from TABLE V by comparing the values of  $\sigma_P [MW]$  and  $\sigma_V [p.u.]$ , and the

results are proved to be the same compared to the previous two sections.

## V. CONCLUSIONS

This paper provides a probabilistic method for the ranking of uncertain system parameters on power system voltage stability. The uncertain parameters of loading factors, wind power generation and solar power generation are introduced in the test system in order to simulate the stochastic behaviour of a future power system. Constant power and constant impedance load models are connected to the test system to investigate the effect of load models on power system voltage stability. Nine study cases with different implementations of uncertain parameters as shown in Table III are discussed in this study. The critical loads in the testing system are first identified considering different operating conditions. The group of load buses 40, 46, 47, 48, all in NYPS area of the system, is identified as the most-probable critical buses in the test system irrespective of which uncertainty parameters and load models are used. System operators should invest more in monitoring equipment around the identified critical buses since they appear to collapse before the others under most of the conditions.

The ranking of uncertain parameters on power system voltage stability is investigated following the identification of critical buses. It was found that the rank of importance of considered uncertainties is loading factor > wind speed > solar irradiation when the system is operating under a higher loading level. At a lower system loading, however, the uncertainty in wind speed becomes the most critical uncertain parameter affecting system voltage stability. It is also noticed that at lower loading the system voltage stability becomes more affected in general by system uncertainties (of any type). Finally, as expected, the study also indicated that the load models can have significant effect on the behaviour of the system voltage collapse point. Constant impedance load models have proved to be a better choice compared to constant power load models since they can cause the system to be less prone to voltage collapse. And by comparing the standard deviations of Total load and Voltage between Study Cases 4, 5 and 6 and 7, 8 and 9, it appears that system voltage stability is more sensitive to the uncertain parameters when constant impedance load models are used. Therefore, it is critical for the system managers to accurately apply load models in voltage stability studies.

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