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Priority Ranking of Critical Uncertainties Affecting Small-Disturbance Stability Using Sensitivity Analysis Techniques

Kazi N. Hasan, *Member, IEEE*, Robin Preece, *Member, IEEE* and Jovica V. Milanović, *Fellow, IEEE*

Abstract—This paper critically evaluates a number of sensitivity analysis (SA) techniques to identify the most influential parameters affecting power system small-disturbance stability. Sensitivity analysis of uncertain parameters has attracted increased attention with the adoption of deregulated market structure, intermittent energy resources and new types of loads. Identification of the most influential parameters affecting system stability using SA techniques will facilitate better operation and control with reduced monitoring (only of the parameters of interest) by system operators and stakeholders. In total, nine SA techniques have been described, implemented and compared in this paper. These can be categorised into three different types: local, screening, and global SA. This comparative analysis highlights their computational complexity and simulation time. The methods have been illustrated using a two-area power system and 68 bus NETS-NYPS test system. The priority ranking of all uncertain parameters has been evaluated, identifying the most critical parameters with respect to the small-signal stability of the test systems. It is shown that for many applications, the Morris screening approach is most suitable, providing a good balance between accuracy and efficiency.

Index Terms — Computational efficiency, probability distribution, sensitivity analysis, small-disturbance stability, uncertainty.

NOMENCLATURE

d_m^+	Distances between each alternative and the ideal solutions.
d_m^-	Distances between each alternative and the non-ideal solutions.
EE_p^i	Elementary effect.
Δ	Magnitude of each step in Morris trajectory.
μ^*	Mean of the elementary effects .
σ^*	Standard deviation of the elementary effects.
n	Uncertainty samples in MADM, FAST and Borgonovo method.

N	Number of Monte Carlo simulation.
p	Number of uncertain (input) parameters.
r	Number of levels in Morris trajectory.
r_p	Output ranking coefficient in MADM.
r_{np}	Elements of normalized decision matrix in MADM.
S_i	Index of Sobol 1 st order effect.
O_i	Impact of relative variation of output (\mathbf{Y}) due to a change in \mathbf{X}_i by a fixed fraction of \mathbf{X}_i 's central value.
ST_i	Index of Sobol total effect.
v_{\max}	Ideal solutions in MADM.
v_{\min}	Non-ideal solutions in MADM.
w_n	Weight obtained from the pdf of each uncertain parameter in MADM.
\mathbf{X}_i	i^{th} input parameter.
\mathbf{Y}_i	i^{th} output parameter.
$\bar{\mathbf{X}}$	Mean value of input parameter samples.
$\bar{\mathbf{Y}}$	Mean value of output parameter samples.
\mathbf{X}_{pm}	MADM decision matrix elements with p parameters and n uncertainty samples.
\mathbf{X}	All input parameter set.
\mathbf{Y}	All output parameter set.
ρ_{XY}	Index of Pearson correlation coefficient.
$\rho_{X_r Y_r}$	Index of Spearman's correlation coefficient.
$\rho_{XY.Z}$	Index of Partial correlation coefficient.

I. INTRODUCTION

POWER system parameters inherently exhibit spatio-temporal variability, which leads to ignorance of their true values and inaccuracies in their estimation. The number of uncertain parameters in power system planning and operation is increasing due to the deregulated market structure, intermittent energy resources and new types of loads. A conventional deterministic analysis methodology neglects these uncertain parameters and does not provide an accurate assessment of the status and capability of a power network, which may lead to overly conservative and non-optimal techno-economic solutions [1].

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A probabilistic approach, conversely, considers uncertain parameters present in the system and can more accurately predict the system behaviour as affected by possible changes in uncertain parameters. The terms ‘parameters’ and ‘variables’ will be used in the paper interchangeably. As the number of system parameters increases with the size of the network and due to the proliferation of new technologies and operational structure, it is computationally intensive and inefficient to address all uncertain parameters present in a realistic system. Moreover, it may not be necessary to model all uncertain parameters as some may have very little or no impact on the system phenomenon of interest [2]. Hence, identification of the most influential parameters of the system will facilitate better operation and control with less monitoring (only of the parameters of interest) by system operators and stakeholders.

Global sensitivity analysis (SA) techniques can numerically identify the most influential parameters from large sets of uncertain system inputs. Global SA can determine the contribution of one input (or a set of inputs) to the change in a specific output (or a set of outputs). Consequently, it enables the analysis of the impact of input variables on the variation of a system output. SA is beneficial for identifying the most influential inputs, determining the non-influential inputs, mapping output variability with respect to specific input variability, and calibrating inputs by observing the consequent changes in outputs [3]. There has been limited application of global SA within power systems research, however a number of applications have been demonstrated in several areas such as flood prediction [3], urban water supply [4], hydrological modelling [5], crop yield [6], cancer models [7], aircraft infrared signature [8], and geolocation systems [9].

The applications of SA techniques in power systems research have been reported in generator ranking [10], load classification [11], voltage stability assessment [12-14], transient response prediction [15], PSS design [16], and frequency support from storage devices [2]. Early applications of sensitivity analysis to power system area consider linear [12, 13, 16], quadratic [14], and trajectory measures [15], which are incapable of assessing the impact of uncertainties across the full range of possible uncertain space [2]. Several global sensitivity analysis methods have been discussed and implemented in [2] to assess the uncertainty importance measures of system frequency excursion and its mitigation by storage devices. However, highly efficient screening methods of sensitivity analysis have not previously been considered for power systems applications, nor have global SA approaches been used to analyse small-disturbance stability.

A recent work [17] by the authors presented the applicability of the Morris screening method in identifying important parameters with varying levels of uncertainty at different system operating conditions. This paper presents a significant extension of [17] and compares the performance of a wide range of SA techniques applied to multiple test systems. It describes and implements the local and global SA methods presented in [2] in addition to the computationally efficient Morris screening method [3, 4, 18] and a multi-attribute decision making (MADM) approach [19-22]. These

methods are all compared with respect to their analysis of the most important parameters affecting the small-disturbance stability of multiple power systems. The main contributions of the paper are:

- Nine widely used numerical sensitivity analysis techniques with significantly different computational procedures and complexity are described, compared and their advantages and disadvantages discussed with respect to their suitability for the identification of the most important parameters affecting the small-disturbance stability of power systems.
- The most suitable techniques are determined and recommended for the identification of the parameters on which modelling efforts should be focused in order to improve the accuracy of small disturbance stability studies of uncertain power system and consequently the overall operation of the power system.

The results are illustrated using a two-area test network with 35 uncertain parameters and a 68-bus NETS-NYPS test system with 49 uncertain parameters. The application of a wide variety of SA techniques in multiple test systems demonstrates the wide ranging potential for further application in other areas of power system analysis.

II. SENSITIVITY ANALYSIS TECHNIQUES

Sensitivity analysis determines how the input variable uncertainty propagates through the process to the output [4]. SA methods can be classified as: (i) local, (ii) screening and (iii) global, where the computational cost and complexity increases from (i) to (iii) [18]. When the impact of a small-perturbation in input is studied on the system output, this is known as local sensitivity analysis. It determines a normalized linear relationship between variables in the local region around the nominal operating point. Screening techniques, on the other hand, change one input at a time in a multidimensional space to evaluate the input-output relationship. A global sensitivity analysis considers the whole range of variation of inputs on the system output.

A. Local Method – One-at-a-Time (OAT)

Local SA methods determine the impact of individual input parameters on the model output, by directly calculating the partial derivatives of the output with respect to input. One such local SA approach is one-at-a-time (OAT) [5, 18].

In the OAT design, one factor is varied over a small interval around its nominal value. This nominal value correspond to a specific point in the input space. Hence, the results are dependent on the choice of the input space. The sensitivity measure (as a relative variation of \mathbf{Y} due to a change of \mathbf{X}_i by a fixed fraction of \mathbf{X}_i 's central value) can be expressed as,

$$O_i = (\mathbf{X}_i / \mathbf{Y}) \cdot (\partial \mathbf{Y} / \partial \mathbf{X}_i). \quad (1)$$

This approach is easy to implement and requires relatively low computational cost (i.e. $p+1$ simulation for p uncertain parameters). The performance of this method can be insufficient when the model is nonlinear and the system output is affected by combinations of uncertainties [2, 18].

B. Screening Method – Morris Method

When a system has a large number of input parameters and it is computationally expensive to evaluate the model, a screening method can be used to identify the most influential parameters. The Morris method is such a screening method.

The Morris screening method creates a multidimensional *semi-global* trajectory within its search space and can efficiently identify the most influential parameters [3, 5, 18]. A prominent feature of Morris method is its low computational cost. It requires $p \cdot r + 1$ simulations. Here, r is the number of levels in Morris trajectory generation and typical value of r is between 4 to 10 [3, 18]. A significantly reduced computational burden with respect to full global SA approaches (which will be discussed in II.C) makes it efficient and feasible for application in realistic power networks with many uncertain parameters.

The Morris method changes one variable at a time by a magnitude of Δ . The standardized (or *elementary*) effect of a Δ change is defined as (2).

$$EE_p^i(\mathbf{X}) = [\mathbf{Y}(X_1, X_2, \dots, X_{i-1}, X_i + \Delta, X_{i+1}, \dots, X_p) - \mathbf{Y}(\mathbf{X})] / \Delta \quad (2)$$

The Morris method proposes two importance measures, which are mean (μ^*) and standard deviation (σ^*) of the *elementary effects* of each input variable, (3) and (4).

$$\mu_p^* = 1/r \cdot \sum_{i=1}^r |EE_p^i| \quad (3)$$

$$\sigma_p^* = \sqrt{1/r \cdot \sum_{i=1}^r (|EE_p^i| - \mu_p^*)^2} \quad (4)$$

In (3), μ_p^* expresses the sensitivity strength between the p^{th} input variable and the output. A high value of μ_p^* demonstrates a high contribution of the input variability to the output variability. On the other hand, an input variable having large σ_p^* has a non-linear effect on the output and it has high interaction with other variables [3, 4].

C. Global Methods

Global sensitivity methods evaluate the importance of parameters across the full range of possible input values. Global SA methods can be subdivided further into: (i) those which generate samples equidistantly across the input space such as MADM, (ii) those which are non-parametric such as correlation coefficients, (iii) those which analyse the influence on output variance such as Sobol indices or the FAST (Fourier Amplitude Sensitivity Testing) method, and (iv) those which analyse output probability distributions such as the Borgonovo method. These methods are typically complex in nature and computationally expensive [5, 18].

1) Multi-Attribute Decision Making (MADM)

The multi-attribute decision making (MADM) algorithms are priority ranking methods including Analytic Network Process (ANP), Decision EXpert (DEX), ELECTRE, Goal Programming (GP), New Approach to Appraisal (NATA), Superiority and Inferiority Ranking (SIR) method, Value Analysis (VA), and Weighted Sum Model (WSM), etc. [23-25]. The version of MADM considered in this study is based

on the TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) method because of its efficiency and simple implementation [19-22]. A decision matrix can be built considering p parameters and n uncertainty samples as in (5).

$$\begin{bmatrix} X_{11} & \dots & \dots & X_{p1} \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ X_{1n} & \dots & \dots & X_{pn} \end{bmatrix} \quad (5)$$

In (5), X_{pn} are decision matrix elements. Each column of the matrix represents different uncertain parameters and each row represents the same parameter at different uncertain values.

The decision matrix normalization, weighting and ideal, non-ideal solutions is obtained by using (6)-(8).

$$r_{np} = X_{np} / \sqrt{\sum_1^n X_{np}^2} \quad (6)$$

$$v_{np} = w_p \times r_{np} \quad (7)$$

$$v_{\max} = \left(\max v_{np} \mid n \in n^+, \min v_{np} \mid n \in n^- \right) \quad (8)$$

$$v_{\min} = \left(\min v_{np} \mid n \in n^+, \max v_{np} \mid n \in n^- \right)$$

Distances between the outputs related to various uncertainties of ideal and non-ideal solutions have been calculated using (9).

$$d_p^+ = \sqrt{\sum_1^n (v_{np} - v_{\max})^2}, \quad \text{and} \quad d_p^- = \sqrt{\sum_1^n (v_{np} - v_{\min})^2} \quad (9)$$

Finally, the MADM output ranking coefficient r_p is determined as (10).

$$r_p = d_p^- / (d_p^+ + d_p^-) \quad (10)$$

2) Pearson Correlation Coefficient

Pearson correlation coefficient is a quantitative measure that determines the linear dependency between the output and the inputs. The inputs (\mathbf{X}) can be ranked according to their influence on the system output (\mathbf{Y}). This method is the most commonly used in science and engineering [2]. The Pearson correlation coefficient is calculated by (11) [3].

$$\rho_{XY} = \frac{N}{\sum_{i=1}^N [(X_i - \bar{X})(Y_i - \bar{Y})]} / \sqrt{\sum_{i=1}^N (X_i - \bar{X})^2 \cdot \sum_{i=1}^N (Y_i - \bar{Y})^2} \quad (11)$$

In (11), the numerator term expresses the covariance between variables, and the denominator shows the standard deviation of the parameters, where,

$$\bar{X} = \frac{N}{\sum_{i=1}^N (X_i/N)}, \quad \bar{Y} = \frac{N}{\sum_{i=1}^N (Y_i/N)} \quad (12)$$

3) Spearman Rank Correlation Coefficient

Spearman's correlation coefficient is the Pearson correlation coefficient among ranked variables. This number varies between -1 and +1 [26].

Spearman's correlation coefficient requires calculating the sum of the squares of the differences of the ranks using (13).

$$\rho = 1 - \left(6 \sum d_i^2 / N(N^2 - 1) \right) \quad (13)$$

where N is the sample size, and $d_i = X_i - Y_i$. If tied ranks exists, (14) is used.

$$\rho_{\mathbf{X}_i \mathbf{Y}_i} = \frac{\sum_i (\mathbf{X}_i - \bar{\mathbf{X}})(\mathbf{Y}_i - \bar{\mathbf{Y}})}{\sqrt{\sum_i (\mathbf{X}_i - \bar{\mathbf{X}})^2 \sum_i (\mathbf{Y}_i - \bar{\mathbf{Y}})^2}} \quad (14)$$

4) Partial Correlation Coefficient

Partial correlation coefficient measures the degree of association between output variable \mathbf{Y} and input variable \mathbf{X}_j when the effects of the other inputs have been canceled.

$$\rho_{\mathbf{X}_j \mathbf{Y}} = \rho(\mathbf{X}_j - \hat{\mathbf{X}}_{-j}, \mathbf{Y} - \hat{\mathbf{Y}}_{-j}) \quad (15)$$

Where $\hat{\mathbf{X}}_{-j}$ is the prediction of the linear model, expressing \mathbf{X}_j with respect to other inputs, and $\hat{\mathbf{Y}}_{-j}$ is the prediction of the linear model where \mathbf{X}_j is absent [3]. Partial correlation is based on the assumption of linear relationship.

5) Sobol Total Indices

Sobol method is a variance-based method, which is very useful in case of non-linear and non-monotonic models. Sobol total indices are the sum of all the sensitivity indices involving all uncertain factors [2, 3, 18].

$$S_T = S_i + \sum_{i < j} S_{ij} + \sum_{i \neq j, i \neq k, j < k} S_{ijk} + \dots \quad (16)$$

$$S_i = D_i(\mathbf{Y}) / \text{Var}(\mathbf{Y}) \quad (17)$$

$$S_{ij} = D_{ij}(\mathbf{Y}) / \text{Var}(\mathbf{Y}) \quad (18)$$

$$D_i(\mathbf{Y}) = \text{Var}[E(\mathbf{Y} | \mathbf{X}_i)] \quad (19)$$

$$D_{ij}(\mathbf{Y}) = \text{Var}[E(\mathbf{Y} | \mathbf{X}_i, \mathbf{X}_j)] - D_i(\mathbf{Y}) - D_j(\mathbf{Y}) \quad (20)$$

Where, S_i is the 1st-order sensitivity index for i , S_{ij} is the 2nd-order sensitivity index describing the interactions between two uncertainties i and j ($i \neq j$). S_{ijk} is the 3rd-order sensitivity index for three uncertainties, i, j, k ($i \neq j \neq k$). These interactions will continue up to p^{th} order for p parameters.

S_i is the Sobol 1st order effect which is determined by obtaining the correlation coefficient of the output vector from two model runs in which all values for variables in \mathbf{X}_i are common, but all other inputs use independent samples.

In determining the Sobol total indices, input data set \mathbf{X} is partitioned into \mathbf{X}_{-i} and \mathbf{X}_i , where \mathbf{X}_{-i} is the set of all input variables which include a variation in the i^{th} index of \mathbf{X} . The total effect is then calculated by (21).

$$ST_i = 1 - S_{-i} \quad (21)$$

where, S_{-i} is the sum of the all terms that include the variation in \mathbf{X}_i . The Sobol method has been efficiently implemented in environmental and hydrological models [3, 5].

6) Fourier Amplitude Sensitivity Testing (FAST)

The FAST method associates input parameter variation with a specific frequency in the Fourier transform space of the system. This variation is then quantified using the statistical variance as presented in (22) [27].

$$s^2 = \frac{n}{n-1} \sum_{i=1}^n (\mathbf{Y}_i - \bar{\mathbf{Y}})^2 / (n-1) \quad (22)$$

where n is the sample size, \mathbf{Y}_i is the i^{th} output and $\bar{\mathbf{Y}}$ is the output mean. The output variances are then separated according to their coherence with the input parameter frequency. The variation of output at a given frequency provides a measure of sensitivity index of that input

parameter. In this way, the multidimensional problem is transformed to just a single dimension [2].

The sampling procedure in FAST defines a sinusoidal function of a particular frequency for each input variable that assigns a value to the search space based on the sample number 1 to the n samples. Applications for systems with large numbers of uncertainties can become computationally intensive due to the determination of a set of p integer frequencies (used during the Fourier transformation). The number of simulations N required within the study is dependent on the maximum frequency of parameter variation used which increases quickly and non-linearly with p [28].

7) Borgonovo Method

The Borgonovo method evaluates the influence of the entire input distribution on the entire output distribution without reference to a particular moment of the output [29]. In the Borgonovo method, \mathbf{X}_i is kept fixed at a given value x_i^* and the remaining inputs \mathbf{X}_{-i} are varied in order to produce a new distribution for the observed output ($\mathbf{Y} | \mathbf{X}_i = x_i^*$). Here, $s(\mathbf{X}_i)$ is defined as (23), and the importance index δ is defined as (24). In (24) the expectation of $s(\mathbf{X}_i)$ is determined by integrating across the full range of X_i , taking into account its distribution, as in (25) [29, 30].

$$s(\mathbf{X}_i) = \int |f_{\mathbf{Y}}(y) - f_{\mathbf{Y} | \mathbf{X}_i = x_i^*}(y)| dy \quad (23)$$

$$\delta = 1/2 E[s(\mathbf{X}_i)] \quad (24)$$

$$E[s(\mathbf{X}_i)] = \int f_{\mathbf{X}_i}(x_i) \left[\int |f_{\mathbf{Y}}(y) - f_{\mathbf{Y} | \mathbf{X}_i = x_i^*}(y)| dy \right] dx_i \quad (25)$$

In (25), $s(\mathbf{X}_i)$ provides an indication of the impact of input on the output. In (23), if \mathbf{Y} is independent of \mathbf{X}_i , then $f_{\mathbf{Y}}(y) = f_{\mathbf{Y} | \mathbf{X}_i = x_i^*}(y)$ and $s(\mathbf{X}_i) = 0$ and $\delta = 0$. Thus δ can take any value between 0 and 1. The Borgonovo method requires a Monte Carlo-based integration across the range of \mathbf{X}_i , using N studies for this *outer integration* loop. The total computational cost is therefore much higher for this index than the others discussed above. This is the price to be paid for a sensitivity measure which accounts for the whole distribution and not just a moment of the distribution and requires $p n N$ simulations to determine δ indices for p parameters.

D. Summary on Sensitivity Analysis Techniques

Fig. 1 presents a graphical representation of working principle of the different SA techniques discussed in two dimensions. OAT changes one factor at a time over a small interval around its nominal value. The Morris method creates a multidimensional trajectory through the search space. MADM generates equidistant samples across the range of each parameter. Correlation coefficients handle thousands of random generated samples within the search space. Sobol samples are generated in a symmetrical geometric orientation. The FAST method translates the analysis into the frequency spectrum. The Borgonovo method integrates the whole space while fixing different parameters at given values.

Selection of an SA technique depends on the characteristics of the model (particularly the number of uncertain parameters) and computational cost [18]. Fig. 2 presents a graphical synthesis adopted from [3] of the total nine SA techniques

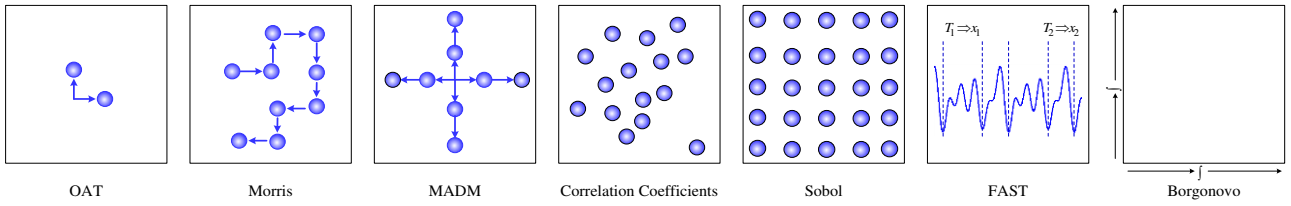


Fig. 1. Graphical representations of the sample generation technique of SA methods.

discussed in this paper, with their relative computational complexity and number of simulations required. SA techniques can be clearly distinguished among local, screening and global with respect to their computational cost. Local method requires very low computational effort. The screening method has medium complexity and relatively low computational cost. Global methods, on the other hand, are generally computationally demanding but also capable of identifying more complex input-output relationships.

There are other sensitivity analysis techniques which have not been considered in this study, e.g., Bettonvil's sequential bifurcation, Green function method, first-order or second-order reliability method (FORM or SORM), Bayesian sensitivity analysis, Taguchi method and High-Dimensional Model Representation (HDMR) [3, 5, 6, 8, 9, 18, 31, 32]. These methods vary widely in implementation complexity and computational cost and remain an ongoing area of research with respect to their suitability for application in small disturbance stability studies.

III. TEST NETWORK AND SYSTEM UNCERTAINTIES

All sensitivity analysis techniques discussed have been illustrated through the simulation of two separate test systems: the two-area test system, and NETS-NYPS test system.

In total 35 and 49 parameters are considered for two-area and NETS-NYPS test system, respectively. Correlation among input parameters has not been modelled in this study.

A. Two-Area Test System

In total, nine sensitivity methods described have been evaluated using the well-established Kundur two-area network [33]. The network, shown in Fig. 3, consists of two areas with four generators and two loads. This system has one poorly damped inter-area oscillatory mode, the damping (real part) of which is selected as the system output of interest.

A variety of system uncertainties are considered in order to thoroughly test the described methods. These have been classified into the following groups:

1) Operating Uncertainty

The electrical power output of all generators (excluding the slack G1) and real and reactive power demand at both loads are considered as uncertain. Seven operating uncertainties are $\{P_{G2-G4}, P_{L7}, Q_{L7}, P_{L9}, Q_{L9}\}$.

2) AVR Setting Uncertainty

Each generator in Fig. 3 is equipped with a fast static exciter, whose parameters [18] (gain K_A and time constant

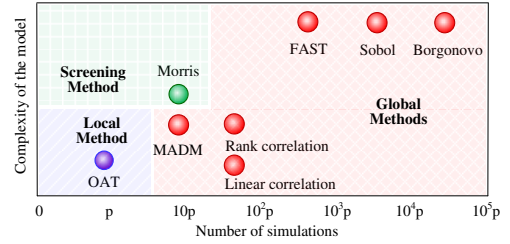


Fig. 2. Relative computational effort and complexity of the SA techniques.

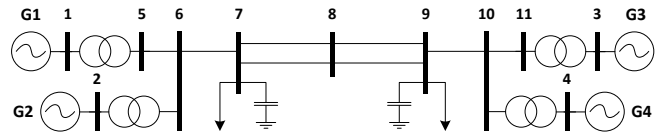


Fig. 3. Two-area test network.

T_A shown in Fig. 4(a)) are considered as uncertain. Eight uncertainties in the AVR settings are $\{K_A^{G1-G4}, T_A^{G1-G4}\}$.

3) PSS Setting Uncertainty

Each generator is controlled using an additional Power System Stabilizer (PSS) to help damp persistent oscillations with the structure shown in Fig. 4(b) [18]. There are a total of 20 uncertainties in the PSS settings, which are $\{K_p^{G1-G4}, T_1^{G1-G4}, T_2^{G1-G4}, T_3^{G1-G4}, T_4^{G1-G4}\}$.

4) Uncertainty Distributions

A total of 35 uncertainties are considered in the two-area system. Probability distributions and probabilistic model parameters of three sets of uncertain input variables are presented in Table I. The operational uncertainties (generation and load) are modelled as normally distributed with nominal mean and standard deviation such that $3\sigma = v$ where v is the *level of uncertainty* (as a percentage of the nominal value). A uniform distribution is selected to represent the uncertainty of the controller parameters K_A, T_A, K_p , and $T_{1..4}$ around the nominal given values, and range of $\pm v$ where v is the *level of uncertainty* (again, as a percentage of the nominal value).

All simulations including load flow and eigenvalue analysis are performed using MATLAB/Simulink.

B. NETS-NYPS Test System

The second test system is a modified version of the NETS-NYPS system (New England Test System – New York Power System) which has five areas, 16 machines and 68 buses, as shown in Fig. 5. Data and more information of the test network are available in [34, 35].

A high amount of distributed energy resources (DER) has been added to the network so that the impact of intermittent resource variability on the small-disturbance stability can be analysed. Renewable wind and solar generators are placed in seven buses of the network, namely bus 17, 26, 33, 53, 57, 60, and 68. Based on the uncertain random sampling of DERs, renewable generation can contribute towards a maximum of 30% of system load.

1) System Uncertainties

The probabilistic system variables considered with the second test system are load demand, wind speed, and solar power, which follow normal, Weibull, and beta distributions.

In total, 49 uncertain parameters (35 loads, 7 wind farms and 7 solar farms) have been modelled probabilistically. The 35 uncertain loads presented in the NETS-NYPS test system are $L_{1,3,4,7,9,12,15-18,20,21,23-29,33,36,39-42,44-52}$, where subscripts are bus numbers in NETS-NTPS system. The 7 wind and solar farms are $W_{17,26,33,53,57,60,68}$ and $S_{17,26,33,53,57,60,68}$, respectively.

Table II shows the probability distributions and probabilistic model parameters of three categories of uncertain input variables. The normal, Weibull and beta distributions are represented through [mean (μ), standard deviation (σ)], [scale parameter (α), shape parameter (β)] and [shape parameter 1 (a), shape parameter 2 (b)], respectively. A 3.33% standard deviation of input parameters has been considered for normal distribution of load (i.e. 3σ is 10%). Weibull and beta distributions, whose parameters are given in Table II, also follow a similar high level of uncertainty.

The uncertainties of AVR and PSS parameters were not considered in simulations with the larger system in order to reduce the number (p) of uncertainties considered and consequently required computational time. The simulation time would increase significantly with larger number of uncertain parameters considered without contributing to accuracy and quality of conclusions drawn with respect to comparison of the methods.

Probabilistic modelling of the input parameters and sensitivity analyses have been performed in MATLAB and OPF simulation has been solved in MATPOWER [36]. Modal analysis has been conducted in DIgSILENT PowerFactory.

C. Number of Simulations and Computational Time

The relative computational cost in terms of both the number of simulations and simulation execution run-time for all presented techniques are shown in Table III. For 35 and 49 uncertain parameters, OAT requires considerably less (36 and 50, respectively) computations. For the Morris method, $r=10$, a moderate number of (351 and 491) simulations are needed to run. The computational cost of MADM is same as Morris method. All correlation coefficients require a high number of simulations (which is in the range of 1000). Sobol, FAST and Borgonovo methods require a very large number of simulations, which are 180,000, 91,941 and 350,000, respectively for two-area system and 50,000, 207,661 and 490,000, respectively for NETS-NYPS system.

All of these sensitivity techniques (except FAST and Borgonovo for NETS-NYPS) have been implemented in this study to identify the most influential parameters. The

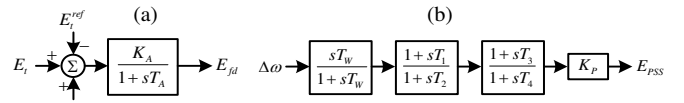


Fig. 4. Simplified (a) AVR and (b) PSS model used during linear analysis.

TABLE I
PROBABILITY DISTRIBUTIONS AND PROBABILISTIC MODEL PARAMETERS OF UNCERTAIN INPUT VARIABLES OF TWO-AREA POWER SYSTEM

Variables	Generators and Load Demand	AVR Gain and Time Constant	PSS Gain and Time Constant
Probability Distribution	Normal	Uniform	Uniform
Modelling Parameters	$v: 10\% \text{ of } \mu$	$v: \pm 10\% \text{ of } \mu$	$v: \pm 10\% \text{ of } \mu$

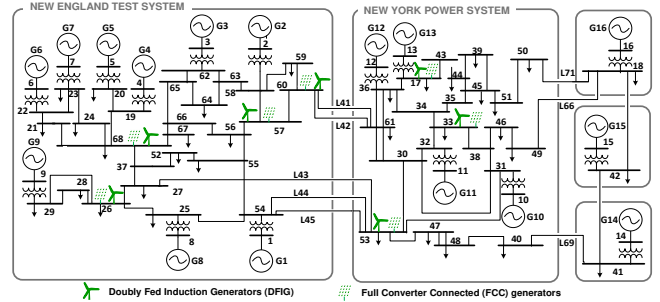


Fig. 5. Modified NETS-NYPS (New England Test System – New York Power System) network with a high amount of wind and solar generation.

TABLE II
PROBABILITY DISTRIBUTIONS AND PROBABILISTIC MODEL PARAMETERS OF UNCERTAIN INPUT VARIABLES OF NETS-NYPS TEST SYSTEM

Variables	Load demand	Wind Speed	Solar Power
Probability Distribution	Normal	Weibull	Beta
Modelling Parameters	$3\sigma = 10\% \text{ of } \mu$	$\alpha = 2.2, \beta = 11.1$	$a = 13.7, b = 1.3$

TABLE III
TOTAL NUMBER OF SIMULATIONS AND COMPUTATIONAL TIME REQUIRED FOR DIFFERENT SENSITIVITY ANALYSIS TECHNIQUES

Sensitivity Techniques	Cost	No. of Simulations		Simulation Time	
		System1	System2	System1	System 2
OAT	$p + 1$	36	50	7 s	4 m
Morris	$p \cdot r + 1$	351	491	66 s	17 m
MADM	$p \cdot n + 1$	351	491	66 s	30 m
Pearson	N	5000	1,000	16 m	40 m
Spearman	N	5000	1,000	16 m	40 m
Partial	N	5000	1,000	16 m	40 m
Sobol	$(p + 1) \cdot N$	180,000	50,000	9 h 25 m	32 h
FAST	$p \cdot f$	91,941	207,661	4 h 50 m	-
Borgonovo	$p \cdot n \cdot N$	350,000	490,000	18 h 20 m	-

application of FAST and Borgonovo is unsuitable for large test system as these requires large number of (207,661 and 490,000, respectively) simulations and extremely high estimated run-times of 5.5 days and 13 days. All the studies are performed using a desktop PC with Intel Core i5-3470 CPU @ 3.20GHz and 8GB RAM processor.

A sufficient number of Monte Carlo run is determined through a stopping rule as in (26) [37].

$$E > \left[\Phi^{-1} \left(1 - \frac{\delta}{2} \right) \cdot \sqrt{\frac{\sigma^2(\mathbf{X})}{N}} \right] / \bar{\mathbf{X}} \quad (26)$$

According to the criterion presented in (26), simulations can be stopped if the calculated sample mean error falls below a specific threshold, E. At a confidence level of $\delta = 0.01$ (i.e. 99% confidence), 5000 and 1000 simulations for two-area and NETS-NYPS test system gives sample mean error (E) 0.14% and 0.3%, respectively. As can be seen from Table III, a reduced number of Monte Carlo runs (1000 instead of 5000) are performed for NETS-NYPS test system to keep the simulation time within a practical limit.

The accuracy of the simulation will be reduced with a reduced number of simulations. The accuracy (percentage error) can be calculated from (26). The sample mean error (E) is increased from 0.18 with N=5000 to 0.32 with N=1000 for system 1 and from 0.14 with N=5000 to 0.30 with N= 1000 for system 2. This, however, does not significantly, if at all, affect the ranking of the most influential parameters. In this case, the ranking of the top 19 (out of 35) and top 23 (out of 49) parameters remains the same with 1000 and 5000 simulations for system 1 and system 2, respectively.

The number of simulation is dependent on the number of input parameters. It is inherently system dependent and independent of the numbers of output parameters being considered. The computational cost of sensitivity analysis techniques depends on the number of parameters for OAT, Morris, MADM, Sobol, FAST and Borgonovo method, as presented in Table III. On the other hand, correlation coefficient methods, Sobol and Borgonovo depend on the convergence criteria as mention in Eq. (26). The convergence of Monte Carlo simulation generally follows the central limit theorem which states that the error reduces by a factor of $1/\sqrt{N}$, where N is the number of simulation [38]. Hence the Monte Carlo convergence is mainly dependent on the scalability of the system and the level of acceptable error.

All of these methods can be processed through high throughput computing (HTC) facilities by using a large numbers of processors, coupled together and run in parallel to solve very large problem sizes. This will significantly reduce the simulation time for all methods. In such a case also, the relative performance of the different sensitivity analysis techniques would be preserved.

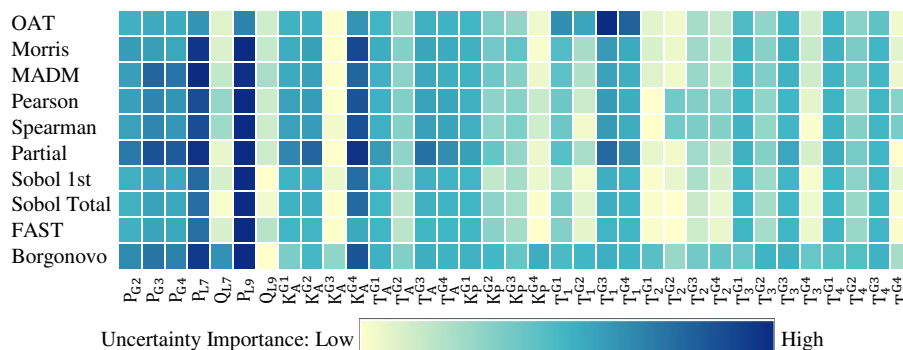


Fig. 7. Heatmap illustrating results of multiple SA techniques identifying the most influential uncertainties in two-area test system.

IV. SENSITIVITY ANALYSIS – RESULTS AND DISCUSSION

A. Probabilistic Modal Analysis

The modal plot displaying the movements of the most critical eigenvalue of NETS-NYPS test system is presented in Fig. 6 including the distribution contours. The movement of the critical eigenvalue over 5000 random simulations has been influenced by the input uncertainties and probability distributions of input parameters. The range of damping (real part of eigenvalues, s^{-1}) spreads over $[-0.12 \sim -0.143]$, and frequency (Hz) varies between $[0.51 \sim 0.55]$. Different input parameters have contributed at different proportion to the movement of eigenvalues on the complex plane. The most influential parameters causing the movement of the eigenvalue have been numerically calculated through SA techniques.

B. Priority Ranking of Two-Area System Uncertainties

For the two-area test system, all 35 uncertainties are considered individually and compared against each other. The sensitivity analysis is completed using a system loading factor of 0.66 pu and a 10% level of uncertainty (i.e. $v = 10\%$). The

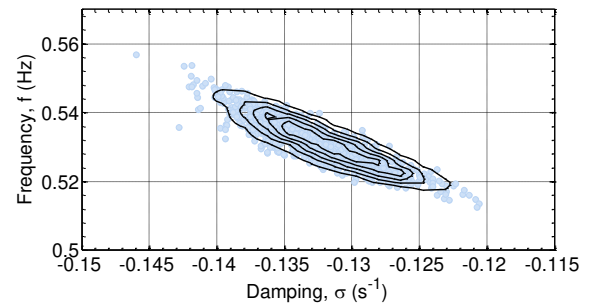


Fig. 6. Contour and *footprints* of the critical eigenvalue in the complex plane as affected by input parameter uncertainties of NETS-NYPS test system.

results from this extensive sensitivity study are presented as a heatmap in Fig. 7 due to the impracticality of tabulating the full numerical results. Both the sensitivity methods and uncertainties have been analysed. It is clearly evident that not all methods produce the same levels of importance for different parameters, but also that key parameters can be identified using various sensitivity measures. It is evident from the heatmap that local method produces a significantly different ranking compared to screening and global methods.

1) Five Most Influential Parameters of Two-Area System

Table IV presents the top five most important uncertainties affecting critical mode damping according to the different sensitivity analysis methods. It can be seen that the same top

five uncertainties (with some ranking differences) are identified by all of the global sensitivity analysis tools. All global methods except MADM agree that P_{L9} is the most important parameter. This may be due to the limited search-space exploration of the MADM approach (illustrated in Fig. 1). Additionally, OAT ranks P_{L9} as third most important, and the method over-quantifies the importance of the T_1 PSS parameter. OAT ranks T_1^{G1} , T_1^{G3} and T_1^{G4} as three of the top five influential parameters. These do not appear in the top five for any of the global measures. This strongly highlights the limitations of only completing a local sensitivity analysis. The effect that a parameter may have on the output *around the nominal equilibrium point* is not necessarily equivalent to the *global* effect across the entire operating range.

The Morris screening method correctly identifies the top three critical parameters same as global methods, though it includes the T_1^{G3} PSS parameter in the top five. This demonstrates the value of evaluating the importance of parameters across a greater region of the search space. It also highlights the limitation of the Morris method due to the simple random trajectory that is used and the limited number of sample points. The MADM identifies the top five influential parameters as being the same as from the global methods, except the top two swapping their position.

The FAST method should reproduce the same results as the Sobol first order effects however it can be seen that this is not the case and that some information is lost during frequency uncertainty encoding and subsequent Fourier analysis. Perhaps most interestingly, it can be seen that the simple Pearson correlation coefficient ranks the top five parameters in the same order as the much more complex Borgonovo δ measure. This suggests that such complex and computationally intensive SA may be unnecessary.

C. Priority Ranking of NETS-NYPS System Uncertainties

The heatmap of sensitivity measures of NETS-NYPS parameters have been presented in Fig. 8. The ranking of all of the uncertain parameters can be seen from the heatmap, which also highlights a comparative ranking by different techniques. Though the underlying theory and computational techniques are different for each method, the results are generally consistent in identifying the most influential parameters. The darker shades in the heatmap around column 10, 11, 25, and 26 represent the most influential parameters identified by almost all SA techniques.

The OAT method overestimates some parameters that are categorized as *non-influential* by the more comprehensive

TABLE IV
TOP FIVE MOST IMPORTANT UNCERTAINTIES IN TWO-AREA SYSTEM AS RANKED BY THE DIFFERENT SENSITIVITY MEASURES

Rank	OAT	Morris	MADM	Pearson	Spearman	Partial	Sobol 1st	Sobol Total	FAST	Borgonovo
1	T_1^{G3}	P_{L9}	P_{L7}	P_{L9}	P_{L9}	P_{L9}	P_{L9}	P_{L9}	P_{L9}	P_{L9}
2	T_1^{G4}	P_{L7}	P_{L9}	P_{L7}	P_{L7}	K_A^{G4}	P_{L7}	K_A^{G4}	P_{L7}	P_{L7}
3	P_{L9}	K_A^{G4}	K_A^{G4}	K_A^{G4}	K_A^{G4}	P_{L7}	K_A^{G4}	P_{L7}	P_{G3}	K_A^{G4}
4	T_1^{G1}	T_1^{G3}	P_{G3}	P_{G3}	P_{G3}	P_{G3}	P_{G3}	P_{G3}	P_{G4}	P_{G3}
5	K_A^{G4}	P_{G2}	P_{G4}	P_{G4}	P_{G4}	P_{G4}	P_{G4}	P_{G4}	K_A^{G4}	P_{G4}

global techniques due to its limited local search around the nominal value. The performance of Morris and MADM are comparable while they identify some of the influential parameters and give low scores to other parameters. These methods are very efficient in identifying the most influential parameters with less computational effort. The global methods, being the most computationally expensive, provide a thorough priority ranking.

1) Five Most Influential Parameters of NETS-NYPS System

The most critical five parameters identified through different sensitivity analysis techniques have been presented in Table V. All methods have a very good agreement in ranking the most influential parameters, where the top four are same for all methods (with some positional differences). L_{17} is the most influential parameter by all SA techniques (except OAT). OAT overestimates L_{18} as 1st and L_{42} as 2nd most influential parameter due to its local search and these parameters rank 2nd and 3rd respectively for all global methods. The ranking performance of Morris screening method is in between local and global methods. Though it identifies the top two

TABLE V
TOP FIVE MOST IMPORTANT PARAMETERS OF NETS-NYPS SYSTEM IDENTIFIED THROUGH DIFFERENT SENSITIVITY ANALYSIS TECHNIQUES

Rank	OAT	Morris	MADM	Pearson	Spearman	Partial	Sobol Total
1	L_{18}	L_{17}	L_{17}	L_{17}	L_{17}	L_{17}	L_{17}
2	L_{42}	L_{18}	L_{18}	L_{18}	L_{18}	L_{18}	L_{18}
3	L_{41}	L_{41}	L_{42}	L_{42}	L_{42}	L_{42}	L_{42}
4	L_{17}	L_{42}	L_{41}	L_{41}	L_{41}	L_{41}	L_{41}
5	S_{68}	L_{40}	L_{20}	W_{17}	W_{17}	W_{17}	L_{50}

Letters represent load (L), wind (W) and solar (S) generators presented at NETS-NYPS test system, whereas the subscripts are the bus numbers.

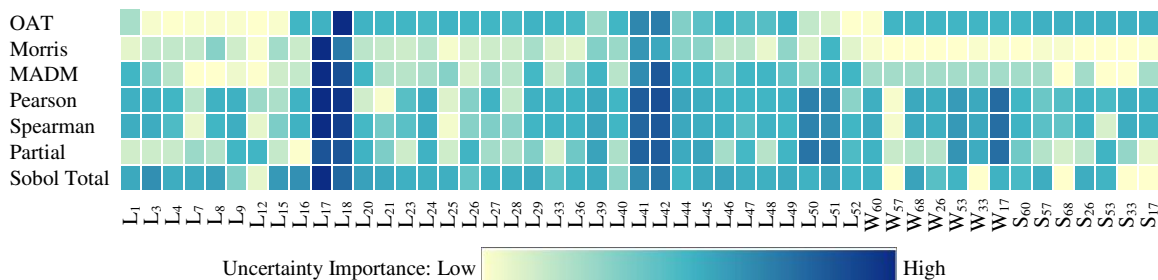


Fig. 8. Heatmap describing results of seven SA techniques identifying most influential uncertainties in NETS-NYPS test system.

parameters same as global methods, the 3rd and 4th parameters swap around compared to global methods.

It is evident that in both test systems power system loads appeared as the most influential parameters, in particular in NETS-NYPS test system where their dominance among the most influential parameters is overwhelming.

D. Physical Significance of the Priority Ranking of System Uncertainties

Fig. 9 compares the locations of critical eigenvalues for 1000 simulations considering $\pm 10\%$ variation in input parameter values for all 49 and for the 5 most influential parameters as identified by Sobol Total method in Table V. It can be seen that the area of eigenvalue dispersion for the five influential parameters covers a larger portion of the range of damping covered by eigenvalues considering all 49 parameters, hence, the criticality of the system stability (measured by the damping of critical eigenvalue) has been properly captured by the identified five most influential parameters. Thus, the resource and effort for developing appropriate models of uncertain power systems for small disturbance stability analysis can be focused on accurate modelling of a small number of important parameters only.

V. CONCLUSIONS

This paper provides a critical assessment of nine sensitivity analysis techniques to assess their suitability for prioritizing uncertain parameters affecting power system small-disturbance stability. Most influential input parameters have been identified and ranked by each of the techniques.

The simplest of all, the one-at-a-time method fails to appropriately identify the importance of the most influential parameters, however, it offers a reasonably good indication of influential parameters with a minimal number of simulations. Morris method and MADM represent good balance between accuracy and computational effort. Correlation coefficients present identical ranking of uncertain parameters, as above, with moderate computational effort. Sobol indices are more thorough and rigorous for identifying influential variables. FAST and Borgonovo methods are not suitable for large scale application due to their high computational cost. Considering that reasonably simple Pearson correlation coefficient provides almost identical results as Sobol, FAST and Borgonovo method, very complex and computationally intensive SA may not be necessary.

In a power system with large number of uncertain parameters it is computationally expensive and quite often unnecessary to evaluate the system performance with respect to uncertainty in all system parameters as not all of them contribute equally to the change in system performance. A screening method instead should be used to identify the critical parameters only, i.e., the parameters affecting the most system performance. The Morris method offers a significant benefits in this respect by providing more accurate results than 'local' and more computationally efficient results than 'global' SA methods. The accuracy of the Morris screening method lies in its trajectory exploration across multi-dimensional semi-global search space. A significantly reduced computational time with respect to full global SA approaches makes it efficient and feasible for application in realistic

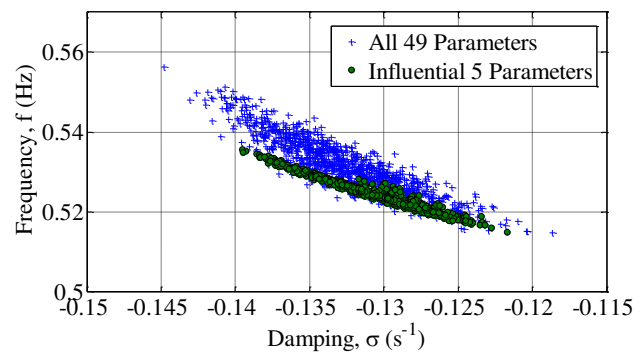


Fig. 9. Location of critical eigenvalues as affected by uncertainty in all 49 and 5 most influential input parameters of NETS-NYPS test system.

power networks with many uncertain parameters.

The presented application and critical assessment of efficient methods for small disturbance stability assessment of two different test systems with numerous uncertainties indicates their potential for applications in other areas of steady state and dynamic analysis of uncertain power systems. Advance identification of dominant uncertainties through an efficient SA technique will facilitate appropriate resource allocation for modelling, monitoring and control of selected parameters and ensure more efficient and secure operation of future, more uncertain, power systems.

The presented methods are applicable to other system variables and any input and output parameters can be chosen to perform this or any other type of system studies. The number of input/output parameters and type of power system study however, may affect the effectiveness and efficiency of the considered methods. For example, the efficiency will be reduced significantly if transient stability is performed instead of small-disturbance stability due to the increased computational burden of the individual studies to be performed. Nevertheless, the relative performance of the different methods would be preserved.

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