

# Methodology for Online Identification of Dynamic Behavior of Power Systems with an Increased Amount of Power Electronics Interface Units

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**Abstract**—A methodology for online and offline dynamic stability assessment, suitable for power systems with high penetration of power electronics interface units is presented in this paper. The increasing penetration of renewable energy resources as well as changing market operations, new types of loads and storage technologies, are causing significant changes to power systems dynamic behavior. Unstable generator groups and generators exhibiting poorly damped oscillatory behavior are identified online, opening the possibility to corrective control actions in order to stabilize the system. Moreover, statistical analysis of the abundant data from simulations provides information on the overall impact of power electronics interface units on system stability.

**Index Terms**—Decision trees, dynamic security assessment, probabilistic transient stability.

## I. INTRODUCTION

IN recent years, power systems are going through significant changes due to the integration of a number of new technologies both on the transmission as well as the distribution side. These new technologies include renewable generation, energy storage devices, electric vehicles, HVDC interconnectors etc. and are primarily interfaced with the power system using power electronics. The connection of such units causes: i) changes in the power systems dynamic behavior due to exhibiting different dynamics compared to synchronous generators, ii) increase in the uncertainties related to the power systems operation, especially due to the intermittent nature of Renewable Energy Sources (RES) and iii) displacement of conventional synchronous generators, either by de-loading or disconnection.

In this context, new methods and tools need to be developed and implemented, that will enable close to real time identification of the increasingly uncertain and complex power systems dynamic behavior. Such methods can in turn enable

corrective control actions to alleviate stress. Machine learning and data analytics can help in this direction, especially with the increasing installation of Phasor Measurement Units (PMUs) that offer abundant data with sufficient sampling time for investigating the dynamic behavior of power systems. More importantly, identifying impending instability for individual generators is a key issue that can guide the informed design of special protection schemes to stop widespread failures.

A number of machine learning tools have been proposed in the literature regarding online dynamic security assessment, including Decision Trees (DTs) and Ensemble DTs [1]–[7], Support Vector Machine (SVM) [8], [9] and Artificial Neural Networks (ANNs) [10]. Most of these approaches focus on binary classification between stable and unstable system. However, there are some approaches in the literature [6], [10], [11], that try to offer additional information on the impending instability. More specifically, the unstable groups of generators that are about to lose synchronism are also identified. Such information is valuable for the design of more effective corrective control actions which can include controlled islanding, fast valving, dynamic braking, generator tripping, load shedding, use of Flexible AC Transmission Systems (FACTS), etc. [6], [12].

Since the power systems dynamic behavior is changing due to the increasing connection of power electronic interface units, the performance of online dynamic security assessment methods needs to be re-evaluated to ensure their effectiveness. Moreover, the uncertainties related to power systems pre-fault operating conditions is increasing significantly due to the intermittent nature of RES, which needs to be accounted for when generating training databases. An extensive training database consisting of various contingencies and possible pre-fault operating conditions is usually required for the purpose of online identification of power systems dynamic behavior. Probabilistic transient stability assessment is therefore closely related to the problem of online identification, since it can be used to generate the required training databases [13]–[18]. Due to spatial and temporal variation introduced by the uncertain behavior of RES, in particular, probabilistic methods are even more suitable to assess various aspects of dynamic behavior of power systems [19]–[22].

In this paper, an overall methodology for the online identification of power systems dynamic behavior is presented. Increased uncertainties due to RES are taken into consideration as well as the different dynamic behavior of power electronic

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interface units. When a disturbance happens, DTs are initially used to predict groups of generators about to go unstable. Afterwards a clustering approach is used in an online manner for the cases where no first-swing instability is detected, to further identify two groups of generators presenting well and poorly damped oscillatory behavior. Furthermore, statistical analysis is applied to the simulated contingencies in an offline procedure to highlight the impact of power electronic interface units and conventional generation disconnection on power systems dynamic behavior.

This paper presents a comprehensive methodology for on-line identification and offline assessment of power systems dynamic behavior, considering both transient stability and subsequent oscillatory behavior of generators. The methodology is then applied i) for the assessment and characterization of dynamic behavior of systems with large penetration of uncertain and stochastic renewable generation connected through power electronics interface and ii) for comprehensive investigation of the overall impact of power electronics connected generation technologies on power systems dynamic behavior. The novelty of the online part of the methodology is the clustering of generators based on their oscillatory responses without pre-specifying the coherent groups of generators while in the offline part of the critical generators, from transient stability perspective, are identified for the first time in a probabilistic manner reflecting both the overall effect of various uncertain parameters as well as the importance of measured signals. These online and offline assessment features of the methodology and the application of the overall methodology for the robust assessment and characterization of the impact of power electronics interface uncertain generation on system dynamics have not been addressed in the existing literature.

## II. METHODOLOGY

The proposed methodology shown in Fig. 1 consists of two main procedures, i.e. online and offline. The core of the methodology is the simulation of a large number of contingencies in a probabilistic manner, taking into consideration the uncertainties present in modern power systems. The simulated contingencies are used in the online part to train Decision Trees (DTs) that are afterwards used to identify the unstable groups of generators about to appear within a given time frame. In case an unstable contingency is identified, predefined corrective control actions are applied to either stabilize the system or prevent cascading events that in the worst case might lead to a blackout.

In case no first-swing instability is detected by the DTs, an online clustering procedure is applied to cluster generators in those who exhibit well damped and poorly damped oscillations. Further corrective measures can be applied in case poorly damped or growing amplitude oscillations are identified.

From the abundant simulated responses, the dynamic stability of the system can be investigated in a probabilistic manner, as part of the offline procedure. Since a probabilistic approach is followed, the overall impact of power electronic interface units as well as of inertia reduction can be investigated. Investigation considering the possible impact of the communication

infrastructure on the online identification of power systems dynamic behavior is also carried out.

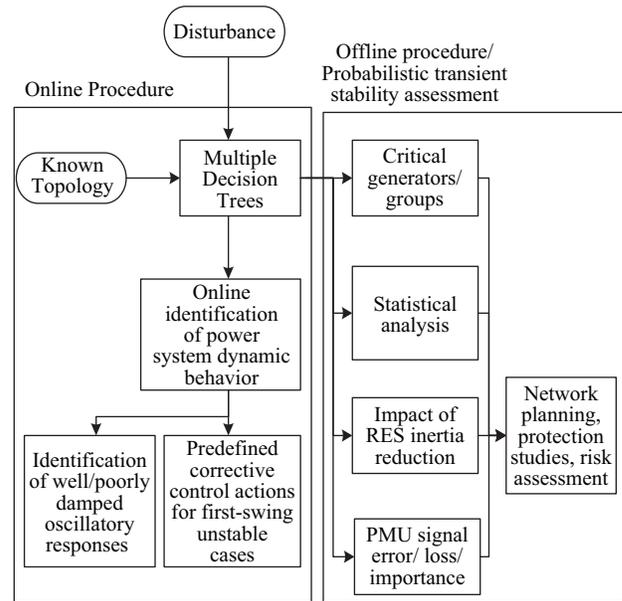


Fig. 1. Schematic of the proposed probabilistic methodology.

### A. Generation of Database of Dynamic Responses

The proposed methodology relies on the execution of  $N_s$  Monte Carlo time-domain, dynamic simulations. The Monte Carlo simulations are used as training and testing datasets for the DTs as well as for the offline probabilistic studies. Uncertainties related to system loading, PV power output, wind generation and fault location and duration are considered in this paper.

Regarding system loading and PV generation, daily curves are initially used, which are obtained from national grid data [23] and from literature [22], respectively. The hour of the day is randomly sampled and appropriate Probability Distribution Functions (PDFs) are used afterwards to model the uncertain behavior within each hour. For the system load, a normal distribution with a mean value determined by the hour of the day (varying between 0.6 and 1 p.u. for the specific study) is used and a standard deviation of 3.33% [6]. For the PV units a beta distribution with  $a$  and  $b$  parameters equal to 13.7 and 1.3, respectively, is used [24]. Regarding wind generation, a Weibull distribution is chosen to model the uncertainty related to wind speed within the day, with parameters  $\varphi = 11.2$  and  $k = 2.2$  [25]. Constant mean wind speed for every hour throughout the day is assumed.

For each individual RES unit and load of the system, the PDFs are separately sampled to consider independent behaviour of each load and RES unit within the system. For example, assuming the total load is 0.8 p.u. for a specific hour of the day, one individual load of the system might end up having a value of 0.75 p.u. while another 0.85 p.u.

After the uncertainties related to system loading and RES generation are considered, an Optimal Power Flow (OPF) is solved to calculate the pre-fault operating conditions. The

disconnection of conventional synchronous generation can be determined based on the required active power output from synchronous generators.

The generator spare capacity  $SC_{ig}$ , is defined in (1) and is a metric representing how loaded a synchronous generator is. In this paper, the spare capacity is used to help define different ways of synchronous generation disconnection, as described below. The subscript  $i$  denotes the dynamic simulation number and  $g$  the generator number.

$$SC_{ig} = 1 - \frac{P_{SG,ig}}{S_{SG,ig} \cdot pf_{SG,ig}} \quad (1)$$

where  $P_{SG,ig}$  is the active power produced by each generator (determined by OPF) and  $S_{SG,ig}$  is the apparent power after considering any disconnection.  $pf_{SG,ig}$  is the corresponding power factor.

There are three main approaches followed in this paper to represent synchronous generation disconnection and consequent inertia reduction.

In the first approach the synchronous generators are treated as being equivalent generators and the nominal apparent power  $S_{SG,ig}$  of each generator is reduced accordingly to represent disconnection. Consequently this corresponds to a respective decrease in the moment of inertia as well as an increase in the generator impedance since the values are given on a p.u. base of the apparent power of each generator. In this first approach, the percentage of apparent power reduction (and consequent disconnection) is constant for each generator and depends on the amount of RES connected to the system (corresponds to Test Case 5 (TC5) presented in Section V-A). The amount of active power produced by each generator  $P_{SG,ig}$  is changing for each simulation  $i$  due to changes in system loading and RES output, while the apparent power  $S_{SG,ig}$  remains constant. Therefore, the spare capacity for each simulated scenario is varying in this case.

In the second approach, synchronous generators are again treated as equivalent generators following the same method described in the first approach. However, a constant spare capacity is considered for each generator, as defined in (1). This means that as the loading and RES output is changing for each simulated case  $i$ , the apparent power of each generation is reduced accordingly to keep the spare capacity constant. TC7 of Section V-A follows this approach.

In the third approach, synchronous generators are not treated as equivalent and entire generators (e.g. entire G2, G10, etc.) are disconnected to account for the RES connection. The overall percentage of synchronous generation disconnection again depends on the amount of RES connected in a similar manner as the first approach. TC6 of Section V-A follows this approach.

The fault location is treated as an uncertain parameter and it follows a uniform distribution. This means that faults may happen at any point of any line with equal probability for the purpose of this study. Additionally, the uncertainty related to fault duration is considered to follow a normal distribution (mean value 13 cycles, standard deviation 6.67%) as in [6]. The framework allows for probability distribution functions being derived based on historic data of specific systems to

be used for more realistic representation, if known. The considered disturbances are three phase self-clearing faults but the methodology can include other contingencies since it relies on time domain simulations.

After the simulations are performed, the rotor angles of each generator are obtained and used to later train and test the DTs. Moreover, the rotor angles are used to calculate stability indices, used in the offline statistical analysis of the results.

### B. Clustering of First-swing Unstable Cases

For the entire database of simulated contingencies, a clustering approach is used to identify the unstable generator groups for each simulated response. Observing the unstable generator grouping patterns that might appear for the specific system, can also provide information on the impact of power electronic interface units on transient stability. Different groups tend to appear with the connection of power electronic interface units due to the different dynamics they exhibit as well as due to the change in pre-fault operating conditions.

It should be noted that the effect of RES intermittency on the uncertainty of possible pre-fault operating conditions is very significant. The effect of other types of power electronic interface devices such as storage devices on pre-fault operating conditions might not be that significant in case they are used to provide only ancillary services (e.g. frequency support after a disturbance). However, the dynamic behavior of such units is expected to alter the dynamic behavior of the system in a similar manner to RES, in case similar controllers are implemented. In the case where other market operations for charging or discharging storage devices are put into place, pre-fault operating conditions will also be affected and might need to be studied in more detail.

A method based on hierarchical clustering is chosen to derive generator instability patterns related to first swing stability. Hierarchical clustering is applied to the generator rotor angle values of each generator at a specific time instant after the clearing of the fault, to identify potential generator groups exhibiting aperiodic, first-swing instability. In this paper, the time is chosen as 1.5 seconds and the Euclidean distance is used as the distance metric, with a cutoff value of 360 degrees [6]. Following this approach, the generators are split in groups where at least one of the generators of the group exhibits a 360 degrees difference from at least one generator of the other groups.

### C. Online Identification of Unstable Generator Groups

DTs have been proven to be suitable for online dynamic security assessment purposes [5], [6]. In this study, DTs are trained as multiclass classifiers to distinguish between the unstable generator grouping patterns obtained from the hierarchical clustering procedure presented in Section II-B. The rotor angle responses of each generator are used as predictors for the DTs, with a duration of 60 cycles.

Multiple DTs may need to be trained considering the current network status in order to improve performance (e.g. with or without RES or other power electronic interface units). The C5.0 boosting algorithm is used to train the DTs since it has been reported in the literature to exhibit good performance [6]

for the multiclass classification problem. After the training is complete, the DT corresponding to the current system status is used online to identify the generator grouping pattern about to happen after a disturbance occurs.

#### D. Clustering of First-swing Stable Cases

For those cases that do not exhibit “first-swing” instability as identified by the algorithm presented in the previous section, a further clustering methodology is proposed. The aim is to distinguish between generators (or groups of generators) exhibiting good and poorly damped oscillatory behavior. For this purpose, Recurrence Quantification Analysis (RQA) is proposed.

RQA is a method for nonlinear data analysis which provides several measures in order to quantify the number and duration of recurrences of a dynamical system presented by its state space trajectory [26], [27]. Several measures of recurrence are available as presented in [27], based on recurrent plots introduced in [28]. In this analysis, two of those basic properties are used, namely the Recurrence Rate (RR) and Determinism (DET). These properties are used as features to represent aspects of oscillatory dynamic behavior of generators. Both RR and DET can effectively help in clustering the oscillatory behavior of power systems and essentially provide information regarding the damping and frequency of observed oscillations.

RR and DET are defined by (2) and (3), respectively.  $\mathbf{R}$  is the recurrence matrix,  $N$  the number of samples of the corresponding responses (time window used) and  $P(l)$  is the number of times a diagonal of length  $l$  occurs within the given time window. The recurrence matrix  $\mathbf{R}$  stores the data points  $R_{i,j}$  of the measured responses that are recurrent, i.e., the distance between the points is less than a specified threshold value. RR is the density of recurrent points and DET quantifies the percentage of recurrent points that form a diagonal of minimum length  $l_{\min}$ . In this study a default value of  $l_{\min}$  is set to 2. More information on RQA can be found in [26]–[28].

$$RR = \frac{1}{N^2} \sum_{i,j=1}^N R_{i,j} \quad (2)$$

$$DET = \frac{\sum_{l=l_{\min}}^N l \cdot P(l)}{\sum_{i,j=1}^N R_{i,j}} \quad (3)$$

The values of RR and DET are calculated for the rotor angle responses of each generator using (2) and (3), for a given time window (with a length of  $N$  samples). Afterwards, a clustering technique is applied using the calculated RR and DET as input features. The generators are consequently clustered into groups (based on the RR and DET values of their rotor angle responses) that represent whether they exhibit good or poorly damped oscillatory behavior. From various tests performed it has been observed that RR and DET can provide information regarding the damping and frequency of observed oscillations, with RR being more closely related to damping and DET to frequency.

In this paper k-means has been chosen as the clustering algorithm due to its simplicity and due to the fact that a

predefined number of groups can be set. The generators are clustered into  $k$  groups based on the two features of RR and DET derived from RQA. K-Means is an iterative partitioning technique that uses a centroid  $c_i$  to represent a cluster. The centroid  $c_i$  is defined as the mean value of the elements belonging to the cluster. In this paper, the centroid is useful and used to represent the oscillatory behavior of the generators belonging to a specific cluster. The iterations start by initially randomly selecting  $k$  points as centroids. The rest of the points are assigned to the respective “closest” clusters from which the Euclidean distance is smallest. The iterative partitioning method afterwards minimizes the sum, over all clusters, of the within-cluster sums of point to cluster-centroid distances [29]. Choosing the number of clusters in this paper follows a simple approach. A constant number of two clusters (i.e.  $k = 2$ ) is used, in order to distinguish generators that are exhibiting poorly damped and well-damped oscillatory behavior. However, more elaborate information on oscillatory behavior of a system can be provided by increasing the number of clusters.

#### E. Offline Probabilistic Transient Stability Assessment

In order to investigate the dynamic behavior of power systems in a probabilistic manner, the Transient Stability Index (TSI), defined in (4), is calculated for all the simulated responses, taking the form of a random variable. TSI is an index that quantifies the maximum angle separation between any two generators of the system and is therefore describing the stability of the whole system for a specific contingency.

$$TSI_i = 100 \cdot \frac{360 - \delta_{\max,i}}{360 + \delta_{\max,i}} \quad (4)$$

where  $\delta_{\max,i}$  is the maximum rotor angle deviation between any two generators in the system for the same time instance.

Various indices based on the available generator rotor angles can be calculated in the same manner. By applying statistical analysis on the calculated indices, the overall dynamic behavior of a power system can be investigated and general tendencies identified. Simple statistical measures (e.g. mean value, standard deviation, etc.) can reveal some information. However, plotting Cumulative Distribution Functions (CDFs) can provide more information for the whole range of the random variables.

#### F. The Importance of PMU Signals

In this paper the measured responses for all the generators of the system are considered to be available. However, in reality all the measured responses might not be available, either due to the lack of installed PMUs or due to unavailability of signals due to communication errors. For this reason, the importance of each measured signal considering the performance of online identification is also evaluated. The most important measured signals, i.e. the ones that are critical for identifying the power systems dynamic signature, are determined. This information can be used to inform decisions on critical communication infrastructure as well as PMU placement for the purpose of online identification of power systems dynamic behavior.

The importance of measured signals, i.e. the rotor angle of each generator, can be determined in order to identify the most influential generators in terms of information obtained from each measured signal. The predictors used by specific DTs can be ranked according to their importance. A sensitivity measure  $S_j$ , as defined in (5) can be computed and then used to calculate the predictor importance  $VI_j$ , which is the normalized sensitivity, as shown in (6). More information on the procedure is available in [30], [31].

$$S_j = \frac{V_j}{V(Y)} \quad (5)$$

$$VI_j = \frac{S_j}{\sum_{l=1}^m S_l} \quad (6)$$

where  $V$  is the output variance when all predictors are considered,  $V_j$  is the variance without taking into consideration predictor  $X_j$  and  $m$  is the overall number of predictors used by the DT.

The predictors in this implementation, are measurement samples  $1 \dots n_{DT}$  of the generator rotor angles corresponding to the time duration until  $t_{DT}$  seconds for a number of  $N_g$  generators in the system. There are  $n_{DT}$  samples for each one of the  $N_g$  generators, so in total there are  $n_{DT} \cdot N_g$  predictors. The most important predictors can be identified after calculating the predictor importance using (6). These important predictors correspond to specific generator rotor angle samples and therefore can point to the most important/influential measured responses. The predictor importance  $VI_j$  of all predictors corresponding to a specific generator can be added to provide a ranking of generators according to how important their rotor angle measurement is, in determining system dynamic behavior (with regards to aperiodic instability). Different important generators considering measured signals are expected to be identified for different network status (i.e. with or without RES).

### III. TEST NETWORK

The IEEE 68 bus standard network is used in this paper, after being modified by adding a number of RES units, as shown in Fig. 2. All synchronous generators are modeled using standard 6<sup>th</sup> order dynamic models with either DC or fast acting static exciters and G9 has a Power System Stabilizer (PSS) installed [32]. All generators have also been equipped with generic governor models for different types of turbines (gas, steam, hydro). Twenty RES units are connected on different buses as shown in Fig. 2, assuming two different types of RES on each bus. Type 3 Doubly Fed Induction Generators (DFIGs), are used to represent wind generators and Type 4 Full Converter Connected (FCC) units for both wind generators and Photo-Voltaic (PV) units. The models are appropriate generic RMS models suitable for large scale stability studies and are available in DlgSILENT/PowerFactory software [33], which is also used for all studies in this paper. The models follow a similar approach to [34]–[36]. The block diagrams of both RES models are shown in Fig. 3 and Fig. 4.

Type 3 and 4 models used are treated as aggregate wind/solar farms, with each unit representing a 2 MW power plant. By varying the number of connected units, the output of the RES units is consequently varied to represent RES intermittent behavior and consequently different penetration levels. All units are assumed to have Fault Ride Through (FRT) capability. The installed capacity of RES described in the following test cases is given as a percentage on the basis of the total installed capacity of conventional synchronous generation of the original network. The mix between Type 3 and Type 4 RES units is then approximately 2/3 DFIGs and 1/3 FCCs (from which 30% is wind and 70% is solar).

Two main TCs are presented in this paper to highlight the impact of RES on system stability. In TC1, the amount of connected RES is 20% of the total installed conventional generation capacity of the system as explained above, while

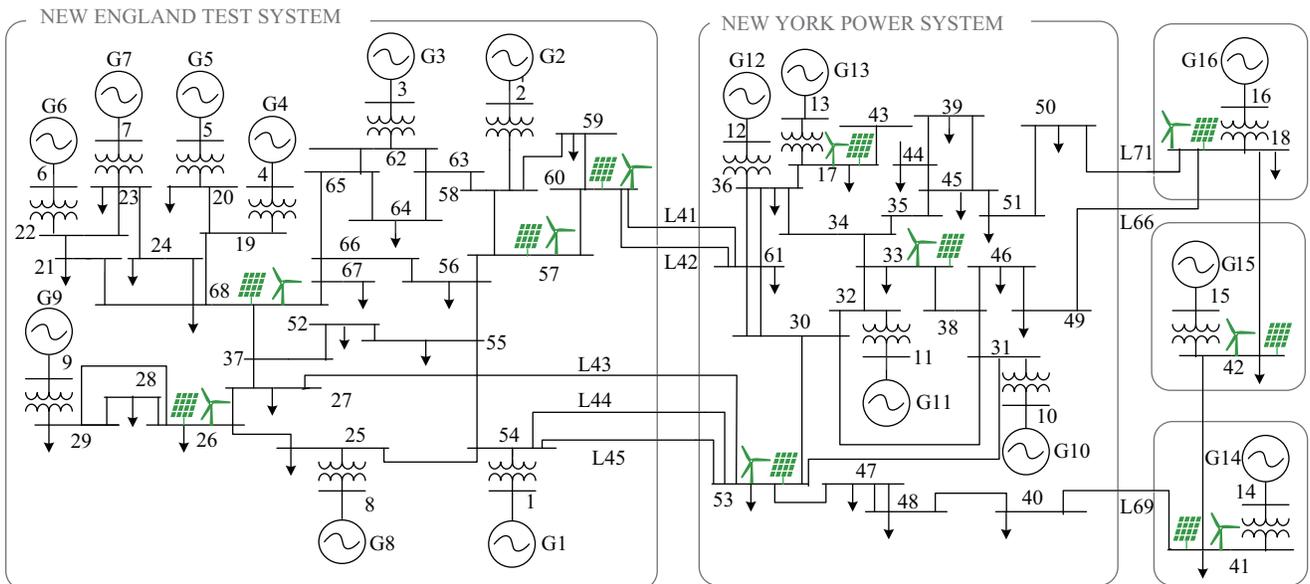


Fig. 2. Modified version of IEEE 16 generator, 68 bus network.

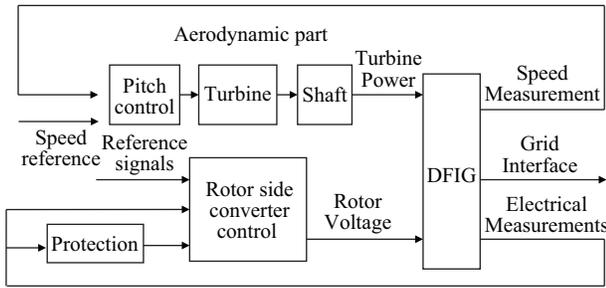


Fig. 3. DFIG control structure.

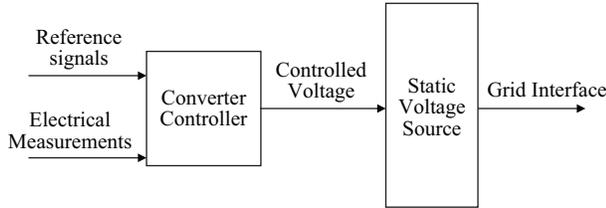


Fig. 4. FCC unit control structure.

in TC2 no RES are connected. This is the nominal/maximum amount of available RES and it varies following the intermittent behavior as presented before.

#### IV. ONLINE IDENTIFICATION OF STABILITY STATUS

For each of the two TCs described in this paper 6,000 Monte Carlo simulations are performed. All the results presented in this section follow the second approach considering inertia reduction presented in Section II-A, with spare capacity  $SC_{ig}$  constant at 15% for all simulated cases.

##### A. Grouping Patterns of Unstable Generators

The time domain dynamic simulations that have been performed using Monte Carlo, are used to train and test DTs for the online identification of unstable generator grouping patterns (regarding first-swing stability) according to the procedure described before. Out of the 6,000 performed simulations, 4,000 cases are used for training and 2,000 for testing purposes. The results presented in Table I show some examples of generator grouping patterns appearing in the two TCs and a new pattern that appears only when RES are connected. The unstable generator groups are indicated with bold letters. New grouping patterns appear when RES are introduced and the frequency of appearance of grouping patterns also changes. In total, 30 patterns appear in TC1 while 32 in TC2. From those, 19 patterns are common between the two TCs. This suggests

TABLE I  
MOST SIGNIFICANT UNSTABLE PATTERNS

Pattern	Grouping		Test Cases	
	Unstable groups	Stable group	TC1	TC2
1	(G9)	(G1–G8, G10–G16)	49.38%	42.96%
2	(G11)	(G1–G10, G12–G16)	22.12%	19.91%
3	(G2–G9)	(G1, G10–G16)	2.65%	7.63%
4	(G4–G5), (G6–G7)	(G1–G3, G10–G16)	1.95%	1.35%
5	(G3)	(G1–G2, G4–G16)	3.01%	4.04%
6	(G4–G7, G9), (G3)	(G1–G2, G8, G10–G16)	0.88%	-

that with the inclusion of RES, both the dynamic behavior and the effect RES have on pre-fault operating conditions need to be accounted for considering online identification of power systems dynamic behavior. As expected, the overall dynamic behavior of the system (i.e. the possible unstable generator groupings) changes when taking into account the effect of RES with their associated controllers, which highlights the need for including them in the training of machine learning algorithms (DTs in this case).

In Table II, the performance of two DTs trained and tested with the respective datasets of TC1 and TC2 (with and without RES) is presented. The rows correspond to DTs trained with the simulations from a specific TC and the columns represent tests with specific TCs. The results from testing the DT trained with the simulations of TC1 with simulations of TC2 and vice versa are also presented. This highlights a possible drop in the performance of up to 10% which suggests the need of using a different DT when RES are available.

TABLE II  
PERFORMANCE OF DTs

Train	Cases used	Test	
		TC1	TC2
TC1	All cases	<b>99.05%</b>	98.06%
	Unstable cases only	<b>91.88%</b>	82.38%
TC2	All cases	98.94%	<b>99.17%</b>
	Unstable cases only	88.75%	<b>92.23%</b>

##### B. Clustering of First-swing Stable Cases

The clustering procedure presented in Section II-D is applied online when no first-swing instability is identified by the respective DT. A representative example of the resulting clusters is presented in Fig. 5 for a case that growing oscillations in some of the generators appear. In Fig. 6, the two resulting clusters are presented. The group consisting of generators G1, G8 and G9 (cluster 2) exhibits growing oscillations while the responses of the generators belonging to the other cluster are positively damped (cluster 1). The group exhibiting oscillatory behavior has low values of both DET (lower than 0.65) and RR (lower than 0.07). G14–G16 (belonging to cluster 1) also exhibits relatively lower damping

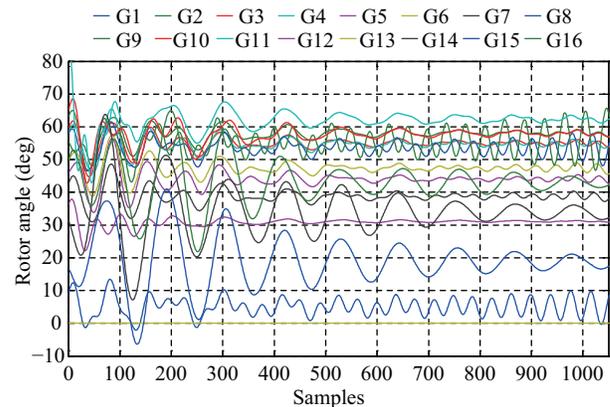


Fig. 5. Rotor angle responses for a case where growing oscillations are observed.

than the rest of the generators of cluster 1, and the values of the RR are higher than 0.07. However, DET has also relatively higher values (higher than 0.9).

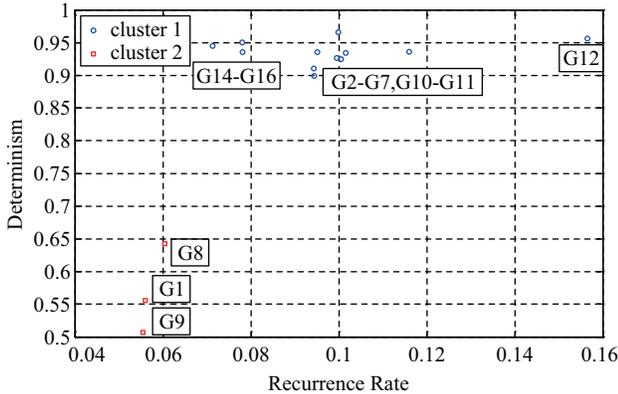


Fig. 6. Resulting clusters for first-swing stable case.

In general, low values of RR (lower than 0.07) and DET (lower than 0.85) indicate oscillatory behavior while high values indicate well damped oscillations. The cluster centroids for the two groups should always be monitored to determine whether there is a group exhibiting oscillatory behavior and which generators belong to that group. Specific thresholds for RR and DET can be set for a specific system from multiple offline studies as also discussed in the following Section V-B.

## V. OFFLINE PROBABILISTIC STABILITY ASSESSMENT

In the existing literature both the positive and negative impact of RES on power system transient and small disturbance stability have been documented. The possible impact of RES was analyzed, discussed and explained considering various mechanisms and physical processes taking place in power systems with RES [21], [37], [38]. It has been determined that reactive power support from RES units with FRT capability typically improves the transient stability of the system [38]. On the other hand, the overall impact of network topology, the RES location and control strategy applied and the disconnection of conventional generators, to accommodate higher penetration of RES in the system, have been determined to be more system specific and can either improve or deteriorate the overall transient stability of the system [37]. Due to a large number of influential and often uncertain parameters in power systems with RES it is important to follow a probabilistic approach, as proposed in this paper, in order to obtain a more realistic assessment of the overall transient stability of the system.

### A. Investigation of Different Methods of Inertia Reduction

Five TCs are presented in this section following different ways of disconnecting conventional synchronous generation and consequently reducing system inertia. The aim of this study is to highlight the impact of reducing inertia on transient stability of individual generators as well as the overall system. In the specific TCs, two opposing effects that together determine the overall system behavior are investigated; FRT control

of RES, which might improve transient stability of some generators, and disconnection of synchronous generation, which tends to have a negative effect.

In TC3, no RES are connected in the system and also no conventional synchronous generation disconnection is considered. Therefore, the synchronous generators are only de-loaded (operating at lower power output), which causes the spare capacity  $SC_{ig}$ , defined in (1), to vary. In TC4, 20% RESs are added based on the total installed conventional generation capacity, and no synchronous generation disconnection is considered. For TC5, 20% RESs are connected and also the first approach to reduce inertia is followed (described in Section II-A). This is achieved by reducing  $S_{SG,ig}$  of all synchronous generators of the system by a fixed 10%. TC6 is similar to TC5 but follows the third approach for inertia reduction where synchronous generators are not treated as equivalent generators. The entire synchronous generators G2, G10 and G15 are disconnected, which eventually leads to an overall inertia reduction of the system slightly higher than 10%. Finally, TC7 follows the second approach for synchronous generation disconnection for the same amount of RES connection (20% as in TC4–TC6). The spare capacity, defined in (1), is kept constant for each generator at 15% for each one of the performed simulations. 1,000 simulations are carried out for each TC for this investigation since they are considered enough to highlight the impact and effect of different methods of disconnecting conventional synchronous generation.

In Fig. 7 the number of times when specific generators exhibit instability is presented for TC3–TC7. In general, TC7 is the case with the highest number of instabilities. However, one of the generators, G11, presents an increased number of instabilities in TC6. This reveals the possibility for local adverse effects to be noticed for specific generators in contrast with general trends which highlights the importance of looking into individual generator stability metrics.

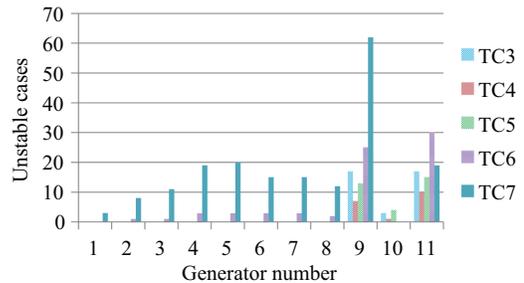


Fig. 7. Number of unstable cases for different ways of disconnecting conventional generators.

Focusing on system wide stability, TSI is used as an index and the CDF of it is shown in Fig. 8. The probability of instability is highlighted by the probability of the TSI to have negative values. For positive values of the TSI, the closer the value to 0 (generally low values of TSI) points to large rotor swings being observed. TC7 has both the highest probability of negative TSI values and also has a relatively higher probability of low positive values compared to the other cases. More specifically, for TC7 the probability that the TSI is lower than

50 is approximately 50%, while for the rest of the TCs, the TSI has a 50% probability to exhibit values being lower, around 55–60. Comparing TC5 with TC6, a similar situation is observed, indicating deterioration in system stability when disconnection of certain entire generators is considered (third synchronous generation disconnection approach described in Section II-A).

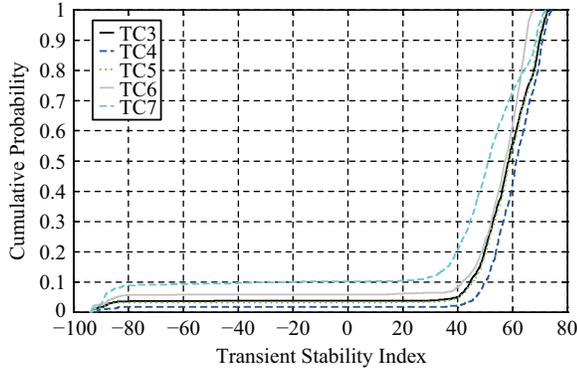


Fig. 8. TSI for different ways of disconnecting conventional generators.

### B. Effect of RES on First-swing Stable Cases

The dynamic behaviour of each individual generator for all the simulated cases where first-swing instability does not occur, is investigated in this section. In this section, k-means is used as a clustering algorithm on features extracted from rotor angle responses of each individual generator, using RQA. The goal is to distinguish between good and poorly damped oscillations for all the MC performed simulations. The features used to cluster the responses are RR and DET and the observations in this approach are the  $N_s$  simulated rotor angle responses for each individual generator. Therefore, for each generator within the system two cluster centroids are obtained that describe the oscillatory behavior of that generator, considering the uncertainties considered (RES intermittency, system loading, fault location, etc.), as described in Section II-A.

The resulting cluster centroids for all synchronous generators of the system are shown in Fig. 9. By observing the locations of the cluster centroids it can be concluded that G1–G10 exhibit in general poorly damped oscillations in some of the simulated cases, i.e. one of the cluster centroids has low RR and DET values. On the contrary, for G11–G16 both the cluster centroids have high RR and DET values, indicating better damped oscillations.

In general, for the given network the connection of RES seems to move the lower cluster centroid (which is the critical cluster for the cases that present oscillatory behaviour) for most generators to even lower values of RR and DET. This indicates increased oscillatory behavior. However, for G1, G8, G9 and G12 a slight increase in RR is observed, indicating better damping. Furthermore, there are some cases such as G9 where the RR of the lower centroid increases (indicating improvement in oscillatory behavior) while DET deteriorates. Since RR is considered to be more closely related to the damping of oscillations, observing RR is more critical to identify poorly damped oscillatory behavior.

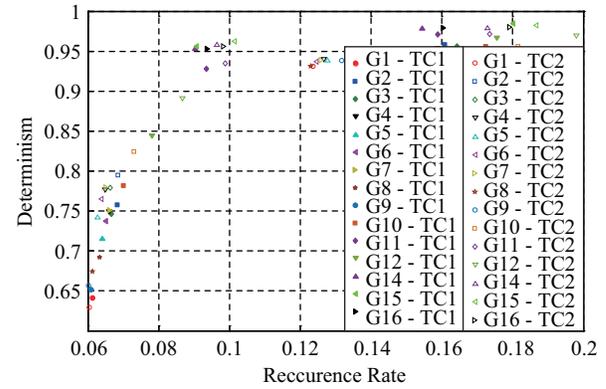


Fig. 9. Cluster centroids for all generators within the system with and without RES (TC1 and TC2).

Therefore, it can be concluded that for a similar reason as mentioned at the beginning of Section V, as well as in [37], the effect of RES on system oscillatory behavior can be either positive or negative. The cluster centroids obtained using the proposed methodology facilitate the assessment of transient stability and can describe the dynamic behavior of individual generators. It should be noted though that individual cases, e.g., generators that have RR and DET values that have relatively large distances from the cluster centroid, might appear. Such behavior may not be represented in detail by the cluster centroid.

### C. Importance of Availability of PMU Signals.

The signal importance for each TC is calculated from the respective DT according to the description of Section II-F and the results are presented for TC1 and TC2, for the three most important generators. The generators that the signals correspond to and the predictor importance calculated by (5)–(6) are shown in Table III. For TC1 the measured rotor angle of G6 is the signal with the highest importance, used for the identification of the power systems dynamic signature, followed by G2 and G11. For TC2, this changes and the rotor angle of G11 becomes the most important, followed by G10 and G9. This information can be used to make informed decisions on the design of the communication infrastructure by identifying the critical signals required to provide a correct prediction of the possible unstable generator groups after a disturbance.

TABLE III  
PREDICTOR IMPORTANCE FOR TC1 AND TC4

TC1		TC2	
Gen.	Predictor Importance	Gen.	Predictor Importance
G6	0.165	G11	0.1859
G2	0.132	G10	0.1017
G11	0.132	G9	0.1001

## VI. CONCLUSION

A probabilistic methodology for the online identification of first swing and oscillatory power systems dynamic behavior with increased penetration of power electronics interface

units is presented in this paper. Although the case studies presented consider power electronics connected wind and solar generation, the methodology is equally applicable to power electronics connected storage technologies. The specific numerical results would have changes in such cases due to different uncertainties and controllers applied, however, the approach presented would remain the same and be equally applicable.

The disconnection of conventional synchronous generation and consequent reduction in system inertia and its possible impact on system dynamics are also considered in a probabilistic manner.

It is demonstrated that new unstable generator grouping patterns appear and also the frequency with which common grouping patterns appear changes, with the connection of power electronics interface units. The oscillatory behavior of first-swing stable cases is also affected and an adverse effect on most of the generators is observed. There are, however, some generators for which an improvement in oscillatory behavior is observed following the connection of power electronics interface units. This indicates the need for: i) power electronic units to be taken into consideration when developing online identification algorithms, ii) investigating the dynamic behavior of individual generators, since different tendencies might appear.

Finally, the study demonstrated that the most important PMU signals for the online identification of dynamic behavior of the system, i.e., system observability by existing PMUs, are also affected by the inclusion of power electronic interface units, hence the observability of system dynamics can be reduced when the conventional generation is replaced by temporally and spatially varying power electronics interface units.

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