Recognition of Post-contingency Dynamic Vulnerability Regions: Towards Smart Grids

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***Abstract*--This paper presents a novel approach for determining post-contingency dynamic vulnerability regions (DVRs), oriented to assess vulnerability in real time as part of Smart Grid applications. Based on the probabilistic models of input parameters, such as load variation and the occurrence of contingencies, Monte Carlo-type simulation is performed to iteratively evaluate the system time domain responses. The dynamic probabilistic attributes are then analyzed using time series data mining techniques, namely Multichannel Singular Spectrum Analysis (MSSA), and Principal Component Analysis (PCA), in order to recognize the system DVRs based on the patterns associated to three different short-term stability phenomena. The vulnerability criterion consists in the possibility of some N-1 contingencies driving the system to further undesirable events (i.e. N-2 contingencies), which could be considered as the beginning of a cascading event. The proposal is tested on the IEEE New England 39-bus test system. Results show the feasibility of the methodology in finding hidden patterns in dynamic electric signals as well as in numerically mapping power system DVRs due to its ability to consider relevant operating statistics, including the most probably severe events that could lead the system to potential insecure conditions and subsequent blackouts.**

***Index Terms*--Data mining, Dynamic Vulnerability Region, MSSA, pattern recognition, phasor measurement units, security, Smart Grids, Vulnerability Assessment.**

I. Introduction

THE inclusion of deregulated markets, the lack of investment, the operation with congested transmission lines, and other technical reasons, such as environmental constraints, have been dangerously pushing the Bulk Power Systems close to their physical limits. Under these conditions, some critical contingencies could initiate cascading events that might eventually provoke blackouts [1], [2]. Hence, the design of some Smart Grid applications that perform timely self-healing and adaptive reconfiguration actions, with the objective of improving the system security and reducing the risk of power system blackouts is required [3]. Thus, an intelligent scheme which provides critical information in real time, assesses vulnerability quickly, and performs timely self-healing and adaptive reconfiguration actions based on system-wide analysis has to be structured (i.e. Self-Healing Grid) [1]. This Self-Healing Grid has some specific requirements such as an adaptive control and protection system, adequate measurement equipment, sophisticated communication networks, and appropriate tools to analyze huge volumes of data in real time. A fundamental task of this smart structure is the vulnerability assessment (VA), since it has the function of detecting the necessity of performing global control actions. Most VA methods are based on steady state (Static Security Assessment -SSA-) or dynamic (Dynamic Security Assessment -DSA-) simulations of N-x critical contingencies [4]. The aim of these methods is to determine whether the post-contingency states are within a “safe region” [5], [6], and accordingly, to decide the most effective preventive control actions. For this purpose, a Dynamic Security Region (DSR) could be established in order to determine the feasible operating region of an Electric Power System [6]. The process consists in determining the boundary of the DSR, which can be approximated by hyper-planes [6], and specifying the actual operating state relative position (or “security margin”) with respect to the security boundary [5]. A fast direct method is presented in [6] in order to compute the DSR hyper-plane boundary for transient stability assessment (TSA), and to enhance the system stability margin by performing appropriate preventive strategies. Also, an approach to achieve on-line VA by tracking the boundary of the security region is outlined in [7]. These approaches have been focused on analyzing only one electric phenomenon (commonly TSA), with the goal of leading the system to a more secure steady state operating condition (by performing preventive control). In recent years, emerging technologies such as Phasor Measurement Units (PMUs), and Wide Area Monitoring, Protection and Control Systems (WAMCP) have enabled developing modern VA methods [4], [5], [8]. Most of the current PMU-based approaches have been designed in order to perform preventive control actions, following the traditional practice. Nevertheless, the use of PMUs has a great potential to allow performing post-contingency dynamic vulnerability assessment (DVA) that could be used to trigger corrective control actions [4]. This paper presents a novel approach to determine the post-contingency Dynamic Vulnerability Region (DVR), taking into account three short-term stability phenomena, which could be used for performing real time post-contingency DVA in order to establish appropriate corrective control actions. The method applies Monte Carlo

This work was supported in part by the German Academic Exchange Service (DAAD), the University Duisburg-Essen, and the National University of San Juan.

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978-1-4673-2729-9/12/$31.00 ©2012 IEEE

simulation with the aim of obtaining post-contingency dynamic data of some electric variables, which could be available directly from PMUs in a real system (voltage phasors, or frequencies), considering several possible operating conditions. Afterwards, a new oscillatory and trend pattern recognition method is applied to the data in order to numerically establish the DVR spatial locations. This pattern recognition method has been developed by applying some time series Data Mining techniques, such as Multichannel Singular Spectrum Analysis (MSSA), and Principal Component Analysis (PCA).

The paper is organized as follows. Section II presents a theoretical framework. Section III depicts the proposed methodology for determining DVRs. Section IV shows a simulation on a test power system that demonstrates the performance of the proposal. A short discussion is shown in section V. Finally, the conclusions are presented in section VI.

II. Theoretical Framework

A. Power System Vulnerability

A vulnerable system is a system that operates with a "reduced level of security that renders it vulnerable to the cumulative effects of a series of moderate disturbances" [8]. Vulnerability is a measure of the system weakness upon cascading events [8]. The concept of vulnerability involves the system security level (i.e. static and dynamic security) and the tendency of changing its conditions to a critical state [9] that is called the "Verge of Collapse State" [10]. Vulnerability is characterized by four different symptoms of system stress such as angle instability, voltage instability, frequency instability, and overloads [10].

This paper focuses on the three symptoms of system stress related to system stability, limiting the time frame of interest to 20 seconds. This window includes the so-called short-term stability phenomena, which comprises transient stability, short-term voltage stability, and short-term frequency stability.

A.1. Transient Stability

Rotor angle stability refers to the ability of synchronous machines to remain in synchronism after being subjected to a disturbance. Transient stability (TS) is a type of rotor angle stability that occurs when the system is subjected to a severe disturbance (e.g. short circuit on a transmission line). The time frame of interest in this phenomenon is usually 3 – 5 seconds following the disturbance [11].

A.2. Short-Term Voltage Stability

Voltage stability (VS) refers to the ability of a power system to maintain steady voltages at all buses in the system after being subjected to a disturbance. Short-term voltage stability involves dynamics of fast acting load components such as induction motors, controlled loads, and HVDC converters. The time frame of interest is in the order of several seconds. Load dynamic modeling is often essential. Short circuits near loads could cause relevant effect in this type of stability [11].

A.3. Short-Term Frequency Stability

Frequency stability (FS) refers to the ability of a power system to maintain steady frequency following a severe system upset resulting in a significant imbalance between generation and load. Short-term frequency instability is characterized by the formation of an under-generated area with insufficient under-frequency load shedding such that frequency decays rapidly causing the area blackout within a few seconds [11].

B. Power System Dynamic Modeling

The actual power system behavior is predicted using computer based simulations. For this purpose, the several physical components of the system are adequately modeled in order to accurately represent the performance of the power system [12]. The aim is to mathematically represent the power system through a set of differential algebraic equations (DAE) (1), whose solution represents the time domain dynamic system trajectory.

$$\begin{aligned} \dot{x} &= f\left(x, y, t\right), \qquad x\left(t_0\right) = x_0 \\ 0 &= g\left(x, y, t\right), \qquad y\left(t_0\right) = y_0 \end{aligned} \tag{1}$$

where f is the set of differential equation, g is the set of algebraic equation, x is the vector of state variables, and y is the vector of algebraic variables.

Simulating the power system with enough detail is a basic requirement in the design of protective strategies. Since VA has the function of detecting the necessity of performing global control actions, system modeling must satisfy this accuracy constraint. Moreover, the simulation software has to be capable of handling detailed models and guarantying reliable results.

B.1. Typical Components

Dynamical simulations require the detailed modeling of power system components which are involved in the time frame of interest for the specific analysis. Some components are typically modeled with enough detail in traditional dynamical studies. These components include: synchronous generators, excitation control systems (AVR, exciter, and PSS), asynchronous generators, turbine and governor controls, HVDC, FACTS, among others.

B.2. Load Modeling

While most of the dynamical simulations consider the modeling of typical components, load modeling is often treated as negligible in stability analysis [13]. However, since load has great influence on power system stability [14], its proper representation in high-voltage buses is strictly necessary in this kind of studies in order to obtain satisfactory dynamic responses during time domain simulations. Furthermore, it is essential to consider that some portion of the load, typically 50% to 70%, is composed of motors. Motors can be considered based on typical induction motor models. It is not strictly necessary to include dynamic motors at every load bus, so long as the desired portion of total load in an area is represented as motors [14].

This paper considers three main aspects in load modeling:

- Some portion of the load is simulated by dynamic motors. The induction machine model "Type 2" has been considered for the simulations [15].
- The remaining load is simulated considering 50% constant impedance model, and 50% voltage-exponential and frequency-dependent static load model [14].
- Three types of load classes are considered: residential, commercial, and industrial. Each one of these classes has different daily load curves and specific model parameters.

B.2. Protection Devices

Due to the fact that the system variables may exceed their admissible reference ranges after the occurrence of most severe contingencies, the tripping of associated protective relays might initiate a potential cascading event. Then, main protection devices related to the simulated phenomena have to be also considered. Three types of protection devices are modeled in this paper: out-of-step relays, under and over voltage relays, and under and over frequency relays. The tripping of one or more of these protection relays is used as the indicator of an imminent cascading event.

C. Dynamic Vulnerability Assessment

Many methods have been proposed for vulnerability assessment [8]. Conventional methods are based on different complex model simulations that usually entail time-consuming tasks [4]. These methods are based on analyzing the SSA or DSA of *N-x* critical contingencies [4], [8]. Emerging technologies, such as PMUs, have enabled developing modern approaches for vulnerability assessment [4], [5], [8]. These methods can fulfill the real time application requirement of not exceeding a couple of seconds in the entire process [5]. In order to achieve this goal, appropriate tools to quickly analyze huge volumes of data are required. PMUs can provide time-synchronized phasor data, which contain valuable dynamic information that might indicate the system vulnerability status and potential collapses [8]. These post-contingency data offer a new framework for assessing vulnerability, which could be named as "Dynamic Vulnerability Assessment". This potential application made PMUs fundamental in the basic architecture of a Self-Healing Grid. However, despite the valuable dynamic information data obtained from PMUs, they could not be able to give any information about the system health by themselves. So, it is necessary to develop mathematical tools capable of quickly analyzing the data in order to assess dynamic vulnerability in real time. Artificial intelligence or modern data mining techniques can swiftly process the data, allowing the identification of patterns that show system vulnerability [4], [8].

From the concept of vulnerability, real time DVA should perform two tasks as quickly as possible. The first task is to assess the system security level and the second is to analyze the system tendency of changing its conditions to the verge of collapse state. These tasks might be achieved by defining a post-contingency DVR, and specifying the post-contingency dynamic state relative position with respect to the DVR boundaries.

D. Dynamic Vulnerability Region

The concept of Dynamic Security Region has been used in order to define a method for security assessment. In this sense, DSA is defined as "the determination of whether the actual operating state is within the DSR". The DSR can be defined in the injection space, depending on the analysis of TSA [6]. This DSR can be approximated by hyper-planes, and the computation of their boundaries allows specifying the actual state relative position (or "security margin") with respect to them [6]. The aim of this assessment is to enhance the system stability margin through performing appropriate preventive control actions.

Using the same concept as DSR, a Dynamic Vulnerability Region can be defined in order to perform post-contingency DVA with the aim of conducting corrective control actions. This DVR can also be specified by hyper-planes as in (2).

$$f\left(\mathbf{x}\right)=c \tag{2}$$

where $\mathbf{x}$ is an n-dimensional vector, and c is a constant that represents the value of the VA boundary [7].

The DVR and the hyper-plane boundaries of a dynamic system can be determined analytically or numerically. However, due to the huge complexity of the bulk power systems, determining their DVRs analytically is not possible [7]. Then, numerical methods offer the possibility of considering the complex power system physical model through simulation of several dynamic operating states. Monte Carlo methods are appropriate for analyzing the complexities in large-scale power systems with high accuracy, at the expense of more computational efforts [16].

III. Proposed Methodology

Based on the system settled operating policies (e.g. pre-defined system topology changes and dispatch rules) and the probabilistic models of input parameters (i.e. as load variation and the occurrence of contingencies), Monte Carlo-type simulation is performed to iteratively evaluate the system time domain responses, which would resemble those recorded by PMUs in real time, with the ultimate goal of structuring a dynamic performance data base. The dynamic probabilistic attributes are then analyzed using time series data mining techniques, namely Multichannel Singular Spectrum Analysis (MSSA), and Principal Component Analysis (PCA), in order to recognize the system DVRs based on the patterns associated to the three above-mentioned short-term stability phenomena. This procedure is schematically summarized in Fig. 1.

A. N-1 Contingency Monte Carlo Simulation

Traditionally, power system contingency analysis has been studied using deterministic methodologies, which consider some extreme operating conditions (different load levels), and selected critical contingencies (associated to some fault types and fault locations) [16]. This type of studies ignores the stochastic or probabilistic nature of real power systems, and therefore certain severe events that could lead the system to potential insecure conditions may be ignored [16].

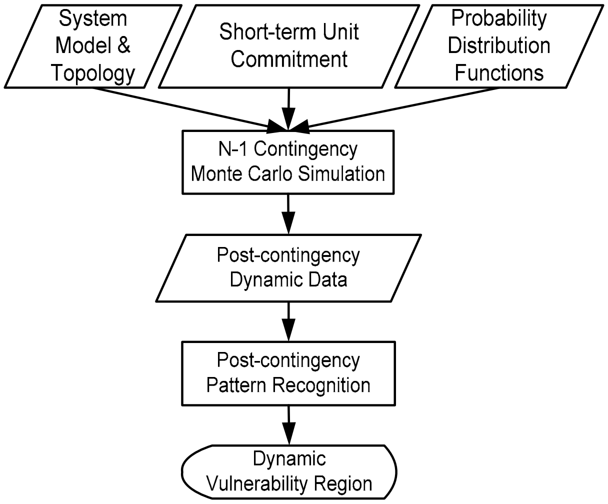

Fig. 1. Methodological framework

Since the huge volume of uncertainties greatly influence the power system dynamic response, it is necessary to apply mathematical tools which allow considering all the probable scenarios. One of the main classes of probabilistic techniques is the Monte Carlo-based simulation, which provides the possibility of obtaining more realistic results, mainly for complex system analysis [16], since it avoids using surrogate models.

The DVRs are proposed in order to take advantage of the great potential of PMUs to allow performing post-contingency DVA that can be used to trigger corrective control actions in real time. Conventionally, these corrective actions are set to perform when specific pre-established operational conditions are reached, and they are unable to work under unconsidered contingencies that could begin cascading events.

This paper proposes using Monte Carlo simulation as a method to obtain post-contingency dynamic data of some electric variables, which would be available directly from PMUs in a real system (i.e. voltage phasors or frequencies), considering several possible operating conditions and contingencies, including the most severe events that could lead the system to potential insecure conditions, and subsequent cascading events. Afterwards, a post-contingency pattern recognition method is applied to the obtained data for numerically establishing the power system DVRs.

Monte Carlo method is a repetitive procedure that consists of evaluating, at each repetition, the system response, using a set of input variables which are generated randomly from their probability distribution functions (PDFs). Hence, numerical random output values are obtained [17]. These numerical outputs are used to determine the DVRs for the bulk power system under analysis. Fig. 2 depicts the Monte Carlo simulation procedure.

In order to adequately apply Monte Carlo simulation and obtain realistic results of the post-contingency dynamic response, some basic considerations and modeling requirements are taken into account.

- Properly PDFs randomly generate the input variables to be considered in the Monte Carlo simulation: i.e. the load in each bus, the type of contingency (e.g. short circuit or generation outage), the faulted element (line or generator), and the short circuit location.
- The DVRs can be defined for either short-term or long-term phenomena. The time frame of interest in this paper comprises several seconds. Therefore, the obtained DVRs focus on three phenomena defined as short-term stability, which comprises transient stability, short-term voltage stability, and short-term frequency stability [11].
- Since the accuracy of the DVR boundaries depends on the accuracy of the models, the dynamic components (generators, motors, loads) and relevant control systems (such as excitation control system, and speed governor systems) are modeled with enough detail [16].
- The simulated events are based on contingencies N-1, and the vulnerability criterion consists in the possibility of this kind of disturbances driving the system to further undesirable events (i.e. N-2 contingencies), which are considered as the beginning of a cascading event.

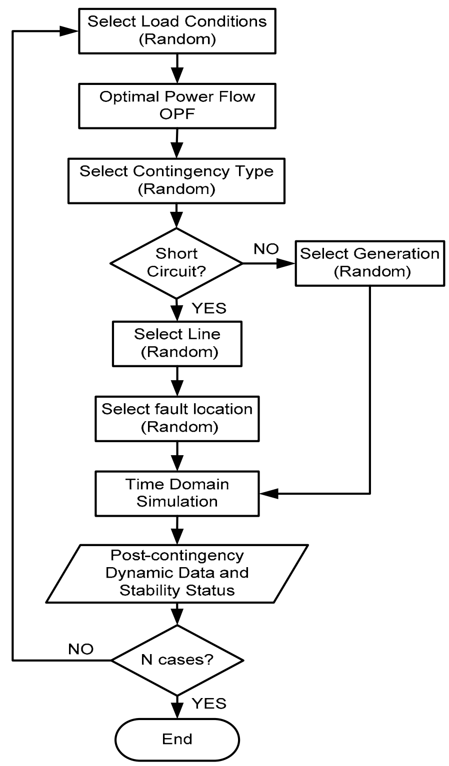

Fig. 2. N-1 contingency Monte Carlo simulation procedure

B. Post-contingency Pattern Recognition Method

The required mathematical tool for achieving the tasks involved in the post-contingency DVA has to be capable of predicting the post-contingency system security status, and specifying the actual dynamic state relative position with respect to the DVR boundaries, with reduced computational effort, and quick-time response. Pattern recognition based methods have the potential to effectively achieve this goal.

Pattern recognition is concerned with the automatic discovery of similar characteristics in data by applying computer algorithms and using them to take some action such as classifying the data into different categories, i.e. classes [18]. Dynamic electric signals can exhibit certain regularities (patterns) alerting a possibly vulnerable condition. However, these patterns are not necessarily evident in the electric signal, though it has some immersed hidden information which can be uncovered by a proper pattern recognition tool [4].

This paper uses a novel methodology for recognizing patterns in post-contingency bus features in order to numerically determine the DVRs of a specific Electric Power System. This methodology was firstly introduced in [4]. The method uses some time series data mining techniques, such as Multichannel Singular Spectrum Analysis (MSSA), and Principal Component Analysis (PCA).

The data consist of measurements of some dynamic post-disturbance synchronized measured variables (voltage phasors, frequencies) at p spatial locations (buses where PMUs are installed) at n different times. The measurements at the different spatial locations are treated as variables and the time points play the role of observations [19], constituting a ($n \times p$) data matrix (**X**).

The method has two stages: the Pattern Decomposition function and the Dimension Reduction function. Fig. 3 presents the scheme of the pattern recognition method.

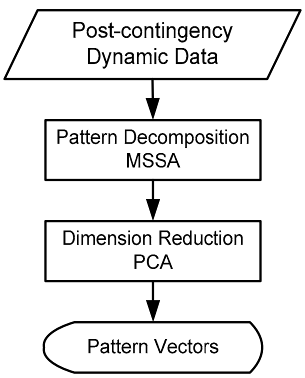

Fig. 3. Post-contingency pattern recognition method

B.1. Pattern Decomposition Function

The Pattern Decomposition function allows analysis of the hidden information in the time series data by identifying its oscillatory and trend patterns. Hence, Multichannel Singular Spectrum Analysis (MSSA) is applied.

Singular Spectrum Analysis (SSA) is a principal component-like technique used to analyze the autocorrelation in the time series data [19]. The main purpose of SSA is to decompose the original series into a sum of series, so that each component in this sum can be identified as a trend, a periodic or a quasi-periodic component [20]. SSA is a principal component analysis done with lagged versions of a single time series as the variables [19], called the *m-lagged* vectors [20]. Multichannel Singular Spectrum Analysis (MSSA) is an extension of SSA to several time series in different spatial locations [19]. The fundamental property of MSSA resides in its ability to detect oscillatory spatial patterns [19].

In order to perform MSSA, the $\mathbf{X}_{n \times p}$ data matrix are rearranged into a larger ($n' \times p'$) matrix ($\mathbf{X'}$), where $n' = n-m+1$, $p' = mp$, and m is the window length of the lagged vectors that is an integer so that $2 \leq m \leq n$ [19][20]. Choosing $m = n/4$ is a common practice [19]. A typical row of this matrix is shown in (3).

$$\mathbf{x}'_i = \left(x_{i1}, x_{(i+1)1}, \ldots, x_{(i+m-1)1}, x_{i2}, \ldots, x_{(i+m-1)2}, \ldots x_{(i+m-1)p} \right) \quad (3)$$

where $i = 1, 2, \ldots, n$, and x_{ij} is the value of the measured variable at the i^{th} time point and the j^{th} spatial location [19].

After the X' data matrix has been determined, PCA has to be performed to this data set. The obtained principal component coefficients (eigenvectors) are the empirical orthogonal functions (EOFs) [19] which represent the orthonormal basis that offer the best interpretable patterns of the multi-spatial time series data. Furthermore, the corresponding principal component scores represent the projection of the data in the direction of the EOFs. The resulting data set corresponds to the main patterns of the dynamic post-disturbance data, and represents a specific pattern trajectory.

B.2. Dimension Reduction Function

The Dimension Reduction function allows reducing the dimensionality of the pattern trajectories obtained from the Pattern Decomposition function. The aim is to represent the patterns through two or three dimensional vectors, which can also be graphically illustrated. Thus, PCA is applied to the obtained data set of patterns in order to maintain as much as possible of the variation presented in them [19].

The principal component scores obtained from the application of PCA form vectors of real numbers that represent the dynamic behavior of the system. These pattern vectors permit mapping the DVRs represented in the coordinate system formed by the main EOFs.

IV. Simulation Results

The methodology is tested on the IEEE New England 39 bus test system [21], lightly modified in order to satisfy the N-1 security criterion. Simulations consist in several contingencies where the causes of vulnerability could be transient instability, short-term voltage instability, or short-term frequency instability. These contingencies are generated by applying the Monte Carlo method. Two types of events are considered: three phase short circuits and generation outage. The short circuits are applied at different locations of the transmission lines, depending on the Monte Carlo simulation. The disturbances are applied at 0.12 s, followed by the opening of the corresponding transmission line at 0.2 s. Likewise, the generation to be tripped is also chosen by the Monte Carlo method, and this type of contingency is applied at 0.2 s. Several operating states have been considered by varying the load of PQ buses, depending on three different daily load curves. Then, optimal power flow (OPF) is performed in order to establish each operating state, using the MATPOWER package [22]. After that, time domain simulations have been performed using the DIgSILENT Power Factory software, so that the post-contingency dynamic data could be obtained. In order to apply the method, it is assumed that four PMUs, with one cycle (16.67 ms) updating period, are installed in the high voltage buses 1, 4, 16, and 28. Fig. 4 shows the single-line diagram of the test system.

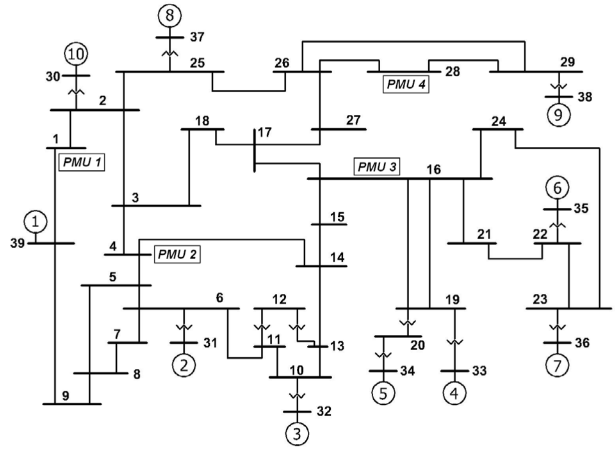

Fig. 4. IEEE New England 39 Bus test system single-line diagram [21]

Both voltage components (magnitude and angle), and bus frequencies are considered as the input variables. A total number of 4,000 cases have been simulated, from which 2,103 are transient unstable, 238 are frequency unstable, 124 are voltage unstable and 1,535 are stable (non-vulnerable).

In order to adequately show the system response for the different stability phenomena, several time windows are analyzed. These time windows are established depending on the Monte Carlo statistics of the relay tripping times. Fig. 5 shows the relay tripping time histograms, where the reference frame corresponds to the time simulation.

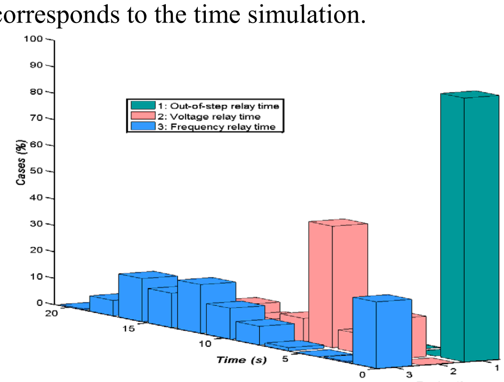

Fig. 5. Relay tripping time Histograms

The out-of-step relay time has a mean of 1.232 s and a minimum value of 0.826 s. These values resemble the quick evolution of TS. Hence, vulnerability assessment has to be done in less than 0.626 s after the fault clearing (0.2 s in this case) in order to be able to carry out some corrective action. For this reason, an adequate data window (DW) for TS phenomenon can be 300 ms starting from the fault clearing. The tripping of frequency relays presents two clearly disjointed distributions, whose boundary is between 4 – 5 s. This situation leads to consider two types of short-term FS: Fast and Slow. Therefore, two different DWs are considered for each type of phenomenon: 0.8 s and 4.8 s, respectively. The voltage relay time shows a mean of 8.66 s and a minimum value of 3.22 s. The chosen DW for VS phenomenon is 1.8 s.

Fig. 6 shows the results of the MSSA applied to the time series data matrix formed by the voltage angles, considering the 300 ms TSA data window. Four different instances are shown: a non-vulnerable case, a transient vulnerable case, a frequency vulnerable case, and a voltage vulnerable case. The obtained trajectories reveal the hidden patterns of the dynamic post-disturbance data.

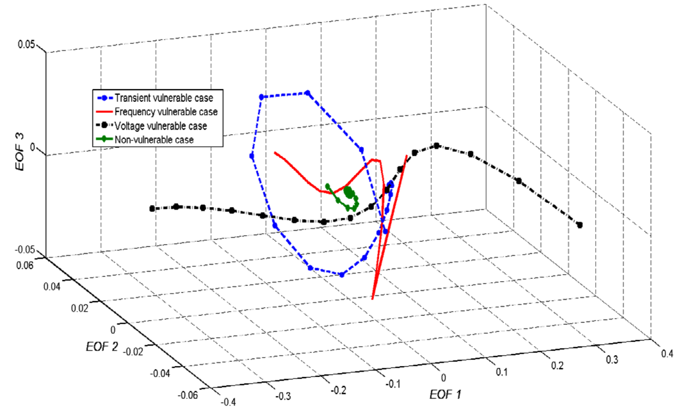

Fig. 6. Pattern trajectories obtained from MSSA

To determine numerically the DVR, PCA is carried out to the obtained pattern trajectories in order to reduce their dimensionality to a set of two dimensional pattern vectors. Then, these vectors are linearly scaled in the range of [0, 1].

Fig. 7 and 8 present the two dimensional distribution of the pattern vectors obtained from the voltage angles and magnitudes, respectively, which determine the DVRs for transient stability. In both figures, the blue areas represent the vulnerable regions (for TS); whereas the white areas correspond to the non-vulnerable regions. These areas have been empirically delimited, bordering the obtained pattern shapes which depend on the pattern vector spatial locations. The shaded yellow areas denote the overlapping between transient stable and unstable cases. The overlapping is due to the high similarity between patterns of those cases in which the operating conditions are quite near to the stability reference limits. This situation would entail a certain risk level regarding the selection of the most suitable corrective control actions, thus pointing out the need of using some kind of expert-knowledge-based decision techniques.

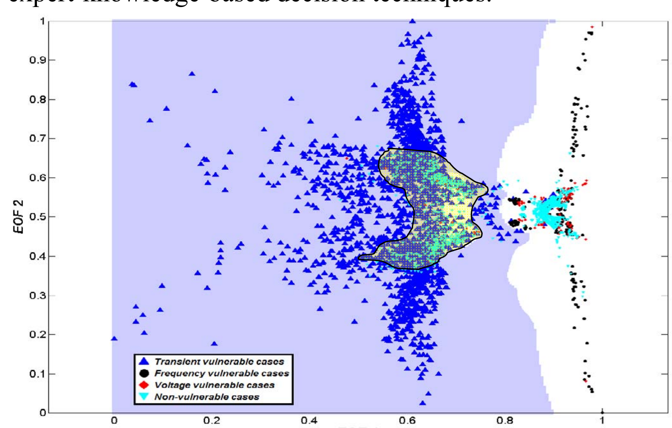

Fig. 7. Voltage-angle-based DVR for TS – 300 ms DW

Note also that the shapes of the patterns and the overlapping areas are different when comparing both figures. It is worth to mention that the stable cases in the overlapping area in Fig. 7 might be confused as unstable, whereas the unstable cases in the overlapping area in Fig. 8 might be confused as stable. Nevertheless, a more comprehensive joint pattern analysis of both features (voltage angle and magnitude) would provide an improved classification.

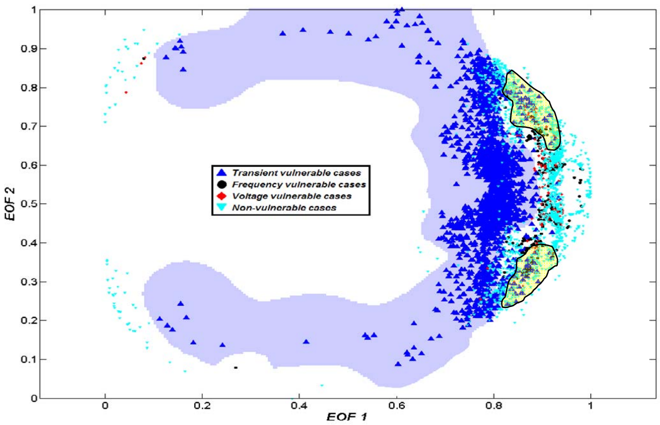

Fig. 8. Voltage-magnitude-based DVR for TS – 300 ms DW

Fig. 9 shows the two dimensional DVR for short-term voltage stability, obtained from the analysis of the voltage magnitudes. In this case, the overlapping is less noticeable as compared to the previous figures. Note the closeness between voltage instability and frequency instability cases. This is reasonable given the strong relationship between both phenomena. Furthermore, this kind of overlapping would not adversely affect the effectiveness in alerting the system stress.

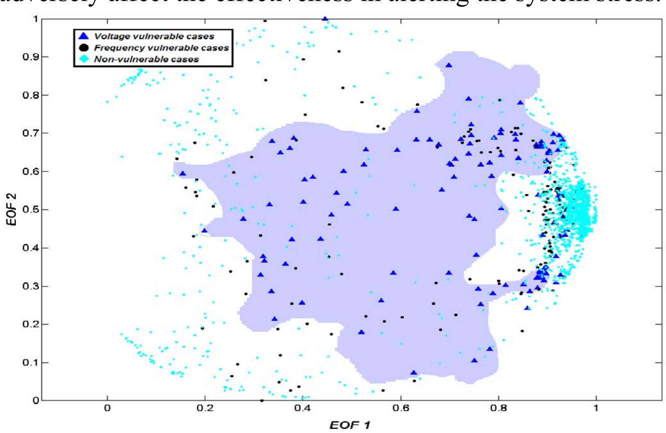

Fig. 9. Voltage-magnitude-based DVR for Short-term VS – 1.8 s DW

Fig. 10 and 11 depict the DVRs for fast and slow short-term frequency stability, respectively. These DVRs are determined by exploring the post-contingency bus frequencies. In these phenomena the overlapping is almost negligible and the separation between stable and unstable cases is well defined.

From the results, it is possible to observe that Monte Carlo simulation and the post-contingency pattern recognition method allows determining numerically the DVRs for different types of stability phenomena. The DVRs are established using only a small window of post-contingency data, which could be obtained directly from PMUs located in some high-voltage transmission buses. Since the DVRs consider time windows less than the minimum relay time tripping, the proposed mathematical tool is capable of predicting the system response. Thus, the methodology can be used to analyze the system tendency of reaching an unstable condition, which constitutes a challenge for performing real time DVA as a part of a Self-Healing-Grid structure.

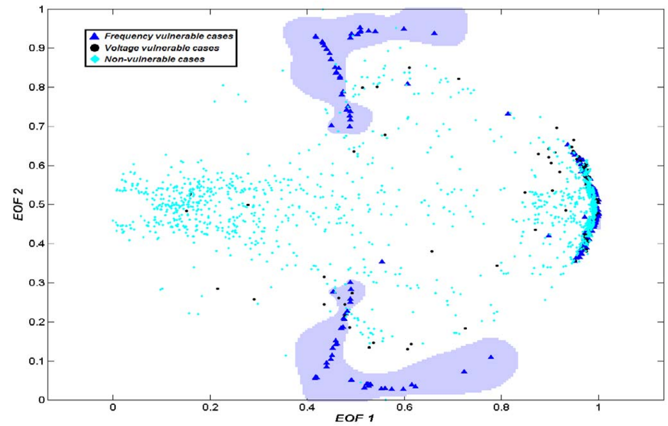

Fig. 10. Frequency-based DVR for Fast-short-term FS – 0.8 s DW

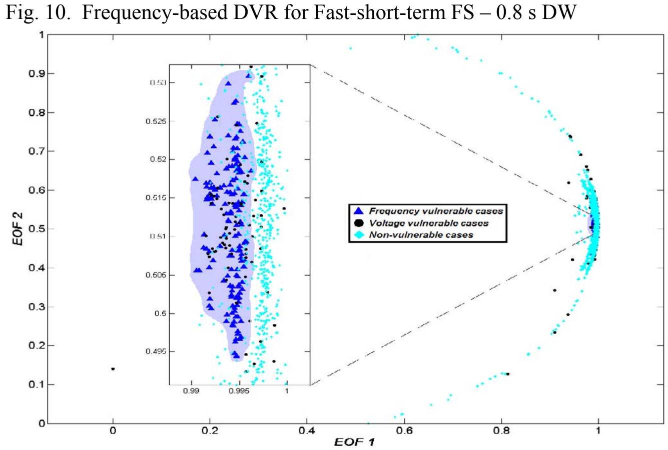

Fig. 11. Frequency-based DVR for Slow-short-term FS – 4.8 s DW

V. Discussion

Commonly, a major system failure is the result of cascading events [2], [5]. Due to the huge amount of uncertainties, deterministic studies cannot consider all the possible scenarios that might drive the system to cascading events and blackouts. Thus, the use of risk-based vulnerability assessment, which considers the multiple possibilities of the system becoming vulnerable, has to be considered [2]. The methodology presented in this paper offers a new dynamic benchmark for determining the range of post-contingency normal system behavior, considering multiple operating scenarios and several stability phenomena. Since the goal is to classify the system status in "vulnerable" or "non-vulnerable" in real time, additional research is needed for technically establishing the boundaries of the DVRs. An alternative might be using an intelligent classifier such as Maps of Kohonen, which uses a type of self-organized neural network, or Support Vector Machine Classifier (SVM-C) [4], which computes an optimal hyper-plane that separates the vector space depending on each class spatial location, and additionally agrees with the hyper-plane-based definition of DVRs laid in this paper. The overlapping between stable and unstable cases show the existence of a certain risk level in classifying the system vulnerability in the stability limits, which should be considered in the decision making policies in order to avoid wrong significant control actions (i.e. generation tripping).

VI. Conclusions and Future Work

A novel methodology for determining post-contingency dynamic vulnerability regions using Monte Carlo simulation and time series data mining techniques has been presented. This proposal considers three different short-term stability phenomena as the potential causes of vulnerability and constitutes a useful tool for empirically mapping DVRs due to its ability to consider relevant operating statistics, including the most probably severe events that could lead the system to potential insecure conditions, and subsequent cascading events. It is demonstrated that time series data mining techniques are valuable to find hidden patterns in dynamic electric signals, which are used for determining the system DVRs. These DVRs could be used to specify the actual dynamic state relative position with respect to their boundaries, which might be established using an intelligent classifier. In addition, the methodology would allow structuring intelligent algorithms for carrying out corrective control actions in real time. Future research work is necessary to reach this task.

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VIII. Biographies

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Delia G. Colomé was born in 1959. She obtained her Electronic Engineer degree in 1985 and her Ph.D. degree in Electrical Engineering in 2009, both from National University of San Juan, San Juan, Argentina. Since 1983, she has been a researcher and a Professor at Institute of Electrical Energy at National University of San Juan. During this time, she has worked as project manager and as senior engineer in numerous technical support projects in Argentina and different Latin-American countries. Her main fields are control and supervision of power systems, modeling and simulation of power systems, and the development of computational tools for engineering teaching.