

# Probabilistic Approach-based PMU placement for real-time Power System Vulnerability Assessment

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**Abstract**--Recently, several smart grid applications have been designed to improve monitoring, protection and control of power systems in real time. Most of these emerging approaches exploit the capabilities of wide-area technologies (wide area monitoring, protection and control - WAMPAC). Since WAMPAC implementation requires distributed phasor measurements throughout the system, phasor measurement units (PMUs) have to be adequately located depending on the real-time application. This paper addresses the problem of PMU placement with the aim of achieving high observability of system dynamics that are associated to transient and other short-term phenomena, in order to perform reliable real-time dynamic vulnerability assessment. Thus, a hybrid approach to determine suitable PMU locations that allows ensuring observability of slow and fast dynamic phenomena is proposed. The proposal uses Monte Carlo-based simulations to iteratively evaluate the system fast dynamic coherency, as well as the bus oscillatory modal observability. The methodology is tested on the IEEE New England 39-bus test system. Results show the feasibility of the methodology for orienting the selection of buses that offer the best PMU location in terms of dynamic observability.

**Index Terms**--Coherency, Monte Carlo, fuzzy inference system, phasor measurement units, observability, vulnerability assessment, WAMPAC.

## I. INTRODUCTION

NOWADAYS, there are important efforts to improve monitoring, protection and control tasks in power systems, which are mainly related to the development of the wide-area measurement system technology (WAMPAC applications). This new technology constitutes an important component of the so-called Smart Grid, since it would allow performing timely self-healing and adaptive reconfiguration actions (i.e. Self-Healing Grid).

WAMPAC involves distributed phasor measurements throughout the network by means of phasor measurement units (PMUs). PMUs have attracted the attention of power engineers, especially for real time applications, since they can provide synchronized measurements of real-time phasors of voltage and currents [1].

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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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A strategic placement of PMUs is basically necessary to effectively ease the real-time processing and interpretation of huge amounts of data arriving at a high sampling rate [2]. This aspect is especially crucial for the development of Dynamic Vulnerability Assessment (DVA) platforms. DVA involves evaluating different symptoms of post-contingency system stress such as angle instability, voltage instability, frequency instability, and overloads, to quantitatively determine the system security level as well as to ascertain whether the system is moving to the verge of collapse state [3]. A reliable DVA is strongly dependent on high observability of system dynamics, which can be achieved by placing an appropriate set of PMUs whose measurements (containing relevant features associated to fast and slow dynamic phenomena) should be trusted to ensure a satisfactory dynamic tracking performance.

In the last decade, significant research work was devoted to the PMU placement problem for static state estimation. Besides, several approaches have been published in recent literature for identifying the amount and placement sites of PMUs with dynamic considerations. In [2] and [4], the problem is tackled through a combination of disturbance-based coherency analysis and fuzzy clustering, whereas it is solved based on graph theory and extended Kalman filter tracking in [5] and [6], respectively. Nevertheless, the literature on PMU location considering simultaneously both fast and slow dynamic coherency, is still scant. Traditionally, slow-coherency is analyzed via model-based eigenanalysis using linearized system models, and has mainly focused on generator coherency assessment and aggregation for network reduction purposes. On the other hand, fast coherency analysis is based on measured transients, which enable capturing hidden fast dynamic phenomena patterns excited when a perturbation occurs in the system, which cannot be observed using linearized models. The characteristics of fast dynamic phenomena are highly dependent on the system loading condition, and the nature and size of the perturbation, which are also reflected in post-contingency coherency.

This paper presents a hybrid approach to determine suitable PMU locations that allows ensuring observability of slow and fast dynamic phenomena in order to accurately perform DVA in real-time. The approach uses Monte Carlo-based (MC) simulations to iteratively evaluate the system fast dynamic coherency, as well as the bus oscillatory modal observability, considering all the possible operating scenarios.

The paper is organized as follows. Section II depicts the proposed methodology. Section III presents simulations on a

test power system that demonstrates the performance of the proposal. Finally, the conclusions are drawn in section IV.

## II. PROPOSED METHODOLOGY

The proposed methodology has the aim of determining the buses that offer the best average dynamic observability based on probabilistic analysis. For this purpose, fast and slow coherencies are analyzed using Monte Carlo simulation.

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: i) the system time domain responses, with the goal of analyzing the system fast dynamic coherency, and ii) the oscillatory modal observability, for determining a probabilistic indicator of area slow coherency.

### A. Fast dynamic coherency

Fast dynamic coherency can be evaluated using measurement of dynamic electric signals, which have some immersed hidden information that might not be observed using linearized models. This type of coherency is highly dependent on the system loading condition, and the nature and size of the perturbation.

After each Monte Carlo iteration, the dynamic attributes are used to decompose the power system into coherent electric areas, using a modified version of the clustering approach presented in [4]. This coherency calculation method is based on Fuzzy C-means algorithm (FCM). Methodological modifications have been integrated in order to incorporate the effects of both voltage (angle and magnitude) and frequency in each bus. For this purpose, principal coordinate analysis (PCA) is included. The proposal is schematically summarized in Fig. 1.

Considering independently voltage (angle and magnitude) and frequency at each bus as the analyzed variables, three dissimilarity matrices are built: one for voltage angles ( $\mathbf{D}_\theta$ ), another for voltage magnitudes ( $\mathbf{D}_V$ ), and the last for frequencies ( $\mathbf{D}_F$ ), taking into account the criteria defined in [4].

$$\mathbf{D} = \begin{bmatrix} 0 & \delta_{12} & \dots & \delta_{1n} \\ \delta_{21} & 0 & \dots & \delta_{2n} \\ \cdot & \cdot & \dots & \cdot \\ \delta_{n1} & \delta_{n2} & \dots & 0 \end{bmatrix} \quad (1)$$

where  $n$  is the number of buses, and  $\delta_{ij}$  is the distance between bus  $i$  and bus  $j$  determined via the Recursive Method for Online Coherency Calculation presented in [4].

After building the dissimilarity matrices, the corresponding Similitude Matrices ( $\mathbf{Q}_\theta$ ,  $\mathbf{Q}_V$  and  $\mathbf{Q}_F$ ) can be obtained by (2), where  $\mathbf{I}$  is the identity matrix and  $\mathbf{1}$  is the all-ones vector [7]. These matrices represent the variability between elements (similar to Covariance Matrices).

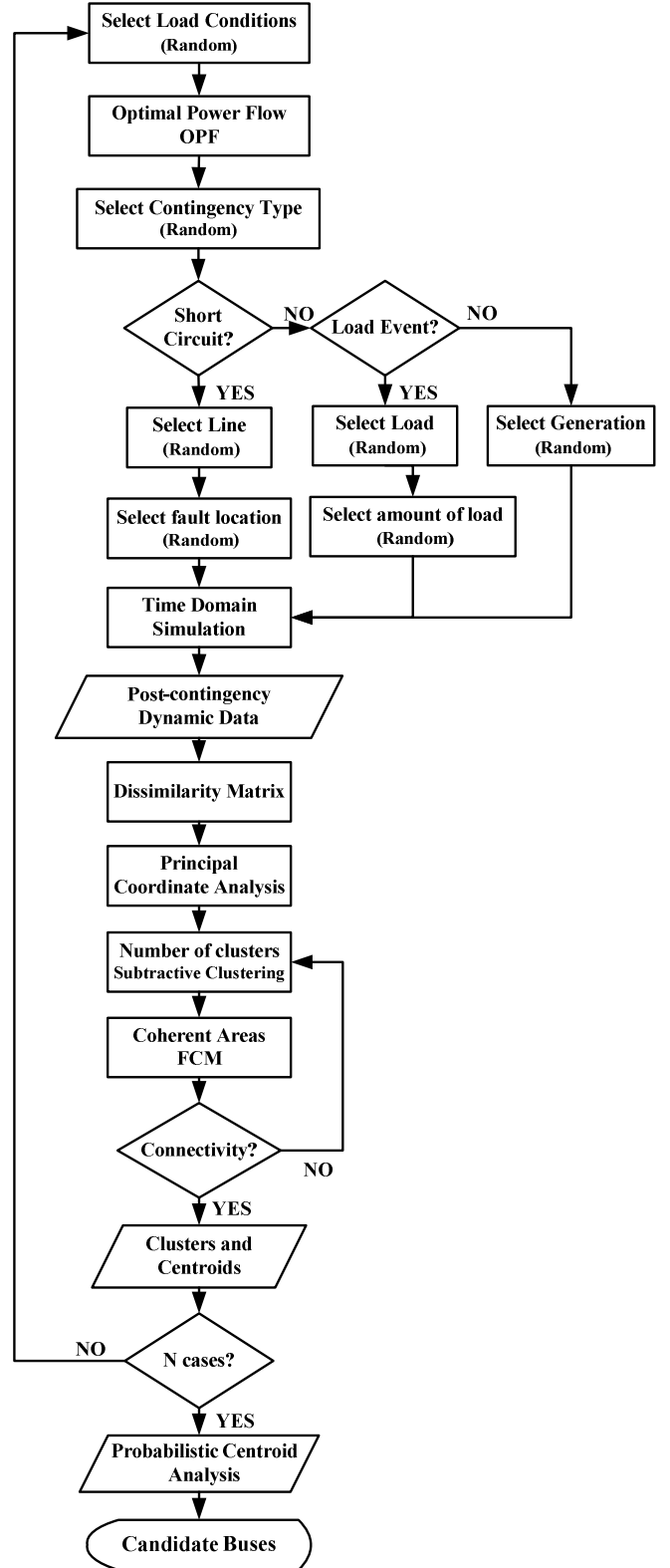


Fig. 1. Fast coherency analysis methodological framework

$$\mathbf{Q} = -\frac{1}{2} \left[ \mathbf{I} - \frac{1}{n} \mathbf{1}\mathbf{1}' \right] \mathbf{D} \left[ \mathbf{I} - \frac{1}{n} \mathbf{1}\mathbf{1}' \right] \quad (2)$$

Using Eigenvalues ( $\Lambda_r$ ) and Eigenvectors ( $\mathbf{V}_r$ ) of the matrices  $\mathbf{Q}_\theta$ ,  $\mathbf{Q}_{VM}$  and  $\mathbf{Q}_F$ , it is possible to calculate their corresponding principal coordinate ( $Y_r$ ) [7], and put them

together to form a multi-dimensional space data matrix ( $X_{0VF}$ ), as shown by (3) and (4).  $Y_r$  is a matrix that contains the new orthogonal variables that keep the original distances (principal coordinates) [7].

$$Y_r = V_r \Lambda_r^{1/2} \quad (3)$$

$$X_{0VF} = [Y_{r\theta} \quad Y_{rV} \quad Y_{rF}] \quad (4)$$

Once the data matrix  $X_{0VF}$  (or  $X_0$ ,  $X_V$ ,  $X_F$ ,  $X_{0F}$ , etc., depending on the considered variables) is determined, their multi-dimensional data points are grouped into a specific number of different clusters using FCM algorithm. Since the number of coherent areas cannot be established a priori, subtractive clustering is used to initialize the FCM.

Since FCM algorithm is a data analysis tool, it does not consider the natural configuration of the grid. In fact, the bus groups that result from application of FCM do not necessarily correspond to real electric areas. Therefore, it is necessary to add an additional routing to the clustering algorithm that checks bus connectivity.

For this purpose, an algorithm that employs the Goderya's theory [8] is used in order to identify bus connectivity. After checking connectivity, new groups of buses can be established and these are the final clusters which represent the electric areas for specific operating states and contingencies. Then, the clustering centroids can be considered as the most suitable locations for PMUs in view of obtaining the best average observability of fast dynamics.

Since coherency may change depending on the operating state and the contingency magnitude, the number and the structure of the electric coherency areas might be different in each Monte Carlo scenario. Therefore, a probabilistic analysis has to be done in order to determine the number of most representative coherent areas ( $n_{areas}$ ), and the buses which constitute their centroids in most scenarios. These buses are then considered as the best candidate buses for PMU location. For this purpose, a decision tree is used in order to track the frequency of the group of buses that constitute centroids at the same time. Fig. 2 depicts the decision tree that tracks the buses being centroids in most scenarios, where  $B_{fmax}$  is the bus that presents the largest frequency being a centroid.

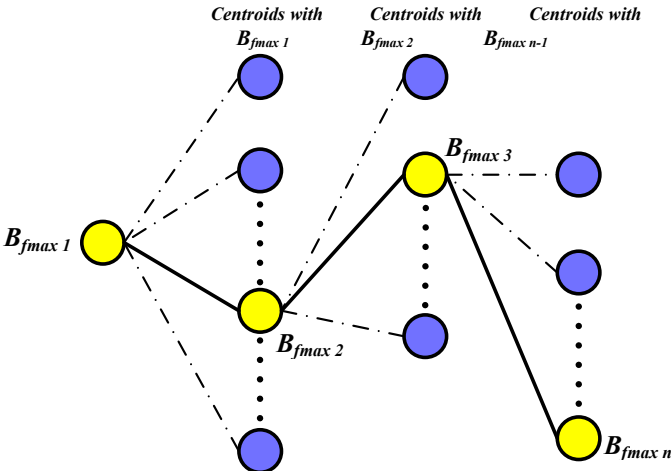


Fig. 2. Decision tree for probabilistic centroid tracking

### B. Slow coherency

After determining the candidate buses from the fast dynamic coherency analysis, the final buses are established considering the maximization of oscillatory observability. This stage can be considered as a slow coherency analysis, since the calculation of the oscillatory mode observability is based on modal analysis. For this purpose, Monte Carlo based probabilistic eigenanalysis (MC-based PE) [9] is performed. The proposed procedure is schematically summarized in Fig. 3.

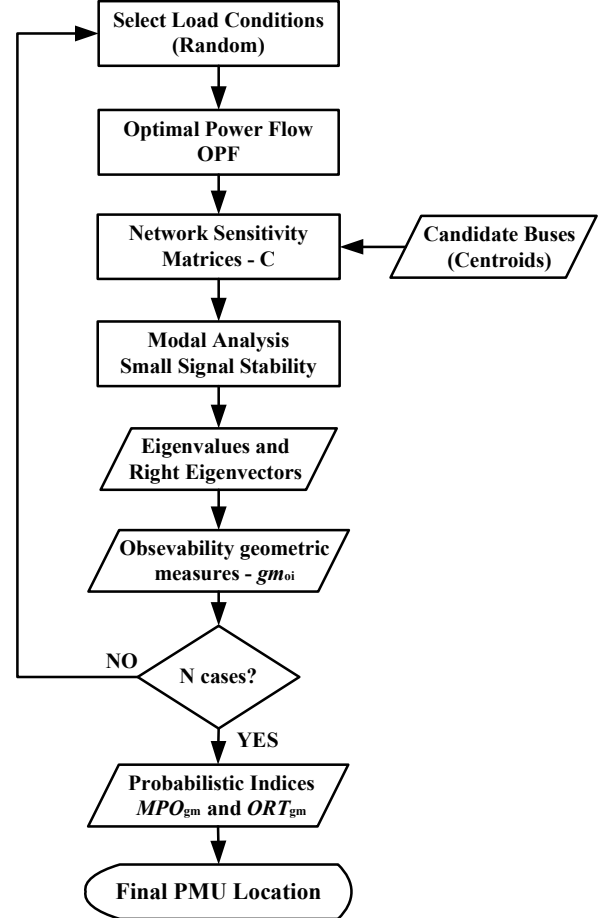


Fig. 3. Slow coherency analysis methodological framework

Once MC-based PE has been completed, probabilistic indexes of observability are calculated. This type of index has been firstly introduced in [9], based on the so-called method of geometric measures of observability (GMO). The geometric measure of observability ( $gm_{oi}$ ), associated with the  $i$ -th mode, is defined by (5).

$$gm_{oi}(j) = \cos(\theta(c_j, \phi_i)) = \frac{|c_j \phi_i|}{\|c_j\| \|\phi_i\|} \quad (5)$$

where  $c_j$  is the  $j$ th row of the network sensitivity matrix  $C$ , corresponding to bus  $j$ ;  $\phi_i$  is the  $i$ th right eigenvector;  $|\cdot|$  and  $\|\cdot\|$  denote modulus and Euclidean norm, respectively;  $\theta(c_j, \phi_i)$  is the geometrical angle between the  $j$ th sensitivity vector and the  $i$ th right eigenvector.

Four different network sensitivity matrices are used, i.e. voltage magnitude sensitivity matrix ( $C_V$ ), voltage angle

sensitivity matrix ( $C_{0v}$ ), current magnitude sensitivity matrix ( $C_1$ ), and current angle sensitivity matrix ( $C_{0i}$ ). These matrices are calculated using the closed-form expressions for network sensitivities presented in [10].

The  $gm_{oi}$  is calculated at each iteration of the MC-based PE, and its corresponding expected value defines the probabilistic measure of observability ( $PO_{gm}$ ), which is introduced in [9].

Since the aim of this paper is to orient the selection of buses that offer, in general, the highest dynamic observability (i.e. average of all dynamics),  $PO_{gm}$  is slightly modified for using the mean of all modes instead of the maximum value, as shown by (6).

$$PO_{gm}(j) = E \left[ \text{mean}_{i=1, \dots, n_i} \left\{ gm_{oi}(j) \right\}_{V, \theta_v, I, \theta_i} \right] \quad (6)$$

where  $E[\cdot]$  is the probabilistic expected value of the  $N$  Monte Carlo scenarios,  $n_i$  denotes the number of eigenvectors related to the considered modes, and  $j$  is the system bus.

Based on the fact that four different network sensitivity matrices are used in order to ensure the observability of dynamics presented in all the possible signals,  $PO_{gm}$  are calculated for these four analyzed variables. Then, an average measure of observability ( $MPO_{gm}$ ) is defined by (7).

$$MPO_{gm}(j) = \text{mean}_{V, \theta_v, I, \theta_i} \left( PO_{gm}(j) \right) \quad (7)$$

Furthermore, the selected buses should give as much information as possible about system oscillatory modes. Then, buses whose modal response is most orthogonal regarding the bus whose  $MPO_{gm}$  is the highest (pivot bus) have to be selected [11], [12]. In this connection, a new index based on the dot product of observability measures is also defined ( $ORT_{gm}$ ).

The first chosen bus will be the one whose  $MPO_{gm}$  is largest, and this bus then constitutes the reference bus for the dot products ( $ORT_{gm} = 1$ ). The rest of buses, at which PMUs will be placed, are the ones whose  $ORT_{gm}$ s are most orthogonal (i.e. closest to zero) to the pivot bus already selected.  $ORT_{gm}$  is defined by (8).

$$ORT_{gm}(j) = \text{mean}_{V, \theta_v, I, \theta_i} \left\{ E \left[ \frac{gm_o(j) \cdot gm_o(pivot)}{\| gm_o(j) \| \| gm_o(pivot) \|} \right] \right\} \quad (8)$$

where  $gm_o$  is a vector whose elements are the geometric measures of observability ( $gm_{oi}$ ), associated with the  $i$ -th mode,  $j$  is the system bus, and  $pivot$  is the first chosen bus whose  $MPO_{gm}$  is the largest.

After calculation of  $ORT_{gm}$ , a joint analysis with  $MPO_{gm}$  has to be performed in order to select the final PMU locations. Since it is possible that several of the candidate buses correspond to the same electric area, these buses have to be clustered into  $n_{areas}$  groups ( $n_{areas}$  is defined by the number of most representative coherent areas obtained from the

probabilistic centroid analysis), depending on the values of  $ORT_{gm}$  and  $MPO_{gm}$ . FCM is also used for this clustering procedure corresponding to the slow coherency stage.

Then, the final buses are those having the maximum  $MPO_{gm}$  and satisfying the most orthogonal values of  $ORT_{gm}$  (i.e. the closest to zero as regards the pivot bus) in each one of the slow coherency clusters. An option might be using the ratio between  $MPO_{gm}$  and  $ORT_{gm}$  as the final indicator of PMU location.

### III. SIMULATION RESULTS

The methodology is tested on the IEEE New England 39 bus test system [13], slightly modified in order to satisfy the N-1 security criterion. Simulations consist on time domain N-1 contingency analysis, and modal analysis. A total of 10,000 scenarios have been considered by applying Monte Carlo method. For fast coherency assessment, three types of events are considered: three phase short circuits, generation outage, and load events. The short circuits are randomly 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 and the load events are also chosen by the Monte Carlo method, and these types of contingencies are applied at 0.2 s. Several short-term 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 [14]. Next, modal analysis and two-second time domain simulations have been performed using the DIGSILENT Power Factory software, in order to determine the post-contingency dynamic data for fast coherency analysis and the geometric observability indices to assess the slow coherency. Fig. 4 shows the single-line diagram of the test system.

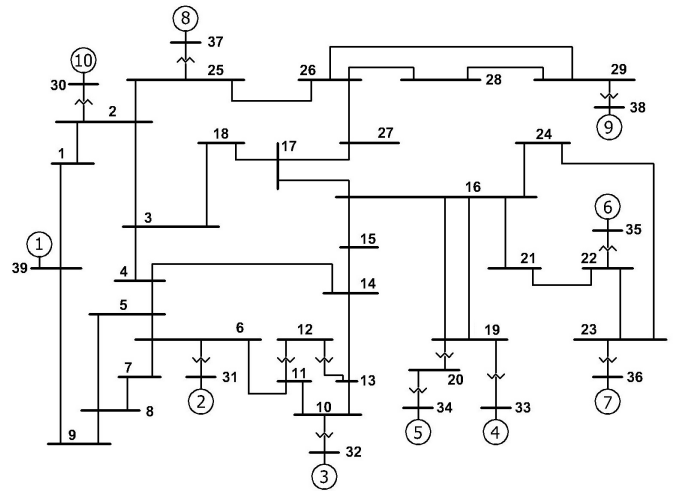


Fig. 4. IEEE New England 39 Bus test system single-line diagram [13]

Fig. 5 and 6 present the bus voltage angles of two different fast coherency MC iterations. Each scenario shows the formation of 2, and 4 coherent areas, respectively.

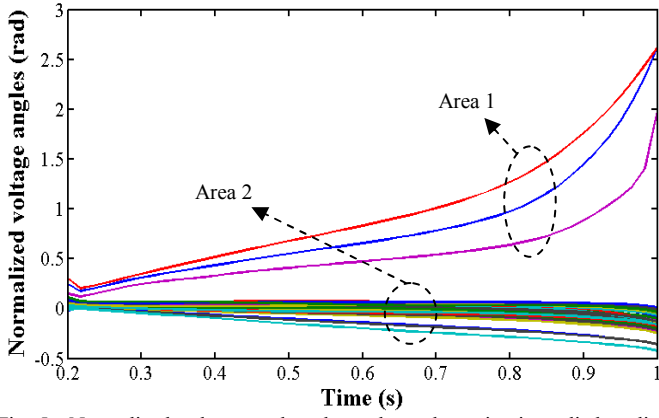


Fig. 5. Normalized voltage angles: three phase short circuit applied on line 26-29 at 38.2% of the line length, high-loaded scenario. Two coherent areas

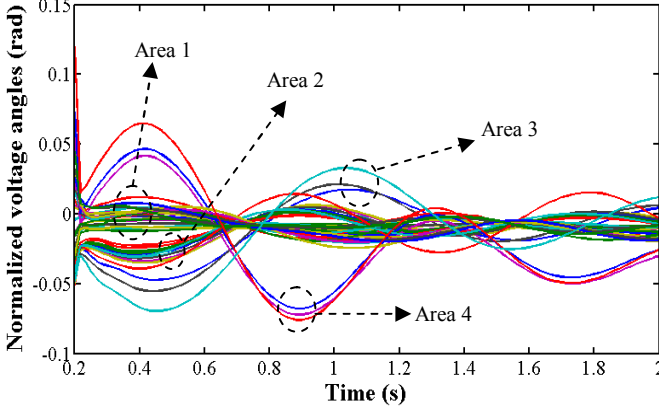


Fig. 6. Normalized voltage angles: three phase short circuit applied on line 26-28 at 91.8% of the line length, low-loaded scenario. Four coherent areas

Based on the previous figures, it is worth to emphasize that electric area coherency may change depending on the operating state and the contingency magnitude, so the number and the structure of the electric coherency areas are different in each Monte Carlo scenario.

Fig. 7 shows histograms of the probabilistic fast coherency area decomposition results, considering four different options of bus variables for structuring the data matrix, i.e. voltage angle, voltage magnitude, frequency, and the combination of these three variables. Although most of the scenarios reveal the formation of 2 or 3 coherent areas, there exist a considerable number of scenarios that present 4 [case (a)], 5 [cases (b) and (c)] and 6 [case (d)] coherent areas. These results correspond to the differences existing between each electric phenomenon (i.e. angle, voltage or frequency) which also provoke the centroids being slightly different in cases (a), (b), and (c). Since the objective of PMU location in this paper is the maximization of dynamic observability considering the several phenomena involved in system vulnerability, the results obtained with the three variables are selected [case (d)]. Then, the adequate number of PMUs for the tested system is 6 (i.e. the maximum possible number of coherent areas).

Afterwards, a probabilistic analysis of the bus centroids considering all the scenarios which present 6 coherent areas has to be done in order to determine the suitable candidate buses. Fig. 8 depicts the frequency of each bus being a centroid for all the six-coherent-area scenarios.

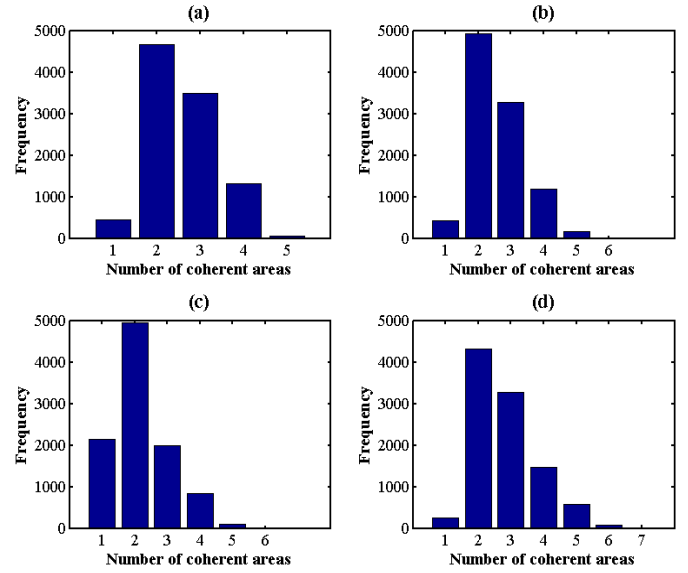


Fig. 7. Fast coherency area decomposition histograms: (a) based on voltage angle -  $X_{\theta}$ , (b) based on frequency -  $X_F$ , (c) based on voltage magnitude -  $X_V$ , (d) based on voltage angle, voltage magnitude and frequency -  $X_{\theta VF}$

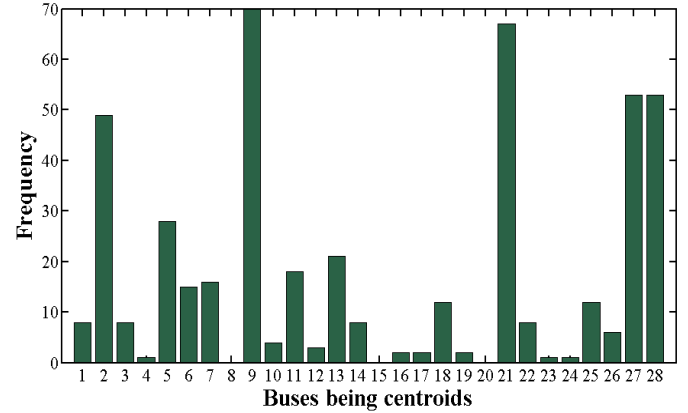


Fig. 8.  $X_{\theta VF}$ -based candidate centroids – for the 6 coherent areas of histogram 7(d)

Since coherency may change depending on the operating state and the contingency magnitude, the coherent areas can be slightly different, and then the centroids can also faintly vary. Fig. 9 shows the six electric areas and the buses which belong to each one for two different MC iterations. It is possible to observe the slightly different distribution of coherent areas in each case.

In this connection, the frequency of each bus being a centroid cannot reveal the most representative group of cluster centroids by itself. Therefore, a decision tree is used in order to track the frequency of the group of buses that constitute centroids at the same time. The groups of centroids which present the highest frequency, considering the three bus signals ( $X_{\theta VF}$ ) as the analyzed variables are:  $\{2, 5, 9, 21, 27, 28\}$ ,  $\{2, 6, 9, 14, 22, 27\}$ ,  $\{1, 7, 13, 21, 25, 26\}$ , and  $\{2, 9, 11, 17, 21, 28\}$ . These buses constitute the best probabilistic candidate buses for PMU location, derived from the fast coherency analysis. The same procedure can followed considering other combination of bus variables, depending on the purpose of the dynamic application.



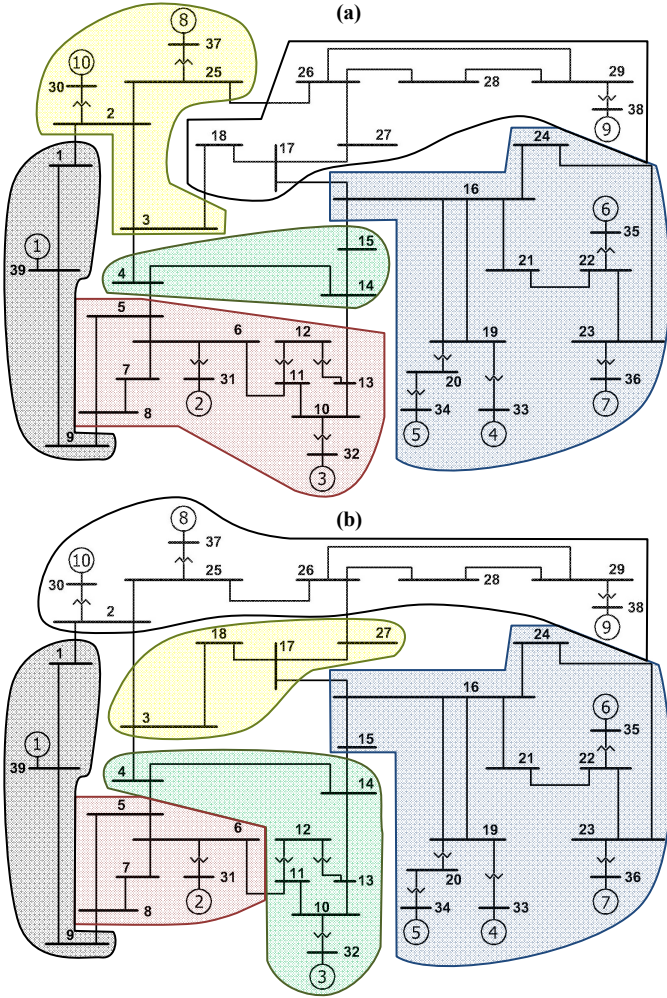


Fig. 9.  $X_{0VF}$ -based six-coherent area formation considering fast dynamics: (a) three phase short circuit applied on line 15-16 at 22.8% of the line length, high-loaded scenario; (b) three phase short circuit applied on line 14-15 at 97.6% of the line length, low-loaded scenario

Once the candidate buses for PMU placement are established,  $MPO_{gm}$  is determined for each one. The bus that presents the maximum value of  $MPO_{gm}$  constitutes the first selected bus (bus 17). This bus is also taken as the pivot for the orthogonality constraint verification, which is performed by comparing the values of  $ORT_{gm}$ . Then, the final buses are those having the maximum  $MPO_{gm}$  and satisfying the most orthogonal values of  $ORT_{gm}$ .

Since more than one of the analyzed buses corresponds to the same electric area, the candidate buses are clustered in six groups depending on the values of  $MPO_{gm}$  and  $ORT_{gm}$ . FCM is also used for this purpose. From these clusters, the buses which present the highest ratio between  $MPO_{gm}$  and  $ORT_{gm}$  in each group constitute the best location of PMUs. In this case, these buses are {2, 9, 11, 17, 22, 28}.

Table I presents the calculated values of  $MPO_{gm}$  and  $ORT_{gm}$ , the clustering formation based on these values, and the selected buses that present the highest ratio between  $MPO_{gm}$  and  $ORT_{gm}$  in each group, which are presented in bold and whose rows are highlighted. Fig. 10 depicts the two-dimensional clustering formation depending on the values of  $MPO_{gm}$  and  $ORT_{gm}$ .

TABLE I  
 $MPO_{gm}$  AND  $ORT_{gm}$

Bus (j)	$MPO_{gm}$	$ORT_{gm}$	Cluster	$MPO_{gm}/ORT_{gm}$
<b>17</b>	0.321	<b>1.000</b>	1	<b>pivot</b>
1	0.204	0.858	2	0.238
6	0.212	0.838	2	0.253
7	0.195	0.844	2	0.231
<b>11</b>	0.223	0.845	2	<b>0.264</b>
<b>2</b>	0.265	0.870	3	<b>0.305</b>
5	0.226	0.896	3	0.252
13	0.253	0.879	3	0.288
14	0.275	0.909	3	0.303
<b>9</b>	0.167	0.805	4	<b>0.207</b>
21	0.281	0.844	5	0.333
<b>22</b>	0.277	0.819	5	<b>0.338</b>
25	0.289	0.858	5	0.337
26	0.313	0.903	6	0.347
27	0.295	0.900	6	0.328
<b>28</b>	0.313	0.865	6	<b>0.362</b>

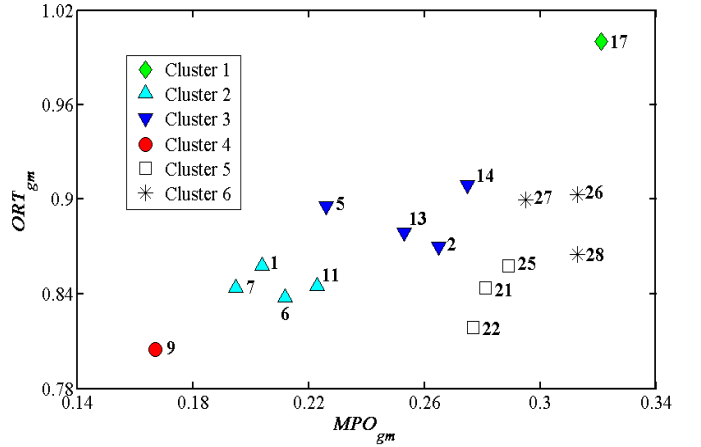


Fig. 10. Slow-coherency clustering formation

The obtained PMU location has to be robust enough, that is the selected buses must allow observing the dynamic in most of the coherent electric areas structured in each Monte Carlo scenario. Fig. 11, 12, and 13 illustrate the considered bus signals (i.e. bus frequencies, voltage magnitudes, and voltage angles) for three different fast coherency Monte Carlo iterations, forming 3, 5, and 2 coherent areas, respectively. Each figure shows that at least one of the selected buses (solid lines) belongs to each of the formed coherent areas, verifying the robustness of the solution.

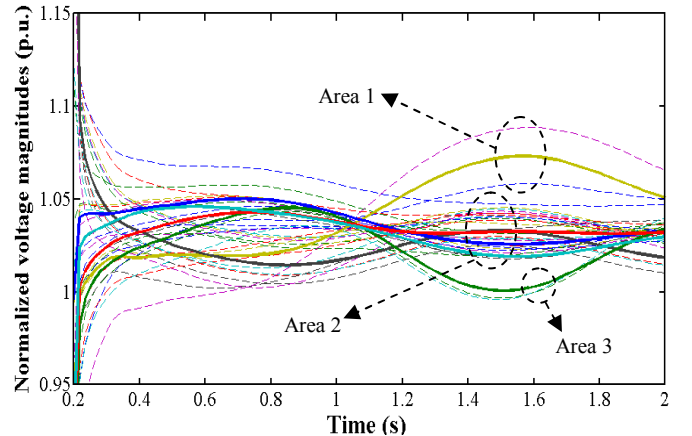


Fig. 11. Normalized voltage magnitudes: three phase short circuit applied on line 13-14 at 51.3% of the line length, high-loaded scenario. Three coherent areas

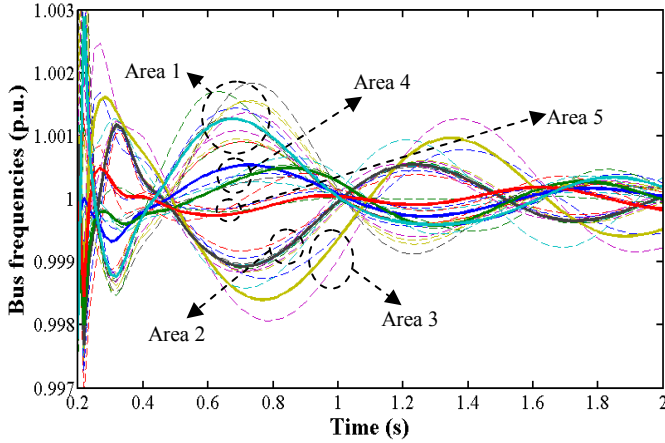


Fig. 12. Bus frequencies: three phase short circuit applied on line 6-11 at 96.0% of the line length, medium-loaded scenario. Five coherent areas

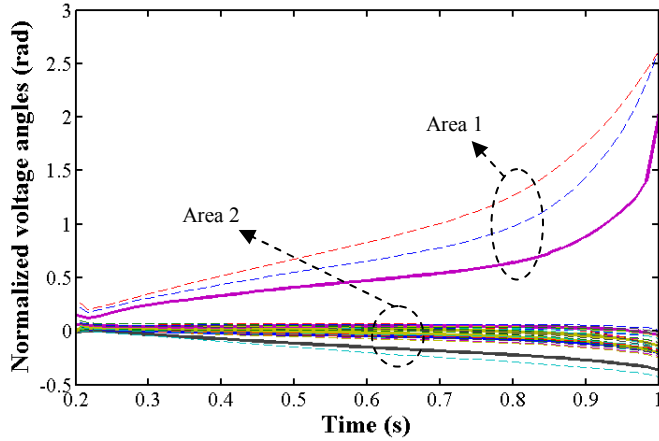


Fig. 13. Normalized voltage angles: three phase short circuit applied on line 26-29 at 38.2% of the line length, high-loaded scenario. Two coherent areas

In general, it is possible to define a criterion of probabilistic observability for evaluating the robustness of the final PMU location, considering the three electric variables independently. This criterion is satisfied if at least one PMU belongs to each electric area in each Monte Carlo scenario corresponding to the fast coherency analysis. Table II presents a comparison of the overall probabilistic observability criterion – OPOC (i.e. for all Monte Carlo scenarios), considering the four groups of centroids obtained only from the fast coherency analysis, and the final set of buses attained from the fast and slow coherency analysis. It is worth to mention that the final set of buses offers the best accuracy in terms of dynamic observability, which is highlighted by a better OPOC accuracy.

TABLE II  
OPOC ACCURACY

Set of Buses PMU location	Variable for coherency analysis / OPOC Accuracy		
	Voltage angle	Voltage magnitude	Frequency
{2,5,9,21,27,28}	98.35%	96.96%	93.38%
{2,6,9,14,22,27}	94.70%	93.87%	90.83%
{1,7,13,21,25,26}	96.44%	97.04%	90.79%
{2,9,11,17,21,28}	99.08%	97.20%	93.87%
<b>{2,9,11,17,22,28}</b>	<b>99.40%</b>	<b>97.41%</b>	<b>95.17%</b>

Finally, for informative purposes a summary of the

computational consuming time is given. Simulations have been run in Windows 7 (64-bit) 3.00 GHz AMD Athlon II X4 640. The elapsed time for the complete methodology was 15 h, being the MC-based dynamic simulations the most demanding task. However, this time might be easily reduced by using modern high – performance computing (HPC) techniques, such as parallel or distributed processing.

#### IV. CONCLUSIONS

A novel hybrid approach to determine suitable PMU locations that allows ensuring observability of slow and fast dynamics has been proposed. The approach uses Monte Carlo-based simulations in order to consider all the possible operating scenarios. Fast coherency clustering allows determining the candidate buses, and the slow coherency analysis guides the final decision regarding PMU placement. Two probabilistic indices have been proposed.  $ORT_{gm}$  allows verifying the orthogonality constraint that ensures obtaining as much information as possible about system oscillatory modes; whereas,  $MPO_{gm}$  reveals the probabilistic oscillatory observability presented by each bus. The methodology has been proved in a test power system, and results have shown the excellent performance of the proposal for orienting the selection of buses whose electric variables offer the highest average dynamic observability, which is highly desirable for structuring dynamic applications like real-time vulnerability assessment tasks.

#### V. REFERENCES

- [1] B. Singh, N.K. Sharma, A.N. Tiwari, K.S. Verma, and S.N. Singh, "Applications of phasor measurement units (PMUs) in electric power system networks incorporated with FACTS controllers," *International Journal of Engineering, Science and Technology*, vol. 3, No. 3, pp. 64 – 82, 2011.
- [2] I. Kamwa, A. K. Pradham, and G. Joos, "Automatic Segmentation of Large Power Systems into Fuzzy Coherent Areas for Dynamic Vulnerability Assessment," *IEEE Transactions on Power Systems*, vol. 22, No. 4, pp. 1974 – 1985, Nov. 2007.
- [3] J. C. Cepeda, J. L. Rueda, I. Erlich, and D. G. Colomé, "Recognition of Post-contingency Dynamic Vulnerability Regions: Towards Smart Grids," in *Proc. IEEE PES General Meeting*, San Diego, USA, July 2012.
- [4] I. Kamwa, A. K. Pradham, G. Joos, and S. R. Samantaray, "Fuzzy Partitioning of a Real Power System for Dynamic Vulnerability Assessment," *IEEE Transactions on Power Systems*, vol. 24, No. 3, pp. 1356 – 1365, August 2009.
- [5] M. A. Rios, and O. Gómez, "Identification of Coherent Groups and PMU placement for Inter-Area monitoring Based on Graph Theory," in *Proc. 2011 IEEE PES Conference on Innovative Smart Grid Technologies - Latin America*, pp. 1 – 7, Oct. 2011.
- [6] Y. Sun, P. Du, Z. Huang, K. Kalsi, R. Diao, K.K. Anderson, Y. Li, and B. Lee, "PMU placement for dynamic state tracking of power systems," in *Proc. 2011 North American Power Symposium*, Aug. 2011.
- [7] D. Peña, *Análisis de Datos Multivariantes*, Editorial McGraw-Hill, España, cap. 1 – 8.
- [8] F. Goderya, A.A. Metwally, and O. Mansour, "Fast Detection and Identification of Islands in Power Systems," *IEEE Transactions on Power Apparatus and Systems*, pp. 217 – 221, 1980.
- [9] J. L. Rueda, and I. Erlich, "Probabilistic framework for risk analysis of power system small-signal stability," *Journal of Risk and Reliability*, special issue paper, pp. 118 – 133, Feb. 2012.
- [10] L. Vanfretti, and J. H. Chow, "Analysis of Power System Oscillations for Developing Synchrophasor Data Applications," in *Proc. 2010 IREP Symposium- Bulk Power System Dynamics and Control – VIII (IREP)*, August 1-6, Buzios, RJ, Brazil.

- [11] E. W. Palmer, and G. Ledwich, "Optimal placement of angle transducers in power systems," *IEEE Transactions on Power Systems*, vol.11, no.2, pp.788-793, May 1996.
- [12] A. M. Almutairi, and J. V. Milanovic, "Optimal input and output signal selection for wide-area controllers," in *Proc. 2009 IEEE PowerTech*, Bucharest, vol., no., pp.1-6, July 2009.
- [13] M. A. Pai, *Energy Function Analysis for Power System Stability*, Kluwer Academic Publishers, 1989.
- [14] D. Zimmerman, "MATPOWER", PSERC. [Online]. Software Available at: <http://www.pserc.cornell.edu/matpower>.

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