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Power System Partitioning via Nonlinear Koopman Modes

Zahra Jlassi [#1], Khadija Ben Kilani[#2], Mohamed Elleuch[#3], Lamine Mili[*4]

[#] *ENIT-L.S.E-LR11ES15, University of Tunis EL Manar*
Tunis le Belvédère, Tunisia
[1]jlassizahra91@gmail.com
[2]khadijakilani@yahoo.fr
[3]mohamed.elleuch@enit.utm.tn

[*] *Electrical Engineering Department, Virginia Polytech. Inst. & State University*
Blacksburg, VA, USA
[4]lmili@vt.edu

***Abstract*— This paper proposes a power system partitioning technique based on a nonlinear Koopman modal decomposition. A partitioning algorithm is developed to determine the exact separation points in a controlled islanding strategy. Koopman spectral analysis of data on bus voltage angles dynamics is performed to identify coherent buses and precisely select the cutsets. The study is conducted on the Kundur two area four machines test power system. A comparison in terms of cutsets identification is made with the conventional slow coherency methods previously applied for power grid partitioning. The results reveal that the proposed partitioning scheme captures intrinsic structural properties of a power system and may identify nonlinear properties that cannot be evaluated with standard linear modal decomposition techniques.**

Keywords*— Electric Power Networks, Koopman Mode Analysis, Koopman Modes Coherency, Power System Partitioning, Large Disturbances

I. Introduction

Because of growing demand on electricity supply, with an economic optimization need and increasing limitations, power systems operate closer to their reliability and stability limits. They are more vulnerable to contingencies and severe disturbances that may cause cascading failures leading to blackouts [1]-[3]. Power system controlled islanding scheme is an efficient corrective measure to limit system blackouts after the occurrence of a large disturbance [4]-[8]. It prevents cascading outages from propagating further throughout the power system by splitting the electrical network into a group of isolated smaller power systems called islands. It is well recognized that a key part of controlled islanding scheme is the most critical and important problem of partitioning, in others words, to decide where to exactly separate a power grid.

Many researchers have outlined different partitioning techniques. In [10]-[12], the authors propose a power grid separation scheme based on the use of the slow coherency method to identify clusters of coherent generators groups, boundaries of which provide the desirable locations of separation. Relevant cutsets are defined by the weakest links connecting the identified coherent generators. The standard slow coherency method is extended in [9] to include load buses to provide directly the power grid partitioning. The slow coherency approach is based on a linearized electromechanical power system model around an operating point. In [13] [15], a new system splitting method based on an ordered binary decision diagram is proposed. It is a typical analytical algorithm of splitting locations searches based on power system characteristics and the graph theory. In [14] [16], the authors propose a power network partitioning technique based on electrical distances that relates power grid topology to active power sensitivities. The incremental change in voltage phase angles that result from an incremental increasing in active power transmission from bus to bus is estimated. Zones are defined as strongly connected buses collections. Cutsets are defined as weakly connected buses between zones. The electrical distance measure is based on information contained in the system admittance matrix.

Most of the existing partitioning strategies are based on graph theoretical methodology and system model linearization. To provide accurate results, they require potentially substantial amounts of detailed electrical network parameters. Because of the difficulties of having all detailed system data, they are constrained by modeling simplifications. Nonlinearities are ignored from the analysis of linearized equations around equilibrium. In this paper, the power grids partitioning problem is performed by utilizing the nonlinear Koopman Modes Analysis (KMA) [18] [21] [25]. This analysis does not rely on system modeling, models simplifications and linearization. It only relies on nonlinear dynamics data in the power system following a disturbance. Computing nonlinear Koopman modes from observation data has been developed in [20] and recently applied to power systems analysis and performance assessment [21]-[25]. The KMA is a nonlinear modal decomposition technique based on the Koopman operator spectrum which provides a linear infinite-dimensional description of dynamics nonlinear evolution [17]-[19]. Each Koopman mode oscillates by definition with a single frequency. Thus, it is relevant for capturing spatio-temporal pattern of large scale power system dynamics.

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In this paper, an algorithm for partitioning power systems is proposed based on applying the nonlinear Koopman modes analysis on sampled dynamics of buses voltage angles. The notion of Koopman modes dynamics coherency is used for identifying the partitions of a target electric power network. Coherent buses groups are identified by focusing on their angles coherency. Relevant cutsets are derived. The study is conducted on Kundur two area four machines test power system. A comparison in terms of cutsets identification is made with the conventional slow coherency method previously applied to power grid partitioning problem. Results are presented and discussed. Conclusions are provided.

II. THE KOOPMAN MODES ANALYSIS

A. Koopman Modes Theory

The Koopman modes analysis is a mathematical technique of dynamics modal decomposition based on the spectral analysis of the Koopman operator [18] [20]. This analysis does not rely on system modeling, models simplifications and linearization. It only relies on nonlinear dynamics data. The Koopman operator is defined for arbitrary dynamical systems. It is a linear operator able to capture nonlinear phenomena [19]. Recently, the Koopman spectral analysis is used for power systems applications [21]-[25].

In the following, the development is based on [20]. A discrete time system evolution on a smooth manifold M is considered as:

$$x_{k+1} = f(x_k) \tag{1}$$

where f is a nonlinear time invariant map from M to itself.

Let consider from (1) a scalar observable $g: M \to \mathbb{R}$. The observable is defined as a mathematical measurements model of the power system dynamics. The Koopman operator U is applied on the observable. It maps g to a novel function $U\, g$ as:

$$(Ug)(x) \coloneqq (gof)(x) = g(f(x)) \tag{2}$$

where the observable g is composed with f. The Koopman operator is linear. As a result, it is natural to execute the spectral analysis. The Koopman eigenvalues $\lambda_i \in \mathbb{C}$ and the Koopman eigenfunctions $\varphi_i : M \to \mathbb{C}$ are defined as:

$$U\, \varphi_i = \lambda_i\, \varphi_i,\ i = 1,2, \dots \tag{3}$$

Let consider a vector valued observable:

$$g(x) \coloneqq \left(g_1(x),\, g_2(x), \dots,\, g_m(x) \right)^T : M \to\ \mathbb{R}^m \tag{4}$$

If all components of the observable g lie within the span of the eigenfunctions φ_i , $g(x)$ can be expanded in terms of the Koopman eigenfunctions as follow:

$$g(x) = \sum_{i=1}^{\infty} \varphi_i\,(x)\, v_i \tag{5}$$

where $v_i \in \mathbb{C}^m$ are vector valued coefficients of the decomposition called Koopman modes which depend on the observable choice. Thus, the time evolution of the observable $g(x_k)$ at a certain time t_k from $g(\mathrm{x}_0)$ at time 0 is expanded as follows:

$$g(x_k) = \sum_{i=1}^{\infty} \varphi_i\,(x_k)\, v_i = \sum_{i=1}^{\infty} \lambda_i^k\, \varphi_i\,(x_0)\, v_i \tag{6}$$

This demonstrates that the nonlinear evolution in power system dynamics is characterized by the Koopman operator spectrum. The analysis based on (6) defines the Koopman Modes Analysis.

B. Koopman Modes Analysis Algorithm

It is shown in [20] that the Arnoldi-type algorithm produces decomposition for a finite series of a same type as (6). Thus, Koopman modes may be numerically approximated as described in [20] by an Arnoldi algorithm. It is shown that Ritz values $\widetilde{\lambda_\iota}$ approximate Koopman eigenvalues λ_i and Ritz vectors $\widetilde{v_\iota}$ approximate factors $\varphi_i(x_0)v_i$ in (6) which refer to Koopman modes. Let's consider $\{\ g(x_0), \dots, g(x_N)\ \}$ as (N+1) vectors of data where the vector $g(x_k)$ is a vector measuring the observables at a discrete time k. The finite series approximation of (6) is presented as follow:

$$\left. \begin{aligned} g(x_k) &= \textstyle\sum_{i=1}^{N} \widetilde{\lambda_\iota}^{\,k}\, \widetilde{v_\iota},\ k = 0, \dots, N-1 \\ g(x_N) &= \textstyle\sum_{i=1}^{N} \widetilde{\lambda_\iota}^{\,N}\, \widetilde{v_\iota} + r \end{aligned} \right\} \tag{7}$$

where $r \in \mathbb{R}^m$ is a residue that represent a small approximation error, defined as:

$$r = g(x_N) - \sum_{i=0}^{N-1} c_i g(x_i) \tag{8}$$

The choice of constants c_i must satisfy:

$$r \perp span\ \{\ g(x_0), \dots, g(x_{N-1})\ \} \tag{9}$$

With $c = [\ c_0, \dots, c_{N-1}\ ]$ and $M = [\,g(x_0), \dots, g(x_{N-1})\ ]$, (8) together with (9) gives:

$$M^T r = 0 = M^T g(x_N) - M^T M c^T = B - Ac \tag{10}$$

Where: $A = M^T M$ and $B = M^T g(x_N)$

Therefore, the constants vector c is given by:

$$c = A^{\dagger} B \tag{11}$$

With $A^{\dagger}$ is the Moore-Penrose pseudoinverse of A defined as a generalized inverse of any non-square matrix.

The Ritz values $\widetilde{\lambda_\iota}$, i.e., an approximation of Koopman eigenvalues, are defined as the eigenvalues of the companion matrix C given by:

$$C = \begin{bmatrix} 0 & 0 & \dots & 0 & c_0 \\ 1 & 0 & \dots & 0 & c_1 \\ 0 & 1 & & 0 & c_2 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & \dots & 1 & c_{N-1} \end{bmatrix} \tag{12}$$

The Ritz vectors $\widetilde{v_\iota}$ which refer to Koopman modes are defined as the columns of:

$$V = [\ g(x_0), \dots, g(x_{N-1})]T^{-1} \tag{13}$$

Where the matrix T called the Vandermonde matrix is defined as follow:

$$T = \begin{bmatrix} 1 & \widetilde{\lambda_1} & \widetilde{\lambda_1}^2 & \dots & \widetilde{\lambda_1}^{N-1} \\ 1 & \widetilde{\lambda_2} & \widetilde{\lambda_2}^2 & \dots & \widetilde{\lambda_2}^{N-1} \\ 1 & \widetilde{\lambda_3} & \widetilde{\lambda_3}^2 & \dots & \widetilde{\lambda_3}^{N-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \widetilde{\lambda_N} & \widetilde{\lambda_N}^2 & \dots & \widetilde{\lambda_N}^{N-1} \end{bmatrix} \tag{14}$$

Each Koopman eigenvalue characterizes the temporal behavior of corresponding Koopman mode. The phase of the eigenvalue determines the mode frequency and its magnitude determines the mode growth rate. Koopman modes frequencies f_i are defined as [21]-[26]:

$$f_\iota = (arg\widetilde{\lambda_\iota} * f_s)/2\pi \quad (15)$$

With: f_s is the sampling frequency of dynamics data and $arg\widetilde{\lambda_\iota}$ called the Koopman modes arguments are defined as:

$$arg\widetilde{\lambda_\iota} = Im(ln(\widetilde{\lambda_\iota})) \quad (16)$$

The Koopman modes growth rates GR_i are defined as complex modulus of Koopman eigenvalues given by:

$$GR_i = \|\widetilde{\lambda_\iota}\| \quad (17)$$

The growth rates evaluate the sampled dynamics damping. Large growth rate indicates small damping ratio. A growth rate equal or larger than unity defines a non-oscillatory power system dynamic. But a growth rate smaller than unity defines a positively damped oscillatory mode [20]-[25].

The contribution magnitude of a given Koopman mode in the dynamics data is quantified by its norm. The Koopman modes norms noted $\|\widetilde{v_\iota}\|$ are defined as [21]-[25]:

$$\|\widetilde{v_\iota}\| = \sqrt{\widetilde{v_\iota}^T \widetilde{v_\iota}} \quad (18)$$

The algorithm1 provides the Koopman modes analysis of dynamics data. The input of this algorithm is the observables sampled data matrix (such as: buses voltage angles), the sampling frequency of data and the desired number of Koopman modes to be computed. The outputs of this algorithm are: the Koopman eigenvalues, the Koopman modes and their norms, frequencies and Growth rates.

Algorithm 1: Koopman Modes Analysis

Requires: observables dynamics data; sampling frequency; number of Koopman modes to be computed
Ensure: KMA
1: Computation of the companion matrix C
2: Koopman eigenvalues $\{\widetilde{\lambda_\iota}; i \in N\} \leftarrow$ eigenvalues of C
3: Computation of the matrix V of Ritz eigenvectors
4: Koopman modes $\{\widetilde{v_\iota}; i \in N\} \leftarrow$ columns of V
5: Computation of Koopman modes norms $\{\|\widetilde{v_\iota}\|;\ i \in N\}$
6: Computation of Koopman modes frequencies $\{f_i; i \in N\}$
7: Computation of Koopman modes growth rates $\{GR_i; i \in N\}$

C. Coherency in Koopman Modes

The Coherency identification from the observables data via Koopman modes analysis was first proposed in [23] and theoretically was refined in [18]. For a derived Koopman mode v_i , called Koopman Mode i, with $[v_i]_j = A_{ij}\angle\alpha_{ij}$ where $i \in N$, $j \in \{1, \dots, m\}$ and m: is the observables number, A_{ij} is called the amplitude coefficients of modal dynamics and α_{ij} stands for the initial phases of modal dynamics, defined as follow for each mode i and observable j (such as generator rotor speed $w_j$or bus voltage angle θ_j) [21]-[23]:

$$A_{ij} = \sqrt{(Re[\varphi_i(x_0)v_i]_j)^2 + (Im[\varphi_i(x_0)v_i]_j)^2} \quad (19)$$

$$tan\,\alpha_{ij} = (Im[\varphi_i(x_0)v_i]_j)/\ (Re[\varphi_i(x_0)v_i]_j) \quad (20)$$

Where: the notation $Re[\varphi_i(x_0)v_i]_j$ determines the *j-th* component of the vector $Re[\varphi_i(x_0)v_i]$ and the notation $Im[\varphi_i(x_0)v_i]_j$ determines the *j-th* component of the vector $Im\,[\varphi_i(x_0)v_i]$.

To identify for a particular Mode *i* coherent dynamics in phase and frequency, it is mainly sufficient to check both amplitudes coefficients A_{ij} and initial phases α_{ij}. A set of scalar observables $J \subseteq [1..m]$ is defined as coherent group with respect to a given Koopman mode *i*, if all $j \in J$ have similar amplitudes coefficients and initial phases [21]-[23].

D. Proposed KMA Based Partitioning Algorithm

The proposed method demonstrated in this paper of partitioning power systems based on Koopman modes analysis is outlined as follow. The KMA is performed based on voltage angles dynamics of buses following a disturbance. Splitting the power system with respect to coherent buses groups is expected to form partitions with coherent generators able to keep synchronism. Thus, power grid partitions are derived based on coherent buses determined in terms of dominant Koopman modes. Cutsets are identified for each partition as a set of transmission lines connecting different coherent groups. The pseudocode of this proposed method is provided in Algorithm2.

Algorithm 2: KMA Based Partitioning

Requires: $\{\theta_1, \dots, \theta_N\}$: data set of buses voltage angles dynamics; G: power transmission grid
Ensure: Cutsets
1: $\{(\widetilde{\lambda_\iota}, \widetilde{v_\iota}); i \in N\}$ ←KoopmanModesAnalysis ($\{\theta_1, \dots, \theta_N\}$)
2: $N_d \subseteq N \leftarrow$ DominantKoopmanModes $(\tilde{\lambda}, \tilde{v})$
3: $\{A_i; i \in N_d\} \leftarrow$ AmplitudesCoefficientsVectors $(\tilde{v}, N_d)$
4: $\{\alpha_i; i \in N_d\} \leftarrow$ InitialPhasesVectors $(\tilde{v}, N_d)$
5:$\{CG_i; i \in N_d\} \leftarrow$ IdentifyCoherency $((A_i, \alpha_i); i \in N_d)$
6: IdentifyCutsets (CG_i, G)

The different steps of the proposed algorithm to identify cutsets are outlined in the following:

1) Consider the set of buses voltage angles dynamics acquired under uniform sampling: $\{\theta_1, \dots, \theta_N\}$. By applying the KMA algorithm to this finite time data set, N pair $(\widetilde{\lambda_\iota}, \widetilde{v_\iota})$ with $i \in N$ of Koopman eigenvalues and Koopman modes are obtained (Koopman Modes Analysis).
2) Select the Koopman modes with the largest growth rates and norms to represent the dynamic information in the study set of data. These are the dominant Koopman modes identified as the set $N_d \subseteq N$ (DominantKoopmanModes).
3) For each dominant Koopman mode i, the amplitudes coefficients vector A_i is calculated (AmplitudesCoefficientsVectors).
4) For each dominant Koopman mode i, the initial phases vector α_i is computed (InitialPhasesVectors).
5) For every pair (A_i, α_i) of each dominant Koopman mode i, a grouping matrix $CG_i = [CG_{i1}, \dots, CG_{iNCG}]$ is identified

containing the coherent groups, where NCG is the number of coherent groups (IdentifyCoherency).

6) With identified coherent groups CG_i, the cutsets are simply determined by finding in the power transmission grid, the transmission lines connecting the buses of different groups (IdentifyCutsets).

III. Study Case

The proposed KMA based partitioning algorithm is applied to sampled data on bus voltage angles dynamics following a short-circuit disturbance in study Kundur two area four machines power system [26]. The study sampling frequency is 80Hz. Simulations are executed by means of an open-source electric power network analysis toolbox of MATLAB named PSAT [27].

The test system is depicted in Fig. 1, consisting of four synchronous equivalent generators. In each test power system area, there are two generation units, a load and a capacitor. The active power capacity of load is: 967 MW in area 1 and 1767 MW in area 2. The reactive power capacity of load is: -100MW in area 1 and -250 MW in area 2. Each generation capacity is 700 MW. Totally, 2800 MW of power generation are installed in the Kundur two areas four machines test power system. From area one to area two, 400 MW is exported. All generators are equipped with automatic regulators excluding generator G4 of area two.

The studied three-phase fault is applied at time t=1s in area 1at bus 1of Kundur test system. The short circuit is cleared after duration of 150ms. The oscillatory response results of bus voltage angles under this tested fault are shown in Fig. 2, Fig. 3 and Fig. 4. We note that voltage angles of buses 2, 5 and 6 of area 1 swing together in phase and frequency. However, voltage angles of buses 1 and 7 demonstrate different dynamics compared to those of buses 2, 5 and 6 in area1.Voltage angles of buses 3, 4, 9, 10 and 11 of area 2, show another coherent dynamics excited by the study applied disturbance. Voltage angle of bus 8, which is the interconnection bus between the two areas, shows a different dynamic motion compared to those of area 1 buses and area 2 buses.

The cutsets identification for partitioning power system is compared for both techniques: the proposed KMA based partitioning and the conventional slow coherency method previously applied to power grid partitioning problem.

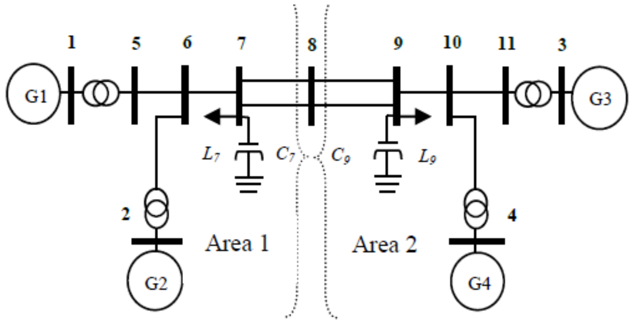

Fig. 1. Tested Tested two area four machines power system [26]

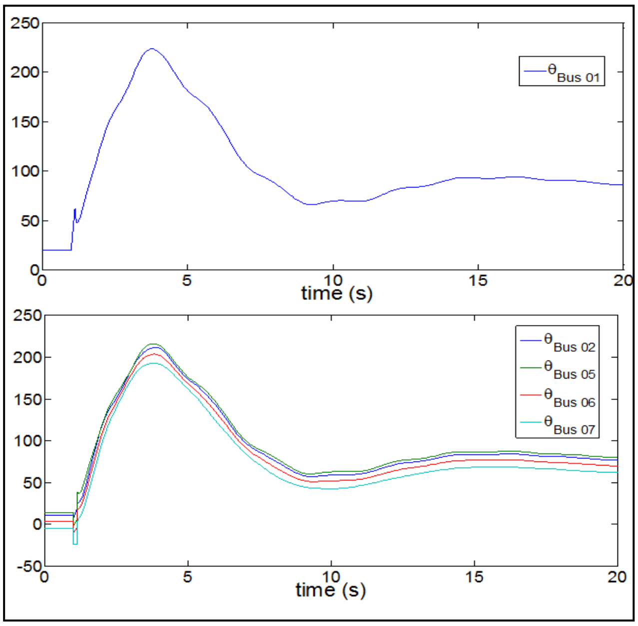

Fig. 2. Voltage angles dynamics of area1 buses under the tested fault for two area four machines test power system

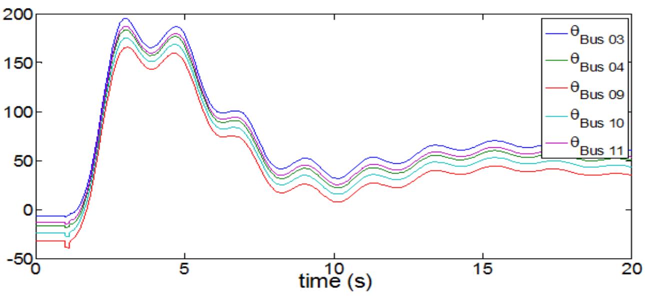

Fig. 3. Voltage angles dynamics of area2 buses under the tested fault for two area four machines test power system

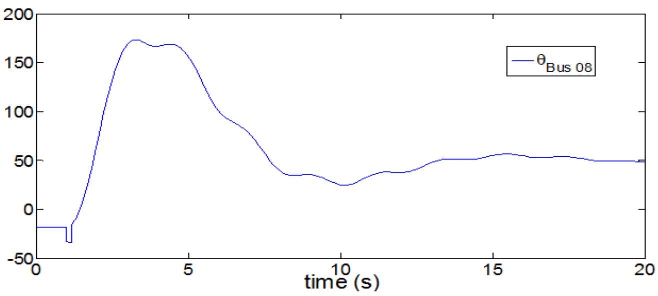

Fig. 4. Voltage angle dynamic of bus 8 under the tested fault for two area four machines test power system

IV. Partitioning Results

By means of applying the KMA algorithm on buses voltage angles data, the Koopman modes are identified. The three most dominant oscillatory Koopman modes with largest growth rates and norms are listed in Table I. Based on buses coherency of this dominant modes, partitions for the test power system are derived. This identification of coherent buses groups is performed by utilizing the K-means clustering technique.

TABLE I.
OBTAINED DOMINANT KOOPMAN MODES FOR VOLTAGE ANGLE DYNAMICS DATA SHOWN IN FIG.2,FIG.3 AND FIG.4

Mode Number	Mode Frequency (Hz)
1	0.1
2	0.044
3	0.14

The initial phases α_{ij} versus the amplitudes A_{ij} are plotted for every bus j = 1,…,11 and for every dominant Koopman mode i= 1,…,3. The phase versus amplitude plot of buses voltage angles for Mode 1 of frequency 0.1 Hz is depicted in Fig. 5. Grouping of coherent buses with respect to this Mode as illustrated in Fig. 5 leads to five buses groups. One group corresponds to the buses of area 2. The interconnection bus 8 forms another group. The buses of area 1 are divided into 3 sub-groups: the bus 1 where the disturbance is applied forms one group, the bus 7 forms another group and the rest of area 1 buses (2, 5 and 6) have different phases and amplitudes compared to those of bus 1 and 7. Thus, they form another group. The phase versus amplitude plot of buses voltage angles for Mode 2 of frequency 0.044 Hz is depicted in Fig. 6. Based on this mode, grouping of coherent buses as shown in Fig. 6 leads to the same five buses groups based on Mode 1. The phase versus amplitude plot of buses voltage angles for Mode 3 of frequency 0.14 Hz is illustrated in Fig. 7. The grouping results of coherent buses based on this mode lead to the same five buses groups based on Mode 1 and Mode 2. The power system partitioning is constructed by considering all grouping results of coherent buses based on different dominant Koopman modes. Power system cutsets are defined by the combination of cutsets according to each dominant Koopman mode. By combining the resulting partitions for Mode 1, Mode 2 and Mode 3, a partition with four disjoint parts of the Kundur two areas four machines test power system is obtained. This partition is given in Fig. 8.

Based on the slow coherency method, a partition with two disjoint parts area 1and area 2 for the studied two areas four machines power system is defined as shown in Fig. 8. The buses of area 1 form one group and those of area 2 form another group. Slow coherency is defined by the fact that states in the same area are coherent with a respect to the slowest modes which are poorly damped modes with low frequencies. This method is based on the selection of the interarea modes through linear modal analysis of simplified power system model to identify weakly connected coherent groups [9]-[12].

The comparison between cutsets identification of the two partitioning methods reveals that: the KMA based partitioning pattern is different with the slow coherency partitioning pattern. This difference is mainly the effect of nonlinearity neglect in the linearized modal analysis. The proposed partitioning scheme based on nonlinear Koopman modes captures intrinsic structural properties of a power system by identifying weakly connected coherent groups and may identify nonlinear properties that cannot be evaluated with standard linear modal decomposition.

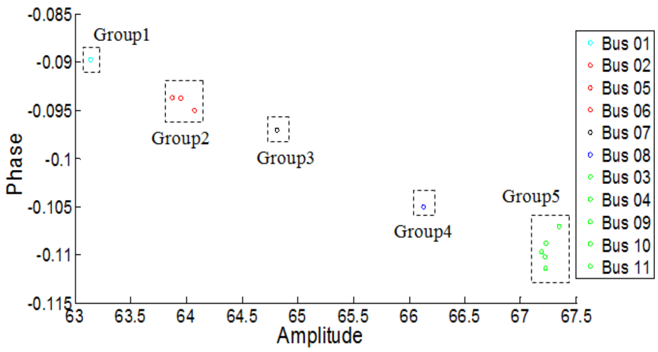

Fig. 5. Phase versus amplitude plot of buses voltage angles for Mode 1 of frequency 0.1 Hz

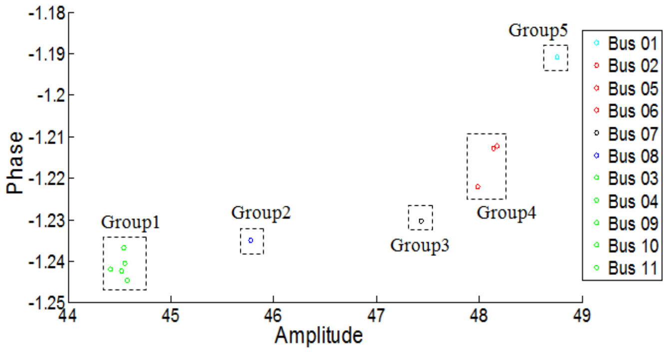

Fig. 6. Phase versus amplitude plot of buses voltage angles for Mode 2 of frequency 0.044 Hz

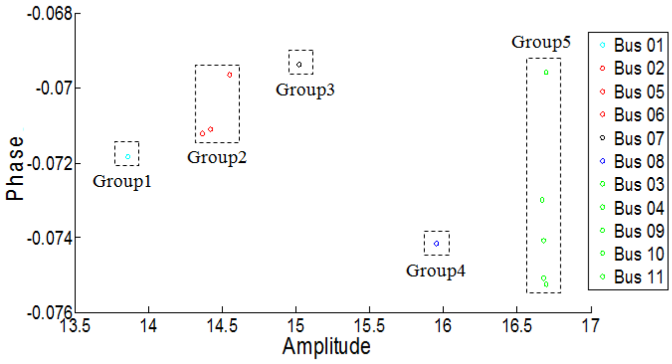

Fig. 7. Phase versus amplitude plot of buses voltage angles for Mode 3 of frequency 0.14 Hz

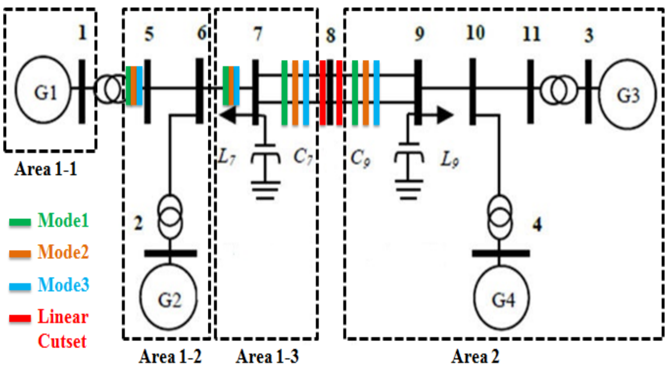

Fig. 8. Partitioning of the Kundur test power system according to Mode 1, Mode 2, Mode 3 and Linear Cutset. The cutsets are indicated by colored lines.

V. Conclusion

This paper proposes an algorithm for partitioning power systems based on applying the nonlinear modal decomposition technique named Koopman modes analysis on sampled dynamics of buses voltage angles. This proposed algorithm determines exactly the separation points in a controlled islanding strategy. The notion of dominant Koopman modes dynamics coherency is used for identifying the partitions of a target electrical network. Dominant Koopman modes correspond to predominant frequencies identified in the dynamics of power system following a disturbance. Coherent buses groups are derived by focusing on their angles coherency to precisely select the cutsets. The identification of coherent buses groups is performed by utilizing the K-means clustering technique. The study is conducted on Kundur two area four machines test power system. A comparison in terms of cutsets identification is made with the conventional slow coherency method previously applied to power grid partitioning problem. This method is based on the selection of the interarea modes through linear modal analysis of simplified power system model to identify weakly connected coherent groups. The results reveal that the KMA based partitioning pattern is different with the slow coherency partitioning pattern. This difference is mainly the effect of nonlinearity neglect in the linearized modal analysis. The proposed partitioning scheme based on nonlinear Koopman modes captures intrinsic structural properties of a power system by identifying weakly connected coherent groups determined by the slow coherency based partitioning method and may identify nonlinear properties that cannot be evaluated with standard linear modal decomposition.

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