Novel Clustering Method for Coherency Identification Using an Artificial Neural Network

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Abstract - A novel clustering method using an artificial neural network (ANN) is presented to identify the coherent generators for dynamic equivalents of power systems. First, a new frequency measure is devised to indicate the degree of coherency among system generators. Incorporating with the frequency measure, a neural network implementation of the K-means algorithm is then proposed to identify clusters of coherent generators. The rotor speeds at three selected instants in time are used as the feature patterns for the learning algorithm. To verify the effectiveness of the proposed method, extensive analyses are performed on two different power systems of varying sizes with rather encouraging results.

Keywords: coherency identification, artificial neural network.

1. INTRODUCTION

In the dynamics study of large power systems, it is necessary to model the external system by their dynamic equivalents to improve the solution speed and to reduce the problem to solvable size [1-6]. One approach of building up a dynamic equivalent is to identify generators in the external system with high coherency. A group of generators in the external system is said to be coherent if they are similar in terms of terminal behavior. The formation of coherent group depends on both the nature and location of the disturbance. With the growing size of the interconnected power systems, the coherency identification becomes increasingly difficult.

In the last two decades, many notable methods of coherency-based dynamic equivalencing have been developed to reduce the computational effort required in power system dynamics study [1-11]. Lee and Schweppe [7] suggested a pattern recognition approach to identify coherent generators, which was based on the criteria involving generator inertia, admittance, and machine acceleration. Spalding et al. [8] determined coherent generators using the pre-fault stable operating point and the post-fault unstable equilibrium point (UEP). Podmore [3] proposed a method of coherency

detection by solving a set of linearized swing equations, and treating the rotor trajectories through a clustering algorithm. Recently, Haque et al. [9] utilized the rotor angles and the electrical coupling measure to identify coherent machines. Afterwards, they [10] proposed the concept of energy function at the approximate unstable equilibrium points (AUEP) as well as the relative rotor angles to identify coherent groups.

The main purpose of this research is to develop an efficient clustering method suitable for the identification of coherent generators in power systems. This method is based on the measuring coherency in terms of frequency deviation and the application of ANN technique. One of the major strengths of artificial neural network lies in its excellent ability to pattern recognition [11-15]. On the other hand, the problem of coherency identification is equivalent to clustering generators into various coherent groups, each group being related to different patterns. In view of this, this paper takes advantages of the ANN technique for coherency analysis. The representative input patterns of the ANN consist of the rotor speeds of each generator at three distinct instants during the transient period. As will be shown later, the speed feature is superior to the angle feature and appears to be reliable patterns for ANN classification. A neural network implementation of the K-means algorithm [12,16] using the adaptive resonance theory (ART) model [14] is then proposed for the classification of coherent generators. Experimental results obtained show that the presented clustering method is computationally efficient and seems a promising way to perform clustering in large-scale power systems.

2. FORMULATION OF COHERENCY IDENTIFICATION

2.1 Power System Model

In the standard simplified description of an n-machine power system, the disturbed motion of the i-th machine with respect to a synchronously rotating frame can be expressed by

$$\dot{\delta}_i = \omega_i$$
$$M_i\dot{\omega}_i = P_{mi} - P_{ei} \qquad for\ i = 1, 2, ..., n. \qquad (1)$$

where

$$P_{ei} = E_i^2 G_{ii} + \sum_{\substack{j=1 \\ j \neq i}}^{n} (C_{ij} \sin \delta_{ij} + D_{ij} \cos \delta_{ij}) \qquad (2)$$

$$\delta_{ij} = \delta_i - \delta_j$$
$$C_{ij} = E_i E_j B_{ij}$$

$$D_{ij} = E_i E_j G_{ij}$$

The following standard notation is used:

δ_i, ω_i: rotor angle and rotor speed with respect to the synchronously rotating reference frame,

M_i: inertia constant,

P_{mi}: mechanical input power,

P_{ei}: electrical output power,

E_i : voltage behind the direct axis transient reactance,

G_{ii}: driving point conductance,

B_{ij}: transfer susceptance,

G_{ij}: transfer conductance.

In the above, the network of the power system has been reduced to the generator internal bus. With common simplifying assumptions, M_i, P_{mi}, and E_i are assumed to be constant throughout the transients, and all loads are modeled as constant impedances.

2.2 Coherency Consideration

A generator pair (i, j) is considered to be coherent if [9]

$$\delta_i(t) - \delta_j(t) \in [D_{ij} - \varepsilon, \ D_{ij} + \varepsilon] \quad for \ 0 \le t \le t_{max} \quad (3)$$

where $\delta_i(t)$ and $\delta_j(t)$ are the rotor angles of the i-th and j-th machine respectively, D_{ij} is one particular constant, ε is a small tolerance of rotor angle, and t_{max} is the maximum time of interest for coherency identification. A group of generators is coherent if each pair of generators in the group is coherent. Each generator pair (i, j) is said to be perfectly coherent if the tolerance ε equals zero. An alternative formulation considering coherency is to check the absolute relative rotor angle deviations,

$$\left| \delta_{ij}(t + \Delta t) - \delta_{ij}(t) \right| \le \sigma \quad (4)$$

where $\delta_{ij}(t) = \delta_i(t) - \delta_j(t)$ and σ denotes tolerance. The rotor angles of the i-th and j-th generator for a small time increase Δt could be approximated as:

$$\delta_i(t + \Delta t) = \delta_i(t) + \omega_i(t)\Delta t \quad (5)$$
$$\delta_j(t + \Delta t) = \delta_j(t) + \omega_j(t)\Delta t \quad (6)$$

where $\omega_i(t)$ and $\omega_j(t)$ denote respectively the rotor speeds of the i-th and j-th generator at the instant of t. Subtracting (6) from (5) gives:

$$\delta_{ij}(t + \Delta t) - \delta_{ij}(t) = (\omega_i(t) - \omega_j(t))\Delta t \quad (7)$$

For a fixed time interval Δt, comparing (4) with (7), a new frequency measure of coherency can be derived as

$$\left| \omega_i(t) - \omega_j(t) \right| \le \rho \quad (8)$$

where ρ denotes a tolerance parameter. Therefore, a pair of machines (i, j) can be considered coherent if they satisfy (8) during study period. As will be illustrated in Sec. 4.2, the speed criterion can provide computational advantage over angle criterion and shows to be more reliable feature patterns in the use of an artificial neural network for the coherency identification.

2.3 Feature Selection

A key step in the application of pattern recognition approach is to select a proper set of features with which the input data will be represented. In this study, the speeds at three distinct instants are used for each generator as patterns representative of the dynamic behavior of the generator. They consist of the following features:

(a) $\omega_i(t_c)$: the rotor speed at the instant of fault clearing,

(b) $\omega_i(t_c + 0.2)$: the rotor speed at $t_c + 0.2$ s in the post-fault period,

(c) $\omega_i(t_c + 0.4)$: the rotor speed at $t_c + 0.4$ s in the post-fault period.

The choice of these features is mainly motivated by the simple idea that two machines having the same speed at three distinct instants of time should have parallel trajectories and hence should be coherent if those speeds can properly represent the terminal behavior of each machine. In general, the fault duration of a physical power system is short and the variation of generator acceleration is small during that period. Usually, the abrupt change of the system occurs at the instant of fault clearing. Therefore, item (a) is adopted to account for faulted acceleration, which governs the system dynamics for the fault-on period. Because generators that are coherent during the faulted period may actually fall apart in the post-fault period, items (b) and (c) are used to accommodate the post-fault system dynamics. Since the natural frequencies of the rotor angle oscillations typically range from 0.25 Hz to 2 Hz [3], the sample time of 0.2 s is satisfactory for the representation of the post-fault system dynamics.

2.4 Prediction of Generator Rotor Speeds

The rotor speed of each generator can be evaluated by directly integrating the system differential equation. However, since the intention of this study is to fast identify coherency without simulation of the entire system dynamics, it is most desirable to improve the computing speed. The Taylor series expansion (TSE) technique [9,17] is one of the most efficient numerical methods suitable for the prediction of rotor behavior. Our experience shows that the TSE gives good agreement with the actual trajectories up to 0.6 s by taking up to the 4-th order derivatives. If the prediction on a larger time interval is wanted, a multi-step TSE in both the fault-on and the post-fault period may be used without significant loss of accuracy [9]. In addition, larger clearing time seldom occurs in physical situations, since it corresponds to a fault condition that may not leave a network in an emergency state.

3. ARTIFICIAL NEURAL NETWORK COMPUTING

In recent years, artificial neural network computing has become an important branch of artificial intelligence, which has numerous applications in the engineering field. Among these applications, the pattern recognition is one of the task that the artificial neural network succeeds. In this respect, the ART model [14] may be one of the notable representatives in this category. The ART network is like an adaptive pattern recognition system. It can quickly and stably learn to categorize input patterns in real-time process, and permit fast adaptive search for best match and variable error criterion in response to external environment. In view of its excellent ability in pattern recognition, the ART network can be beneficially used for the implementation of the K-means algorithm [12,16] for coherency identification.

3.1 Architecture of the ART Neural Network

Fig. 1 depicts the schematic structure of the ART employed in the present study. It comprises both the input layer and the output layer. The rotor speeds at three selected instants in time are used for each generator as patterns representative of the dynamic behavior of the generator. So three nodes are required in the input layer for the identification of coherent generators. The nodes in the input layer receive an input feature pattern and an image of the input pattern is generated by using a set of weighted parameters. This image is further enhanced in the process characterized by the output layer. The output layer is a strong lateral inhibition network called MAXNET [15]. Each unit of the MAXNET has a positive feedback on itself and a negative feedback on the other units. Only one output unit in the output layer remains active to indicate a classification of the input pattern.
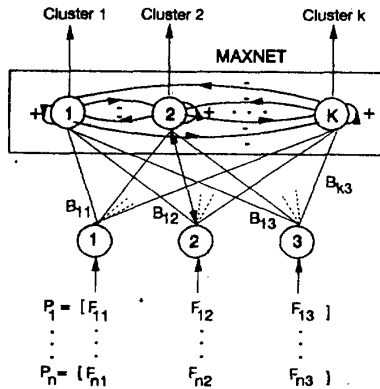

Fig. 1. The architecture of the ART neural network.

3.2 Neural Network Implementation of K-means Algorithm

In this section, we use the ART model to implement the K-means clustering algorithm, which was developed by Pao et al. [12] for critical clearing time assessment. The K-means algorithm [16] is based on the minimization of a performance index that is defined as the sum of the squared distances from all points in a cluster domain to the cluster center. The

clustering process is performed according to the similarities discovered among the input features, and is controlled by a distance threshold called the vigilance parameter (VP). The VP is a user-made parameter which must be judiciously determined from an engineering knowledge of the system requirements. The overall solution procedure for coherency identification can be summarized in the following steps:

Step 1: Read system data, fault condition, and the number of study generators,

Step 2: Build the prefault, fault-on, and postfault admittance matrices,

Step 3: Compute the input patterns of the external generators :

$$P_i = (F_{i1}, F_{i2}, F_{i3}) \quad \text{for } i=1,2,...,n_e \quad (9)$$
$$F_{i1} = \omega_i(t_c)$$
$$F_{i2} = \omega_i(t_c + 0.2)$$
$$F_{i3} = \omega_i(t_c + 0.4)$$

where

n_e: the number of external generators,

P_i: the pattern vector of the i-th generator,

F_{im} : the m-th feature of P_i.

Step 4: Produce the first cluster,
$$k=1$$
$$N_k = 1$$
$$C_k = P_1$$
or, equivalently,
$$(B_{11}, B_{12}, B_{13}) = (F_{11}, F_{12}, F_{13}) \quad (10)$$
where

k: the number of existing clusters,

N_k : the number of patterns belonging to C_k ,

C_k : the center of the k-th cluster,

B_{km}: the m-th coordinate of C_k.

Step 5: Read the input pattern vectors by letting $i=2$,

Step 6: Read the i-th input pattern $P_i = (F_{i1}, F_{i2}, F_{i3})$ and calculate the Euclidean distance ED_j

between $P_i = (F_{i1}, F_{i2}, F_{i3})$ and the $C_j = (B_{j1}, B_{j2}, B_{j3})$.

$$ED_j = \sqrt{\sum_{m=1}^{3}(F_{im} - B_{jm})^2} \quad \text{for } j=1,2,...,k \quad (11)$$

Step 7: Find the minimum Euclidean distance to the existing clusters,
$$ED_p = min(ED_j) \quad \text{for } j=1,2,...,k \quad (12)$$

Step 8: If $ED_p > VP$, then create a new cluster center,
$$k=k+1$$
$$C_k = P_i$$
Or, equivalently,
$$(B_{k1}, B_{k2}, B_{k3}) = (F_{i1}, F_{i2}, F_{i3}) \quad (13)$$
$$N_K = 1$$

else,

the pattern $P_i = (F_{i1}, F_{i2}, F_{i3})$ belongs to the cluster p, and update the coordinates of C_p,

$$B_{pm}^{new} = \frac{N_p}{N_p + 1} B_{pm}^{old} + \frac{1}{N_p + 1} F_{im} \quad \text{for } m=1,2,3 \quad (14)$$

$$N_p = N_p + 1$$

Step 9: If pattern vector P_i changes from the cluster "o" (the old one) to "k" (the new one), then the coordinates of C_o are modified as:

$$N_o = N_o - 1$$

$$B_{om}^{new} = \frac{N_o + 1}{N_o} B_{om}^{old} - \frac{1}{N_o} F_{im} \quad \text{for } m=1,2,3 \quad (15)$$

Step 10: Repeat Step 6-Step 9 until all the patterns have been compared with the existing clusters,

Step 11: If the clustering process has converged, end; otherwise, return to Step 5.

With the advent of neurocomputer, the parallel distributed processing capability can potentially endow the ANN based clustering algorithm with a speed advantage over other series processing in the application of large power systems.

4. SIMULATION RESULTS AND DISCUSSION

4.1 Test Condition

To verify the effectiveness of the proposed method, a comprehensive testing of various fault locations is conducted on two different systems:

(a) The 10-machine New England system,
(b) The 34-machine Taipower system.

The disturbance is a three phase short circuit fault on the generator buses (GB) and the load buses (LB), cleared with and without line switching. Unless otherwise stated, the fault clearing time is set 0.2 s, and the study period is [0, 2] s throughout the simulation. Statistical assessments for evaluating the coherency degree of a generator pair are defined in terms of

$$\begin{cases} \bar{\varepsilon} = \frac{1}{n} \sum_{i=1}^{n} \varepsilon_i \\ \varepsilon_{max} = max(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n) \end{cases} \quad (16)$$

where ε_i is the absolute angle difference of the i-th sample with respect to the initial separation, $\bar{\varepsilon}$ and ε_{max} denote the corresponding average and maximum angle difference of the rotor trajectories, respectively, over the study period [0, t_{max}]. The sample time of the statistical data is set 0.01 s. Totally, 200 samples are compared for each generator pair over [0, 2] s. For a coherent group containing many machines, pairwise comparisons must be made to indicate the coherency level of this cluster.

Similarly, define the maximum average $\bar{\varepsilon}_{g\,max}$ and maximum absolute angle difference $\varepsilon_{g\,max}$ over all coherent groups as follows:

$$\begin{cases} \bar{\varepsilon}_{g\,max} = max\{\bar{\varepsilon}_1, \bar{\varepsilon}_2, \ldots, \bar{\varepsilon}_p\} \\ \varepsilon_{g\,max} = max\{\varepsilon_{1\,max}, \varepsilon_{2\,max}, \ldots, \varepsilon_{p\,max}\} \end{cases} \quad (17)$$

where $\bar{\varepsilon}_j$ and $\varepsilon_{j\,max}$ denote the average and maximum absolute angle difference of the j-th coherent group, and P is the number of coherent groups identified.

4.2 The New England System

The first test system is a 345 KV bulk transmission network of New England, which consists of 10 machines, 39 busbars, and 46 lines. The single line diagram of the system is shown in Fig. 2 with the data found in [18]. Generator 10 is an equivalent power source representing parts of the USA-Canadian interconnection system. Generator 10 was not considered in the coherency identification process because of its very high inertia constant.
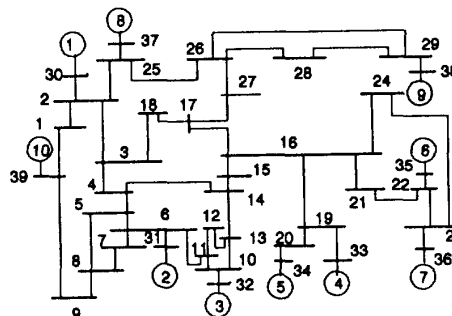

Fig. 2. The New England system [18].

Case 1: (3ϕ fault at bus #29, fault clearing at 0.2 s, line 29-26 tripped)

The generator G9 is selected as the study system. TABLE I shows the identified results for different input features and VP. It is obvious that both $\bar{\varepsilon}_{g\,max}$ and $\varepsilon_{g\,max}$ increase as VP increases in value irrespective of the features employed. According to the need for reduction in model complexity, one can specify an appropriate vigilance parameter. TABLE II illustrates the influence of choosing the rotor angle and speed as input features on coherency study. Also, the influence of the number of features used for ANN classification is explained with two features (sampled at 0.2 s and 0.4 s) and three features (sampled at 0.2 s, 0.4 s, and 0.6 s), respectively. The sampled swing curves of some representative generators are depicted in Fig. 3. Obviously, an inspection from the swing

TABLE I
IDENTIFIED RESULTS FOR DIFFERENT INPUT FEATURES

Input features	VP	Coherent group	$\bar{\varepsilon}_{g\,max}$ (deg)	$\varepsilon_{g\,max}$ (deg)
Angle	0.03	(6,7)	0.4	0.7
	0.05	(6,7)(2,3)	0.6	1.4
	0.07	(4,6,7)(2,3)	1.7	5.7
	0.1	*(4,5,6,7)(2,3)	3.9	14.3
	0.12	(4,5,6,7)(1,2,3)	4.7	16.4
	0.14	(1-8)	6.36	33.5
Speed	0.2	(6,7)	0.4	0.7
	0.4	(6,7)(2,3)	0.6	1.4
	0.5	(4,6,7)(2,3)	1.7	5.7
	0.6	*(2,3,4,6,7)	3.4	10.5
	1.0	(1-7)	5.8	33.5
	2.4	(1-8)	6.36	33.5

TABLE II
THE INFLUENCE OF INPUT FEATURES AND NUMBER OF FEATURES

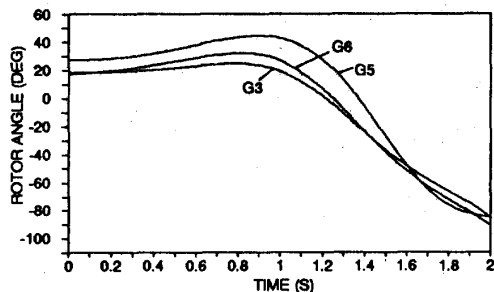| t_{max} (s)	No. of features	Coherent group	Euclidean distance (ED)		$\bar{\varepsilon}$ (deg)	ε_{max} (deg)
			angle (deg)	speed(rad/s)		
0.6	2	(6,3)	6.3	0.47	3.94	8.46
0.6	2	(6,5)	2.7	0.18	1.34	2.53
2.0	3	(6,3)	10.3	0.48	4.08	8.47
2.0	3	(6,5)	3.4	0.80	6.57	14.26

Fig. 3. Sampled swing curves for a fault 29*-26 of the New England system with the fault cleared at 0.2 s.

curves shows that the generator pair (G6,G5) is more coherent than the generator pair (G6,G3) over [0, 0.6] s and conversely for [0, 2] s, as evidenced by comparing their respective $\bar{\varepsilon}$ and ε_{max} in TABLE II. Physically, the generators with higher coherency must be clustered before those with lower coherency when the distance threshold increases. If the observation is over [0, 0.6] s interval, both the angle and speed criteria work reliably for coherency classification, since smaller ED corresponds to more coherent generator pair. In addition, two features are sufficient for correct coherency identification. However, when the observation is extended to [0, 2] s, the clustering process cannot yield correct results even with the addition of angle feature at 0.6 s. Referring to TABLE I, as VP increases from 0.07 to 0.14, the resulting clustering sequence using the angle features is (G6)⇒(G6,G5)⇒(G6,G5,G3). More features must be added for correct classification. In contrast, as VP increases from 0.5 to 1.0, the use of three speed features yields the correct clustering sequence: (G6)⇒(G6,G3)⇒(G6,G3,G5). Therefore, the rotor angles may be attractive features for coherent identification up to the last observation time, but cannot reliably represent the entire system dynamics from then onwards. On the other hand, because the speed can predict the tendency of the rotor trajectory, the speed criterion requires less number of features than the angle criterion for the identification of coherent generators with the same study period.

Case 2: (3φ fault at bus #25, fault clearing at 0.6 s, without line tripping)

This case is intentionally introduced to illustrate the use of multi-step Taylor series expansion for a larger clearing time. The generator G8 is the study system. The swing curves of some representative generators with the fault cleared at 0.6 s are shown in Fig. 4. Apparently, the generators (G2,G3) and (G4-G7) form two coherent groups from the observed rotor trajectories. To assess the accuracy of the TSE, the root-square

errors (physical distance, abbreviated PD) of rotor speed at three distinct instants of G2 and G3 are listed in TABLE III, which are 2.1 rad/s and 2.0 rad/s, respectively. The Euclidean distances of G2 and G3 are also included for comparison. In view of the great reduction in the error of ED, the presented frequency measure can be favorably used to minimize the errors from the TSE, if the TSE is utilized to predict the rotor speed. More significantly, both feature distributions from the above two methods can identify coherency very reliably.
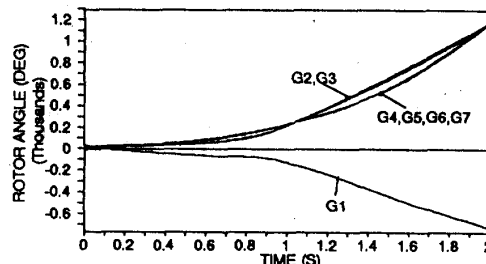

Fig. 4. Swing curves for fault bus #25 of the New England system with the fault cleared at 0.6 s.

TABLE III
COMPARATIVE RESULTS OF THE STEP-BY-STEP AND TAYLOR SERIES EXPANSION

Gen. no.	Step-by-Step			Taylor series expansion			Error
	$\omega_i(0.6)$	$\omega_i(0.8)$	$\omega_i(1.0)$	$\omega_i^*(0.6)$	$\omega_i^*(0.8)$	$\omega_i^*(1.0)$	PD
G2	6.0	11.8	20.7	5.6	9.8	20.2	2.1
G3	6.3	11.8	19.9	5.9	9.9	19.4	2.0
	ED= 0.85			ED*=0.86			ED*-ED=0.01

$$ED = \sqrt{\sum_{n=1}^{3}(\omega_i(t_n) - \omega_j(t_n))^2} \qquad PD = \sqrt{\sum_{n=1}^{3}(\omega_i(t_n) - \omega_i^*(t_n))^2}$$

4.3 The Taipower System

The second test system is the Taipower system, which is a practical medium-sized system in Taiwan. This system has a longitudinal structure covering a distance of 400 KM from north to south. It is divided into three areas: northern area, central area, and southern area, as shown in Fig. 5. This system contains 191 buses, 34 generators and 234 lines. The highest transmission system voltage is 345 KV.

Case 1: (3φ fault at bus #17, fault clearing at 0.2 s, line 17-18 tripped)

In this case, the generator G25 is the study system. Fig. 6(a) shows the number of identified clusters and the number of iterations needed for the convergence of learning process for different vigilance values. If VP is set 0, there are totally 33 clusters in the external system, since each isolated machine is considered as a (singleton) cluster. The set of resulting clusters can only decrease as the VP increases in value. It should be noted that the presented method always converges with the maximum number of iterations not exceeding four. For example, Fig. 6(b) shows the convergence process of the clustering algorithm with VP=0.9. It is obvious that the clustering algorithm converges to a stable pattern after three iterations. TABLE IV lists the identified coherent groups
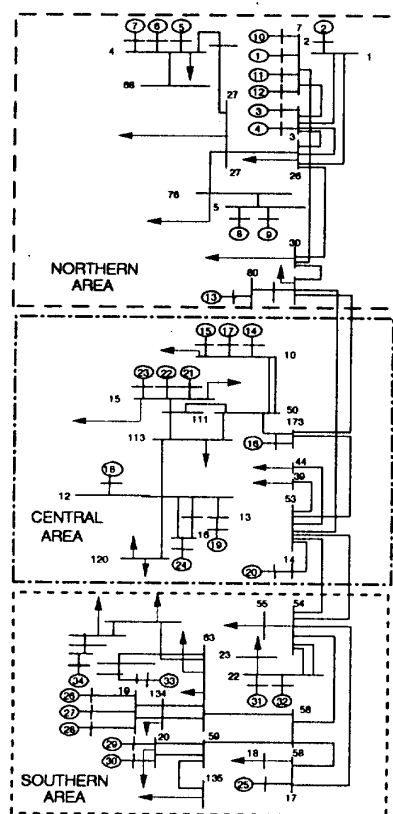
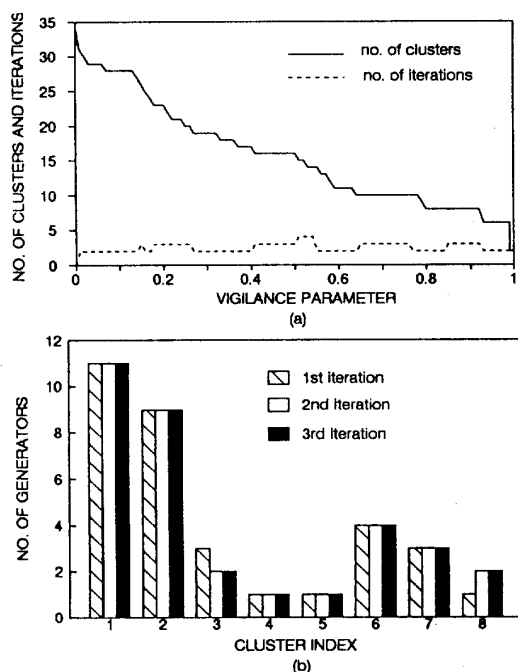Fig. 5. One-line diagram of the Taipower system.

Fig. 6. The number of clusters and iterations for different vigilance values.

TABLE IV
IDENTIFIED COHERENT GROUPS WITH DIFFERENT VIGILANCE PARAMETERS

VP	Coherent group	$\bar{\varepsilon}_{g\,max}$ (deg)	$\varepsilon_{g\,max}$ (deg)
0.1	(1,7,10,11,12)(3,4),(21,23)	0.1	0.5
0.2	(1,3,4,7,10,11,12)(2,6)(8,9)(21-23)(26,27)(15,17)	0.6	1.5
0.3	(1,3,4,7-12)(2,6),(15,17)(5,21-23)(26,27,30)(28,29)	1.2	2.0
0.4	(1,3,4,7-12)(2,6),(15,17)(5,21-23)(26,27,30)(28,29)(32,34)	4.5	5.5

along with the related angle differences observed over [0, 2] s interval for different vigilance values. When VP increases from 0.1 to 0.4, the corresponding $\bar{\varepsilon}_{g\,max}$ and $\varepsilon_{g\,max}$ increase from 0.1° and 0.5° to 4.5° and 5.5°, respectively. In general, the smaller the vigilance value, the smaller the average and maximum angle difference of the coherent generators, i.e., the higher degree of coherency the machines are aggregated.

Case 2: (3φ fault at bus #22, fault clearing at 0.2 s, line 22-23 tripped)

The generators G31 and G32 constitute the study system. For a tolerance of 5°, four coherent groups are identified with VP=0.4, as indicated by the feature distributions in Fig. 7. It is worth noting that (G21,G23) and G22 belong to different coherent groups. The swing curves of generators (G21-G23) with the fault cleared at 0.2 s are shown in Fig. 8. Note that the generators (G21-G23) are connected to the same bus # 15 with identical generator inertia. However, the rotor trajectory of G22 and that of G21 and G23 fall apart. Similar situation occurs for G29 and G30. Hence, the traditional coherency criteria, such as the distance measure [6,7] and generator inertia [7], often adopted to identify coherent generators may not yield reliable results. On the other hand, the coherent groups recognized by the presented clustering method completely agree with those obtained by the time simulation.
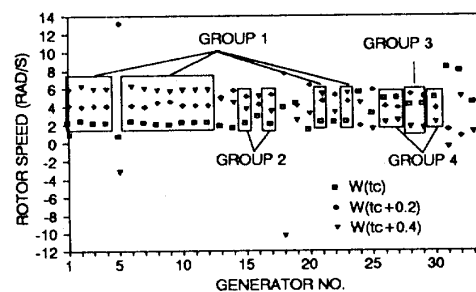

Fig. 7. Feature distributions for a fault 22*-23 of the Taipower system.

From the coherency study on two different power systems, it is found that the coherent groups identified by the presented clustering method in all cases conform to those obtained through direct simulation of the dynamics. According to the need for reduction in model complexity, one can select an appropriate vigilance parameter to cluster the generators into different groups with the specified level of coherency. Based on the comparison of the response of the accuracy of

equivalent with that of the actual system, our experience revealed that if the VP is set 0.4, the swing curves are clustered with the average angle difference less than 5°.
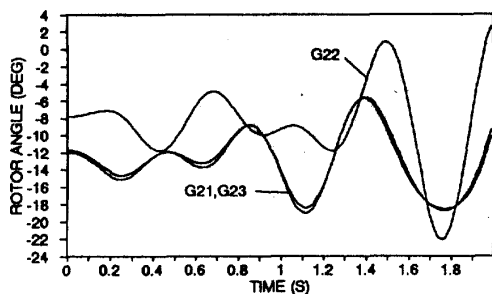

Fig. 8. Swing curves for a fault 22*-23 of the Taipower system with the fault cleared at 0.2 s.

5. CONCLUSION

This paper has tackled the toughest part of the process of producing dynamic equivalents in power systems through coherency identification. An efficient clustering method based on the use of an artificial neural network has been presented. It can reliably predict clustering of generators at different levels of coherency as suggested by the vigilance parameters of the ANN. A new frequency measure of coherency has first attempted to identify the coherent groups for each particular fault. Several computational advantages over the angle criterion can be offered by the speed criterion in the ANN implementation of the clustering algorithm:

(i) Since the speed of the generator can predict the tendency of the rotor trajectory, the number of input features required for ANN classification can be reduced with the same study period.

(ii) Due to the reduction in the number of input features, the computational effort required in the convergence of the learning process can be considerably reduced.

(iii) In (8), the rotor speed can directly be used as input feature for ANN since $\omega_i(0) = 0$. In contrast, the relative rotor angle difference, as indicated in (4), must be computed before the rotor angles are fed into the ANN for coherency identification.

(iv) The presented frequency measure can be favorably used to minimize the errors from the TSE, if the TSE is utilized to predict the rotor speed on a longer time interval.

Although in this study coherency identification has been investigated using the simple classical modeling, more accurate representation with refined generator and regulator modeling could be used without significant alteration to the clustering method.

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