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DYNAMIC-FEATUREXRACTION, ATTRIBUTION, AND RECONSTRUCTION (DEAR) METHOD

(For 7 Machine 29 Bus Power System Model Reductions)

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***Abstract*—This thesis makes an effort approach a method of deriving the reduced dynamic model of the seven machine 29 bus systems. It consists of identification of coherent generators, aggregation of coherent generators and network reduction. Coherent generators are identified by means of time domain simulation. In interconnected power systems, dynamic model reduction can be applied to generators outside the area of interest to reduce the computational cost associated with transient stability studies. The method consists of three step ,namely dynamic-feature extraction, attribution, and reconstruction (DEAR). In this method, a feature extraction technique, such as singular value decomposition (SVD), is applied to the measured generator dynamics after a disturbance. Characteristic generators are then identified in the feature attribution step for matching the extracted dynamic features with the highest similarity, forming a suboptimal "basis" of system dynamics. In the reconstruction step, generator state variables such as rotor angles and voltage magnitudes are approximated with a linear combination of the characteristic generators, resulting in a quasi-nonlinear reduced model of the original system.**

Keywords - **Dynamic response, feature extraction, dynamic modelreduction, orthogonal decomposition, power systems.**

I. INTRODUCTION

In interconnected power systems, dynamic model reduction (DMR) for generators outside the area of interest has been investigated to reduce the expensive computational cost of transient stability studies [1] – [5]. DMR generally consists of identifying and aggregating generators to be reduced, followed by reconfiguring the network model.

Dynamic model reduction (DMR) generally consists of identifying and aggregating generatorsto be reduced, followed by reconfiguring the networkmodel [16].

The process for dynamic reduction of a power systems are divided into three steps:

1. Identification of coherent generator groups.
2. Aggregation of generators in the group.
3. Reduction of the network.

In this paper we proposed new DMR (dynamic model reduction method) is used. Predictable studies about dynamic reduction are mainly focused on getting equivalent model of given coherent groups of generators. DMR performed on the model of the external area to reduce the computational load. A large number of control and safety schemes responding a disturbance can be tested in the study area with a reduced external area model, thus improving the efficiency of both planning and operation of the transmission network. The goal of DMR is to reduce the number of variables and equations used to represent the external area as much as possible, while keeping the responses of internal generators and other relevant devices unchanged to the degree possible. This proposed method consists of three steps:

1. Dynamic-feature extraction,
2 Feature attribution, and
3. Feature reconstruction

In interconnected power systems, dynamic model reduction (DMR) for generators outside the area is used to reduce the expensive computational cost of transient stability studies. Dynamic model reduction (DMR) holds guarantee to represent the real system with proper degrees of rough calculation while maintaining relevant dynamic properties, which enables faster simulations of system responses to disturbances. Successful implementation of DMR is complex for online dynamic security assessments, in which many scenarios need to be considered as part of possibility analysis. In dynamic model reduction coherency is the most common method which is used for the identification step.

A. *COHERENCY METHOD*

Advantage of coherency – obtaining the physical structure of the system compare to other method. This technique is known as "model equivalencing". This technique mainly classifies the coherency.

Coherency based reduction techniques classified in to three types:-

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1. Type I **-** Relies on evaluate linearized models of the system around the operating point. When grid configuration changes lines are tripped after a large disturbances. Recognition result can be obtained for the pre fault system not valid for the post fault system.
2. Type II**-** After the calculation of the result of offline dynamic simulation, we find the coherency groups. These methods are very useful and used in a higher reduction ratio, but the result of reduced model is very limited applicability in real time because both the system configuration and function point are different from the offline studies.
3. Type III – This method basically depend on the online measurement and computation, advanced hardware, with phasor measurement units, broadband communications, and fast computers, and with the probable to address issues linked with the other approaches.

R. Podmore [2] discussed the development and estimation of a method for identifying the coherency behavior of generator for various system disturbances. This information is used for forming dynamic equivalents which can be applied in transient stability. S. E. M. d. Oliveira and A. G. Massaud [3] discussed about the modal dynamic equivalent for electric power system in which is basically based on stability simulation test. While, S. E. M. d. Oliveira and J. F. d. Queiroz[4] discussed about only the theory of modal dynamic equivalent for electric power System.

Type III methods and the dynamic model reduction method (DMR) method is based on the dynamic phasor measurement data of generator.

The projected method is collected of the three steps:-

1. DYNAMIC- FEATURE EXRACTION
2. FEATURE ATTRIBUTION
3. FEATURE RECONSTRUCTION

Combination of all three methods is called DEAR.

1. Dynamic feature extraction: **-** Dynamic feature includes speed, frequency etc. In this method, a feature extraction technique, such as singular value decomposition (SVD), is applied to the measure generator dynamics after a disturbance.
2. Feature attribution:-Characteristic generators that have responses matching the extracted features (e.g., the orthogonal components from SVD) with the highest similarity are then identified.
3. Feature reconstruction:**-** In the reconstruction step, generator state variables such as rotor angles and voltage magnitudes are approximated with a linear combination of the feature generators, resulting in a quasi-nonlinear compact model of the original system.

II. PROCEDURE FOR THE DMR OF GENERATORS IN LARGER SYSTEMS

Step 1) Dynamic-feature extraction—Analyze the dynamic response vectors of the original system for a disturbance, and find the optimal orthogonal bases of these responses.

Step 2) Feature attribution—Identify generators with responses that are highly similar to the optimal orthogonal bases and designate those units as the characteristic generators.

Step 3) Feature reconstruction—Use linear combinations of the characteristic generators to approximate non characteristic generators.

III DYNAMIC FEATURE EXTRACTION: FINDING THE OPTIMAL ORTHOGONAL BASIS

In this section , we discuss about the concept and identification of optimal orthogonal basis system's dynamic responses. For our convenience we assume the classical generator model and rotor angle 'δ' are the state variables. Let the magnitude of the generator internal voltage, *E'*, is to be constant.

Let δ1,**δ2,………δi,…..δm**are the ***m*** rotor angles of the system to be reduced.

δi = n- dimensional row vector representing the dynamic of rotor angle.

Its elements are time series: δi(t1), δi(t2),…….,δi(tn).

Where, δ= $[\delta_1;\ \delta_2;\ \ldots\ldots;\delta_m]$

δ = m*n matrix

Let x = [x1; x2;……. ;xi;……..;xp] = set of optimal orthogonal basis.

p < m

xi= n-dimensional row vector.

Meaning of "optimal" is showing by this relation:

p < m

$\hat{\delta}$= Kx

Where, K =m*p matrix

and the equation is minimized,

$$\left\|\delta - \hat{\delta}\right\|_2 = \sum_{i=1}^{m} \left(\delta i - \hat{\delta} i\right)^T \left(\delta i - \hat{\delta} i\right) \quad (1)$$

x = Optimal orthogonal bases.

$\hat{\delta}$ =Approximation using optimal orthogonal bases.

T = Coefficient matrix between x and $\hat{\delta}$

m = Dimensionality of original space.

p = Dimensionality of reduced space.

K = First r columns of T.

In this paper we used SVD method i.e. singular value decomposition method, according to this method and SVD algorithm we solve the above equation and we find:

$\delta = UDW^T$ (2)
Where,
U= m*m unitary matrix
D= m*n rectangular matrix = Damping ratio of synchronous machine
W^T= n*n unitary matrix

$x = W^T(1{:}p,:)$
(3)
$K = T(:, 1:p)$
(4)
Where, T = UD
K = the first r column of T

IV FEATURE ATTRIBUTION: FIND OUT CHARACTERISTIC GENERATORS

The 'p' optimal orthogonal basis vectors found in the feature extraction step which will give result in negligible errors when used to approximate δ. If each of these basis vectors exactly matches the dynamic angle response of one of the generators, then the angle dynamics of the other generators must have very negligible energy impact because of their singular values are small. It means that we have to keep 'p' generators in the model while ignore the other generators.
The set of characteristics generators as suboptimal bases are representing the entire system.
To determine the characteristics, we have to find

$$\delta = [\delta_1; \delta_2; \dots\dots\dots; \delta_m]$$

In other words we have to find,

$$\varepsilon = [\delta_r; \delta_s; \dots\dots\dots; \delta_z]$$

Therefore, $'\varepsilon'$ is highly similar to 'x'.
According to the last subsection δ_s can be approximated by linear combination of the optimal orthogonal bases.
$\delta_r \approx K_{r_1}x_1 + K_{r_2}x_2 + \dots\dots + K_{r_i}x_i + \dots\dots + K_{r_r}x_r$
(5)

$\delta_s \approx K_{s_1}x_1 + K_{s_2}x_2 + \dots\dots + K_{s_i}x_i + \dots\dots + K_{s_r}x_r$
(6)

Where, x = optimal orthogonal basis and 'δ' is normalized by the given paper K.K.Anaparhi&K.F.Thornhill [8] which gives the coherency identification in power system through principal component analysis.
If $|K_{s_i}|$ is larger and indicates a higher degree of co-linearity between two vectors (δ_s *and* x_i)
For example $|K_{r_i}| > |K_{s_i}|$, it means there is similarity between x_i and δ_s is higher than that between x_i and δ_r.
δ_s have highest similarity to x, if there is inequality therefore the below equation gives the highest similarity and can identified for each orthogonal basis.

$|K_{s_i}| > |K_{r_i}|, for\ \forall\, p \in \{1,2,\dots\dots,m\}\ r \neq s$
(7)
From above equation $'\varepsilon'$ is determined.

V .FEATURE RECONSTRUCTION: MODEL REDUCTION USING THE LINEAR COMBINATION OF CHARACTERISTIC GENERATORS

$$\delta = UDW^T$$

$$\delta_r \approx K_{r_1}x_1 + K_{r_2}x_2 + \dots\dots + K_{r_i}x_i + \dots\dots + K_{r_r}x_r$$

$$\delta_s \approx K_{s_1}x_1 + K_{s_2}x_2 + \dots\dots + K_{s_i}x_i + \dots\dots + K_{s_r}x_r$$

According to these equation 'δ' can be arranged as:
$\delta = \begin{bmatrix}\varepsilon \\ \bar{\varepsilon}\end{bmatrix} \approx \begin{bmatrix}K_\varepsilon \\ K_{\bar{\varepsilon}}\end{bmatrix} x$
(8)
Where,
δ = m*n matrix
$\varepsilon = p * n$ matrix represnting rotor angle dynamics of characteristics gener
$\bar{\varepsilon} = (m - p) * n$ matrix represnting rotor angle dynamics of non − characteristics generators
x = p*n matrix
$K_\varepsilon = p * p$ *square matrix*
$K_{\bar{\varepsilon}}$ = (m-p)*P matrix
K_ε is invertible and linear relation between ε and $\bar{\varepsilon}$ is
$\bar{\varepsilon} = C\varepsilon$
(9)
C = (m – p)*p matrix and can be calculated by the least square method

$C = \bar{\varepsilon}[(\varepsilon\,\varepsilon^T)^{-1}\varepsilon]^T$
(10)

From equation (8) we can get:
$\varepsilon \approx K_\varepsilon x$
(11)

And $\bar{\varepsilon} \approx K_{\bar{\varepsilon}} x$
(12)

Multiplying both sides $K_{\varepsilon^{-1}}$ in equation (11) then we get,
$x \approx K_{\varepsilon^{-1}}\,\varepsilon$
(13)
Putting the value of x from equation (13) in equation (12)

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Therefore equation is: $\bar{\varepsilon} \approx K_{\bar{\varepsilon}} K_{\varepsilon^{-1}} \varepsilon$ (14)

Equation (9) and (14) developed the linear equation between the rotor angle dynamics of characteristics generators and non- characteristics generators.

In truth, with the generator excitation system, also will react dynamically to the disturbance. The dynamics of can be treated in the same way as rotor angle in the DEAR method to improve the reduced model, except that the set of characteristic generators needs to be determined from . This way, both and of non-characteristic generators will be represented in the reduced model using those of the characteristic generators.

Pyo *et al.* [23] present a coherency aggregation method that can handle higher-order models with excitation systems, and apply the method using the IEEE 29-bus system. Here the DEAR method is applied on the same system to compare the Performance.

VI. CASE STUDIES:

A. *Dynamic feature extraction*:

Seven machine system in which has the angle dynamics$\delta_1, \delta_2, \dots \dots \dots \dots . \delta_7$

$$\begin{bmatrix}\delta_1\\ \delta_2\\ \delta_3\\ \delta_4\\ \delta_5\\ \delta_6\\ \delta_7\end{bmatrix} = \begin{bmatrix} T_{11} \dots \dots \dots \dots \dots \dots \dots T_{17}\\ T_{21} \dots \dots \dots \dots \dots \dots \dots T_{27}\\ T_{31} \dots \dots \dots \dots \dots \dots \dots T_{37}\\ T_{41} \dots \dots \dots \dots \dots \dots \dots T_{47}\\ T_{51} \dots \dots \dots \dots \dots \dots \dots .T_{57}\\ T_{61} \dots \dots \dots \dots \dots \dots \dots .T_{67}\\ T_{71} \dots \dots \dots \dots \dots \dots \dots .T_{77}\end{bmatrix} \begin{bmatrix}W_1\\ W_2\\ W_3\\ W_4\\ W_5\\ W_6\\ W_7\end{bmatrix}$$

B. *Feature reconstruction*:

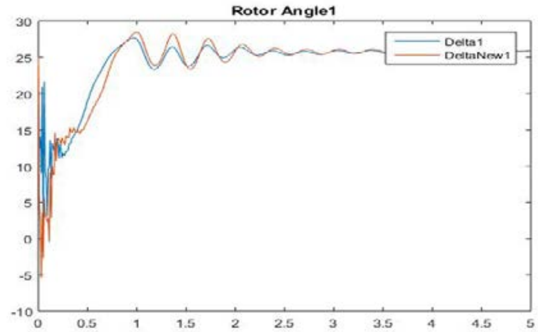
$$K_{\bar{\varepsilon}} = \begin{bmatrix}-530.4841\\ -493.8687\\ -526.9796\\ -512.7631\\ -520.9784\\ -530.4841\end{bmatrix}$$

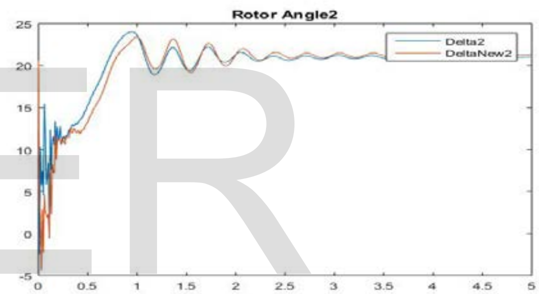
$$\bar{\varepsilon} \approx K_{\bar{\varepsilon}} K_{\varepsilon^{-1}} \varepsilon$$

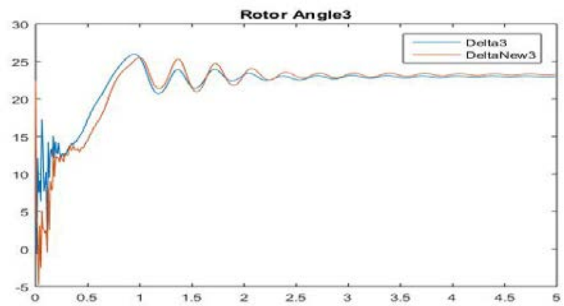
$$\begin{bmatrix}\delta_2\\ \delta_3\\ \delta_4\\ \delta_5\\ \delta_6\\ \delta_7\end{bmatrix} = \begin{bmatrix}-530.4841\\ -493.8687\\ -526.9796\\ -512.7631\\ -520.9784\\ -530.4841\end{bmatrix} \delta_1$$

C. *Graph of different rotor angles:*

Variation of different graphs of $\delta_1, \delta_2, \dots \dots \dots \dots . \delta_7$. Blue line shows old delta and red line shows new delta.







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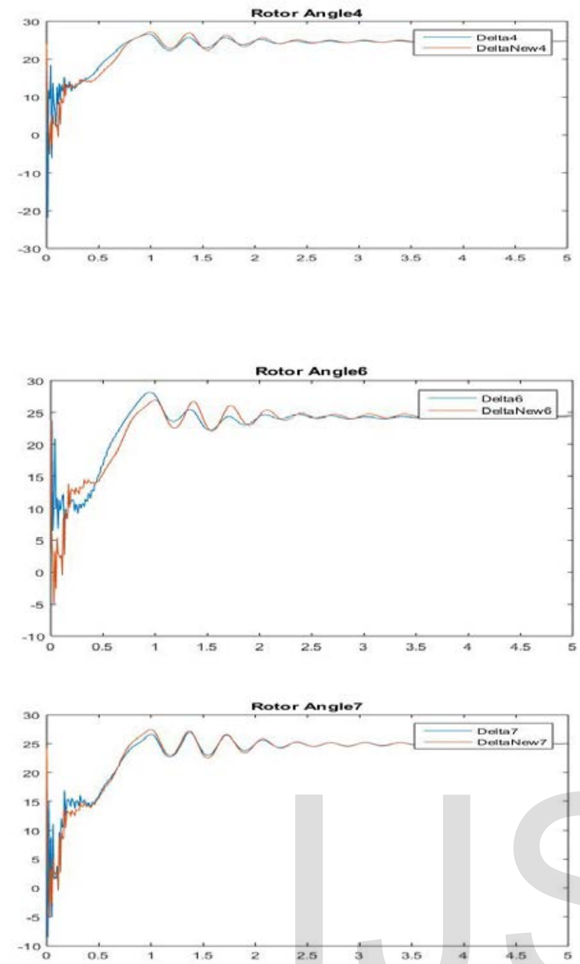

fig.1. Rotor angle dynamics in a seven machine system

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D. *Error function for machine 1*

$$j_{a(i)}=\frac{1}{(t2-t1)}\int_{t1}^{t2}\left|\delta_i^a(t)-\delta_i^f(t)\right|dt$$

$$J_{s(i)} = \sqrt{\frac{1}{(t2-t1)}\int_{t1}^{t2}\left[\delta_i^a(t)-\delta_i^f(t)\right]^2 dt}$$

Here we define an absolute magnitude and a square root of the sum of squares error function of ‘i’ in a time period t1 and t2. Whereδ_i^a; and δ_i^f are the rotor angle of machine iin the aggregate model and the original model, respectively. Using the error functions, we can investigate the optimal aggregation for each area.

Table- 1.1

δ	Ja	Js
δ_1	0.7154	1.8157
δ_2	0.6659	1.3377
δ_3	0.7883	1.6055
δ_4	0.6261	1.9137
δ_5	2.0787	3.6336
δ_6	0.8446	1.9963
δ_7	0.3327	1.0261

E. *Reduction ratio*:

$$\boldsymbol{R = (N_F - N_R)/(N_F)}$$

Where N_R= total number of state variables of the reduced model of the external system.

And,N_F = total number of variables of the original model.

VII. CONCLUSIONS:

A measurement-based dynamic model reduction method that simplifies the external systems through dynamic-feature extraction, attribution, and reconstruction is projected. The new method is named DEAR method. The network model is unchanged in the DEAR method, which makes online applications relatively easier, simple and more flexible (e.g., generators of interest can be retained in the reduced model). DEAR method give ways better reduction ratio and small number of errors than the coherency based aggregation method. It also shows that DEAR method works easily under stable and unstable conditions. Online application of DEAR method is demonstrate using a super set of characteristics generators and refinement of the coefficient matrix.
The performances of the software package developed have been described through a seven machine 29 bus system. For this case, a fault is placed on one of the transmission lines. In this case studies, it is shown that a system can be easily assembled by combining any appropriate selection of component models of the machine, exciter, governor and

network. The simulation results show the responses of the main dynamic indicators of the system such as load angle and speed the actual.

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