Dynamic Equivalence of DFIG Using Model Order Reduction

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Abstract.
The dynamic model of Doubly Fed Induction Generator (DFIG) is essential for deploying advanced control strategies. Real time simulation settings that include advanced control system requirereduced order models so as to reduce computational complexity. The challenge then is to develop reduced order models for efficient and accurate extraction of qualitative and quantitative information from these models for a particular situation. In this paper an overview and comparison of aggregation, modal analysis based and norm based model reduction techniques has been discussed considering a grid connected DFIG model. It has been deduced that the dynamics of the reduced order model using balanced truncation and realization were close to the full-order DFIG model.

Keywords: Doubly fed induction generator, Model order reduction, Norm based methods, aggregation modal analysis
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1 Introduction

Industrial revolution has open out to the advancement in electrical industry, which has become obligatory for society. The requirement for electricity and subsequently more competent power generating units grew rapidly. There are several techniques to generate electricity using non-renewable sources such as coal, nuclear energy and renewable energy sources such as geothermal energy, wind energy and solar energy. However, modern energy policies and technologies are driving the energy industry to decarbonisation and decentralization [1]. Wind energy plays an important role in this key low-carbon and decentralized future. At present, Doubly Fed Induction Generator (DFIG) is the most widely installed wind turbine in power systems. These growing numbers of DFIG based wind farms have extensively increased the complexity and simulation burden in analyzing the stability of power system.

The control structure of DFIG includes back-to-back converter that is connected to rotor of DFIG to supply current of varying frequency. This enables wind turbines to reach various operating speeds in contrast to conventional wind turbines that have fixed turning speeds. The converter controllers have increased the complexity of wind generation model. The size of the dynamic model may also influence the efficiency of stability analysis. The fundamental reason to obtain reduced order model is to simplify the system perceptive, to reduce computational efforts in experimental analysis and so make the controller design more efficient numerically with simpler control laws. The DFIG system has negative damping under varying operating speed because of its low internal resistance. Also, damping of electromechanical oscillations in power systems is poor. The methodology to analyze and control electromechanical oscillations in power system is well established [3]-[4]. The oscillations can be reduced by integrating controllers to generators, flexible alternating current transmission system or high voltage direct current transmission links. Power system stabilizers (PSSs) has been extensively used as damping control devices [5]. However, electromechanical oscillations are accurately characterized by eigen values and eigen vectors of the state matrix of a linearized model of the power system.

A number of theoretical algorithms that can handle eigen value analysis of large power systems have been proposed. The eigen value problems related to these large-scale dynamical systems are usually too large to be solved completely. In stability analysis, dominant eigen values or poles of the transfer function that contribute significantly to the frequency response are of major consideration. As proposed by Davison et al [2]. the dynamic equivalence of a large scale model can be obtained by retaining the dominant poles alone while ignoring the eigen values far away from origin. Hence models with reduced order can be used for small signal stability analysis as it preserves the required information with reduced model complexity [9]. In general model reduction techniques can be classified to three groups. aggregation based, modal analysis based and norm based. This paper presents a comparison between actual and reduced order DFIG model using aggregation, modal and balanced truncation (norm based) techniques.

2 Methodology

2.1 Aggregation Method

Aggregation method is one of the most important model reduction techniques in time domain [7]. The state space equation governing a dynamic system in continuous time is given by

$$\begin{aligned} \dot{X}(t) &= AX(t) + Bu(t) \\ y(t) &= CX(t) \end{aligned} \quad (1)$$

Where X is $n\times n$ state vector, u is the input vector with size $n\times m$, y is the measurement vector of size $p\times 1$. A, B and C are constant matrices that satisfies controllability and observability with dimensions $n\times n$, $n\times p$ and $p\times n$ respectively.

The higher order state space model can be replaced by a reduced order aggregated model given by

$$\begin{aligned} \dot{Z}(t) &= FZ(t) + Gu(t) \\ w(t) &= Hz(t) \end{aligned} \quad (2)$$

Where Z refers to the aggregated state vector whose size is less that n. w is the output vector. F, G, H are the reduced matrices of A, B and C respectively. This reduced order model is considered if for any given input, their outputs are close to the output of full order model. The order, r of the aggregated model is such that m ≤ r ≤ n. The link between the linear dynamic models could be determined by a linear transformation of the form

$$Z = TX \quad (3)$$

Where T is a constant matrix with rank r and size r × n. The equivalence between the full order and reduced order model is achieved provided that the following conditions are satisfied.

$$\begin{aligned} FT &= TA \\ G &= TB \\ Z(0) &= TX(0) \end{aligned} \quad (4)$$

Since the aggregation matrix, T is assumed to be of full rank, it have a pseudo-inverse and hence the least squares solution of F is

$$F = TAT'(TT')^{-1} \quad (5)$$

It is asserted that the reduced order system matrix F obtained as above is an approximate solution and it depends on the aggregation matrix L.

2.2 Selective Modal Analysis

Selective Modal Analysis (SMA) based model order reduction technique is dynamic equivalencing in which the reduced order model retains the natural modes (eigen values and eigen vectors) of the full order model.

Participation factors are non-dimensional quantities that measure the correspondence between natural frequencies and the internal variables (state variables). They relate the sensitivity of the model eigen structure to system parameters and play a key role for obtaining reduced order models. 1760

Participation factor, p_{ji} is termed as the product of the j-th's components of the right eigen vector, v_{ij} and left eigen vector w_{ij}, i.e. $p_{ji}=w_{ij}v_{ij}$. Also, the sum of participation factors of all variables in a mode and the sum of the participation of all modes in a variable are equal to one

$$\sum_{j=1}^{N} p_{ji} = \sum_{i=1}^{N} p_{ji} = 1 \qquad (6)$$

The iterative procedure for model reduction based on eigen value and eigen vectors is given in [6]

2.3 Balanced Truncation Realization

The first step in obtaining a reduced order model using balanced truncation and realization is to obtain the balanced realization of the system. In balanced realization, the key property is that there exists a coordinate transformation such that controllability and observability grammians are equal to grammian matrix, Σ. i.e. $P = Q = \Sigma = \mathrm{diag}(\sigma_1 I_{n_1}, \sigma_2 I_{n_2}, \sigma_1 I_{n_1})$ with Hankel singular values $\sigma_1 > \sigma_2 > \sigma_1$

Then an appropriate reduced order, r is chosen. After which the system is partitioned as

$$G_r = \begin{bmatrix} \bar{A}_{11} & \bar{B}_1 \\ \bar{C}_1 & \bar{D} \end{bmatrix} \qquad (7)$$

The controllity grammian, P and observability gramian, Q are computed such that it satisfies the Lyapunov equations

$$\begin{aligned} AP + PA' + BB' &= 0 \\ A'Q + QA + CC' &= 0 \end{aligned} \qquad (8)$$

The balanced grammian matrix $\sum$ is partitioned as $\Sigma = \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix}$ viz. $\sum_1$ representing most energetic modes and $\sum_2$ represents less energetic modes. Hence the system can be truncated accordingly

$$G = \begin{bmatrix} \bar{A}_{11} & \bar{A}_{12} & \bar{B}_1 \\ \bar{A}_{21} & \bar{A}_{22} & \bar{B}_2 \\ \bar{C}_1 & \bar{C}_2 & D \end{bmatrix}$$

Thus the system with most energetic modes, $\sum_1$ as its balanced grammian would be a good approximation of the original system.

3 Results and Discussion

In this case analysis, DFIG based wind power system connected to grid is considered. Accurate linear state space model was derived for small variations from nominal operating conditions [8] with seven states including five electrical quantities: stator current in direct and quadrature axes, field current, damping current in direct and quadrature axes and two mechanical quantities: power angle and speed of rotation. Field voltage and mechanical torque are the system inputs and machine voltage, power angle and speed of rotation are considered as measured variables. The system matrix (A), input matrix (B) and output matrix (C) is numerically given as

$$A=\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & -52.08 & -23.54 & 9.415 & -23.54 & -99.2 & 27.88 \\ -541.2 & 0.6953 & -2.216 & -36.23 & 24.15 & 664.2 & -362.3 \\ -1136 & 1.46 & -0.664 & -76.08 & -12.08 & 1395 & -760.8 \\ -541.2 & 0.6953 & 1.328 & -36.23 & -38.65 & 664.2 & -362.3 \\ 398 & 3.403 & 897.1 & -1346 & 897 & -53.83 & -26.91 \\ 298.5 & 2.552 & 672.9 & -1009 & 672.9 & -40.37 & -35.89 \end{bmatrix}$$

$$B=\begin{bmatrix} 0 & 0 \\ 0 & 52.08 \\ 2.121 & 0 \\ .6642 & 0 \\ -1.328 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} C=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ -0.17 & 0 & 0 & 0.318 & 0 & -0.0375 & 0 \end{bmatrix}$$

The system is reduced by the three model reduction methods and the eigen value comparison is given in Table 1.The frequency response comparison between original and reduced model for aggregation method, selective modal analysis and balanced truncation and realization is given in figures 1, 2, 3 respectively. It is observed that balanced truncation and realization method give a more close frequency response to original system compared to other techniques.

Table 1. Comparison of eigen values.

Method	Eigen value
Original model	-71.25 ± i636, -48.85, -27.88, -36.67, -2.47, -0.37
Aggregation	-71.25±i636, -48.85, -2.47, -0.37
Selective modal analysis	-35.06, -0.95, -2.38
Balanced truncation	-48.91,-38.74,-28.19, -38.74, -2.47

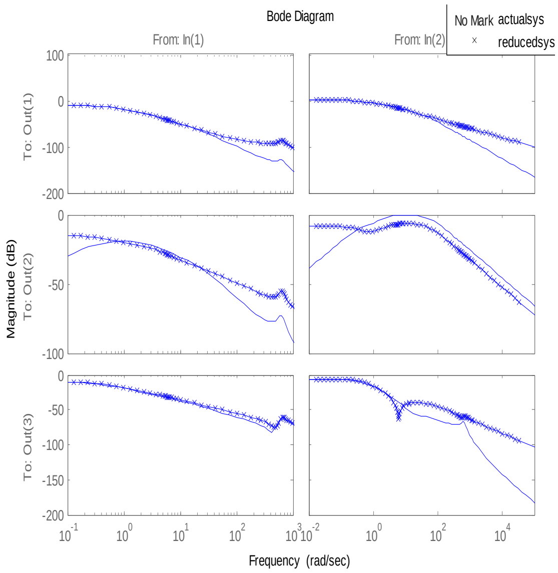

Fig. 1. Frequency response comparison of actual and reduced system using aggregation

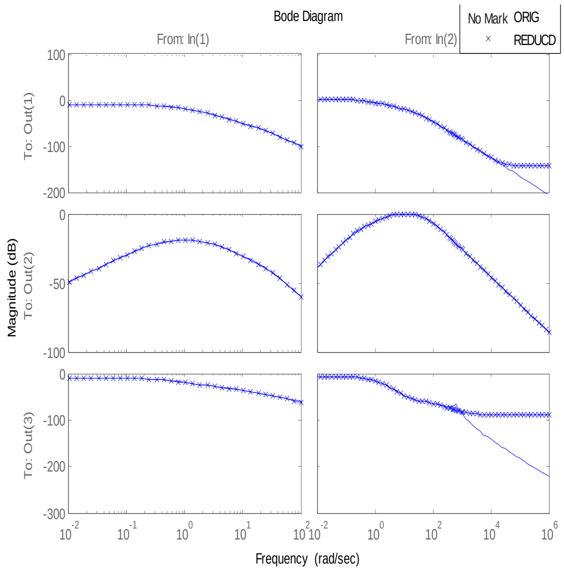

Fig. 2. Frequency response comparison of actual and reduced system using balanced realization

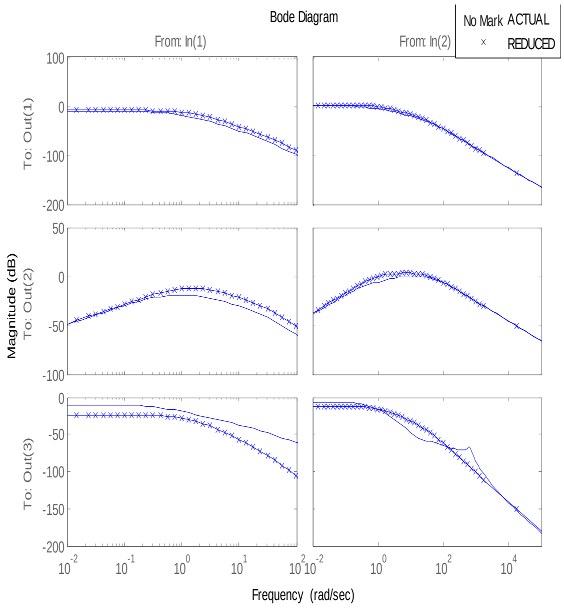

Fig. 3. Frequency response comparison of actual and reduced system using selective modal analysis

4 Conclusion

In this paper three model reduction techniques, aggregation, modal analysis based and norm based techniques have been discussed. An electric power system consisting of salient-pole synchronous generator connected to an infinite bus-bar is reduced using the three techniques and it is observed that balanced truncation and realization gives a more accurate and closer frequency response to the original system compared to aggregation technique and modal analysis and also the eigen values of original and reduced order system are close to each other.

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