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Identification of synchronous generators using adaptive wavelet networks

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Abstract

Application of wavelet networks for the identification of a synchronous generator is described in this paper. Parameter adaptation laws are used to track the variations in the parameters, following changes in the generator operating conditions. The adaptation laws have been developed using a Lyapunov function. This guarantees the stability of the identification algorithm and also ensures the convergence of parameters and variables. The proposed method has been tested on a synchronous machine. Experimental results show good accuracy of the identified model and robustness of the algorithm following severe changes in the operating conditions.

Keywords: Synchronous generators; Nonlinear identification; Wavelet networks

1. Introduction

With the increased complexity of the modern interconnected power systems, analysis of the dynamic performance of such systems has become very important. For the analysis of the dynamic performance and stability of the system, a valid dynamic model is a basic requirement. For this reason, identification and modeling of different parts of the power systems, has attracted many researchers.

Synchronous generators play a very important role in the stability of the power systems. A valid model for synchronous generators is essential for a valid analysis of stability and dynamic performance. Almost three quarters of a century after the first publications in this area [1,2], the subject is still a challenging and attractive research topic.

The traditional methods of modeling of synchronous generators are well specified in IEEE standards [3]. These methods assume a known structure for the synchronous machine, using well-established theories like Park transformation. They address the problem of finding the parameters of the known structure. Usually, the procedures involve difficult and time-consuming tests. These approaches include short-circuit tests, standstill frequency response (SSFR) and open circuit frequency response (OCFR). These tests can mainly be carried out when the machine is not in service.

To overcome the shortcomings of the traditional methods, identification methods based on on-line measurements have gained attention during the recent years [4–8]. These methods can be divided into two categories. In the first category [4–6], assuming a known structure for the synchronous machine (as the traditional methods), the physical parameters are estimated from on-line measurements. The second category [7,8] deals with black-box modeling of synchronous generators using input–output data. In the black-box modeling, the structure of the model is not assumed to be known a priori. The only concern is to map the input data set to the output data set.

Identification of linear dynamic systems has theoretically been well established and many good approaches are available [9,10]. However, identification of nonlinear systems such as synchronous machines, is still an active research topic. Many different approaches, like Nonlinear Least Squares, Volterra series, Weiner series, Wavelets,

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Neural networks, Fuzzy logic and Genetic algorithm have been developed for identification of nonlinear systems. A survey of techniques prior to the 1980s is given in [11]. A good recent review of the nonlinear identification approaches can be found in [12].

Among many methods developed for black-box modeling are neural networks [13] and the recently introduced wavelet decomposition [14–16]. These tools have become useful in many scientific areas, among which are signal processing and system identification. Although the approaches are based on different theoretical basis, there are some similarities when the final optimization index is obtained. Therefore, efforts have been made to find some common ground for the mentioned methods. Wavelet networks, which have been developed using both the feed-forward neural networks and wavelet decompositions, combine the advantages of both approaches [17–19]. The main idea is to use wavelet functions and scaling functions as the nonlinear functions required in the neurons.

In this paper, the aim is to identify a nonlinear black-box model for a synchronous generator using wavelet networks. Such black-box models can be used for system analysis and controller design, especially designing power system stabilizer (PSS). The model can be used either in a predictive control structure for an on-line PSS design, or used as a simulator to test an off-line design. The paper is organized as follows.

In Section 2, the identification method is described. In this section, first the wavelet decomposition and then the adaptation laws for parameter estimation are introduced. Section 3 describes the model of the system. Experimental setup and data collection on a micro-machibe are discussed in Section 4. In Section 5, the application of the proposed method is carried out on the micro-machine and the experimental data is compared with the simulated nonlinear model of the synchronous generator. Section 6 concludes the paper.

2. Identification method

A detailed description of the theory of the wavelet transform can be lengthy and complicated. A brief description of the identification of nonlinear systems using wavelet networks is described here. For a detailed treatment of the subject one may refer to [14,19].

To use wavelet transform, a wavelet function should be defined. A wavelet function, $\psi(x)$, is a function whose binary dilation and dyadic translations are enough to represent all functions in $L^2(\mathcal{R})$. In other words, if a function $f(x)$ is measurable and

$$\int_{-\infty}^{+\infty} |f(x)|^2 \mathrm{d}x < \infty \tag{1}$$

then it can be represented by the series

$$f(x) = \sum_{j,k} c_{j,k}\psi_{j,k}(x) \tag{2}$$

where

$$\psi_{j,k}(x) = 2^{j/2}\psi(2^j x - k) \tag{3}$$

If $f(x)$ is known, the wavelet coefficients $c_{j,k}$ are given by

$$c_{j,k} = \langle f, \psi_{j,k}(x)\rangle = \int_{-\infty}^{+\infty} f(x)\overline{\psi_{j,k}(x)}\,\mathrm{d}x \tag{4}$$

where $\overline{\psi_{j,k}(x)}$ is complex conjugate of $\psi_{j,k}(x)$.

Using multiresolution analysis (MRA) [14] of the wavelet transform, for some integer value j_0 (usually zero), Eq. (2) can be replaced by

$$f(x) = \sum_k a_{j0k}\varphi_{j0k}(x) + \sum_{j\geq j0}\sum_k b_{j,k}\psi_{j,k}(x) \tag{5}$$

where $\varphi(x)$ is called the scaling function and $\varphi_{j0k}(x) = 2^{j0/2}\varphi(2^{j0}x - k)$. The scaling function and the wavelet function are related to each other and one can be obtained using the other [14]. For n-dimensional case, Eq. (5) is replaced by

$$f(\underline{x}) = \sum_{\underline{k}} a_{j0k}\Phi_{j0\underline{k}}(\underline{x}) + \sum_{j\geq j0}\sum_{\underline{k\in Z^n}}\sum_{i=1}^{2^n-1} b^i_{j,\underline{k}}\Psi^i_{j,\underline{k}}(\underline{x}) \tag{6}$$

where $\underline{k} = [k_1, k_2, \ldots, k_n]^{\mathrm{T}} \in Z^n$ and

$$\Phi_n(\underline{x}) = \varphi(x_1)\varphi(x_2), \ldots, \varphi(x_n) \tag{7}$$

and also $\Psi^i(\underline{x}), i = 1, 2, \ldots, (2^n - 1)$ are obtained by substituting some $\varphi(x_j)$ by $\psi(x_j)$ in Eq. (7). In practical use of Eq. (6), some limited number of j and k is quite adequate. Therefore, Eq. (6) becomes:

$$\hat{f}(\underline{x}) = \sum_{\underline{k}\in Z^n} a_{j0k}\Phi_{j0\underline{k}}(\underline{x}) + \sum_{j=j0}^{N}\sum_{\underline{k}\in Z^n}\sum_{i=1}^{2^n-1} b^i_{j,\underline{k}}\Psi^i_{j,\underline{k}}(\underline{x}) \tag{8}$$

Using MRA, it can be shown that the bigger N and wider range of k would result in a better approximation of the function [14,19]. Eq. (8) is called the wavelet network as it takes the form of a neural network and the wavelet functions are used in its formulation.

Now consider a continuous dynamic nonlinear system described by

$$\dot{\underline{x}} = \underline{f}(\underline{x}, \underline{u}) \tag{9}$$

where $\underline{x} \in \mathcal{R}^n$ is the state vector and $\underline{u} \in \mathcal{R}^r$ is the input vector and $\underline{f}(\underline{x}, \underline{u}) = [f_1(\underline{x}, \underline{u}), f_2(\underline{x}, \underline{u}), \ldots, f_n(\underline{x}, \underline{u})]^{\mathrm{T}}$ is a nonlinear function vector. Eq. (6), which was written for a scalar function can now be extended to the vector function $\underline{f}(\underline{x}, \underline{u})$. Note that the number of variables has changed from n to $m = n + r$ in the state space description of