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Parameters identification of nonlinear state space model of synchronous generator

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ABSTRACT

Synchronous generator (SG) modeling plays an important role in system planning, operation and post-disturbance analysis. This paper presents an improved algorithm named Particle Swarm Optimization with Quantum Operation (PSO–QO) to solve both offline and online parameters estimation problem for SG. First, the hybrid algorithm is proposed to increase the convergence speed and identification accuracy of the basic Particle Swarm Optimization (PSO). An illustrative example for parameters identification of SG is provided to confirm the validity, as compared with Linearly Decreasing Inertia Weight PSO (LDW-PSO), and the Quantum Particle Swarm Optimization (QPSO) in terms of parameter estimation accuracy and convergence speed. Second, PSO–QO is also improved to detect and determine parameters variation. In this case, a sentry particle is introduced to detect any changes in system parameters. Simulation results confirm that the proposed algorithm is a viable alternative for online parameters detection and parameters identification of SG.

1. Introduction

Accurate model for SG not only provides a great support for stability and dynamic performance analysis of power system, but also is significant in power system planning, operation and post-disturbance analysis. A wide range of linear and nonlinear analytical techniques such as Least Square (LS) (Emile Mouni et al., 2008), Volterra Series (Fard and Karri, 2005), Hartley Series (Melgoza et al., 2001) and H∞ identification method (Dehghani et al., 2010), etc., have been developed for parameters or models identification of linear and nonlinear systems. Some of them have been used for parameters or models identification of SG.

Usually, it is considered that LS method is simple to use and cost little computation but large estimation error occurs when the system is influenced by colorful noises (Modares et al., 2010b). Although Volterra Series is useful in SG model identification but large number of Volterra kernels need to be selected and determined (Abbas and Bayoumi, 2004). Hartley series can be successfully used for parameters identification of SG but the assumption of the differentiability and continuity of the input and output variables are needed. Although H∞ identification method can be used for synchronous machine model parameters estimation but the calculation is complex.

Other analytical techniques, such as stochastic search techniques have been widely studied and used for parameters identification of nonlinear system or SG. Usually, these techniques only depend on the objective function and some of them can be used for online identification. Due to this, Genetic Algorithm (GA) was used to estimate parameters for nonlinear systems (Wang and Gu, 2007; Tavakolpour et al., 2010) and SG (Ma and Wu, 1995; Niewierowicz et al., 2003). Although GA is efficient in finding the global minimum of the search space and the solutions are independent on initial values of the parameters, it consumes too much search time which is not proper for online identification reported in the literature (Sabat and Coelho, 2009; Sabat et al., 2010). Comparing to GA, Particle Swarm Optimization (PSO) is easy to implement and convergences quickly and it was improved and widely used in parameters identification such as parameters estimation of permanent magnet synchronous motors (PMSM) (Liu et al., 2008), induction motors (Ursema and Vadstrup, 2004) and chaotic dynamic system (Modares et al., 2010a; Sun et al., 2010). However, it shows some shortages such as premature convergence (Cai et al., 2007). Much effort has been put in improving the performance of PSO. With introducing quantum theory into PSO, a novel variant of PSO named quantum-behaved PSO (QPSO) algorithm was proposed in Sun et al. (2004). In QPSO algorithm, it assumes that the position and velocity of an individual cannot be determined simultaneously and a wave function is cited to describe the status of individuals. By employing the Monte Carlo method, the iterative equation of particles position is derived from the quantum probability density function. Comparing to PSO algorithm, it has a global searching ability (Sun et al., 2004) and it has been used for system identification (Sabat et al., 2010; Luitel and Venayagamoorthy, 2010), multi-objective optimization (Omkar et al., 2009), controller design (Shayeghi et al., 2010) and other fields.

In this paper, to increase convergence speed and improve the identification accuracy of LDW-PSO, quantum operation is embedded in the evolution procedure and an improved algorithm

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called PSO–QO is proposed to solve the problem of parameters identification of SG. Moreover, PSO–QO algorithm is also improved to detect and track system parameters variation. If any change in parameters occurs, a sentry particle alerts the swarm to reset their best location memories and then the algorithm runs further to find the new optimum values. Finally, the performance of the proposed algorithm is demonstrated through identifying parameters of SG. Comparison study show the hybrid algorithm has faster convergence speed, higher precision and better nonlinear system identification ability than LDW-PSO and QPSO in the parameters identification of SG. The simulation results also confirm the feasibility and efficiency of the proposed algorithm for online parameters identification of SG.

The rest of the paper is organized as follows: In Section 2, SG model is introduced. Section 3 illustrates the identification strategy based on PSO–QO algorithm. The proposed PSO–QO algorithm is introduced in Section 4. Sections 5 and 6 contain simulation results and conclusions, respectively.

2. The SG model

According to different assumption, SG can be modeled in different way. Detail nonlinear SG model can be found in Yu (1983) and Kundur (1994). In this paper, neglecting the electromagnetic characteristic of damper windings, and assuming the generator unit connecting to an infinite bus, then the dynamic process of the generator unit can be described by a third order differential equations formulated in (1). Meanwhile, neglecting the effect of the magnetic saturation, parameters x_d, x_q and $x_{d'}$ can be assumed as constants. The study system is shown in Fig. 1

$$\begin{cases} \dot{\delta} = w_b*(w-1) \\ \dot{w} = \frac{1}{J}(T_m - T_e - D(w-1)) \\ e'_q = \frac{1}{T'_{do}}(E_{FD} - e'_q - (x_d - x'_d)*i_d) \end{cases} \tag{1}$$

where

$$i_d = \frac{e'_q - V\cos\delta}{x'_d}$$

$$i_q = \frac{V\sin\delta}{x_q}$$

$$T_e = P_e \cong \frac{V}{x'_d} e'_q \sin\delta + \frac{V^2}{2}\left(\frac{1}{x_q} - \frac{1}{x'_d}\right)\sin(2\delta)$$

where δ is the rotor angle in rad; w is the electrical speed in per unit, $e_q{}'$ is internal voltage of the armature, T_m is the input mechanical torque, T_e is the output electric torque, D is the damper coefficient, $T_{do}{}'$ is the constant of field winding, V is voltage of the infinite bus.

3. The identification strategy

For the model of SG illustrated by (1), parameters J, D, x_d, $x_d{}'$, x_q and T_{dop} are unknown and usually provided by manufactures through tests such as short-current tests, standard frequency response and open circuit frequency response tests. However, these

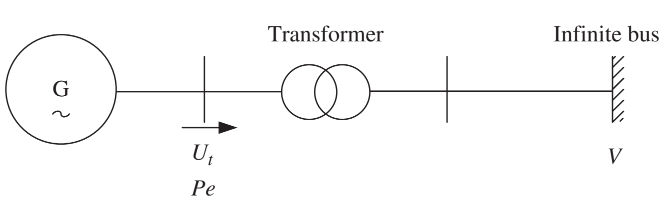

Fig. 1. Structure of the study system.

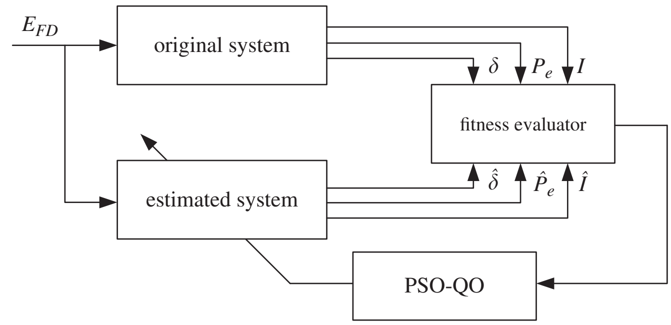

Fig. 2. Parameters identification of SG using PSO–QO algorithm.

tests are time-consuming and can be carried out when SG is not in service (Abbas and Bayoumi, 2004; Escarela-Perez et al., 2004). In this study, an improved optimization algorithm named PSO–QO is provided to solve this problem.

The basic idea of parameters estimation using heuristic optimization algorithms is to convert the problem of parameters identification into an optimization problem. Those unknown parameters are usually set as some particles or genes in chromosomes and a performance function measuring how well the model response fits the system response is built to optimize. In this study, considering that different parameters compositions may result in the same system outputs and assuming that the field voltage, rotor angle, the electrical power and stator current can be measured, an improved fitness function is defined as (2)

$$fitness = \frac{1}{N}\left(\sum_{i=1}^{N}(\delta_i - \hat{\delta}_i)^2 + \sum_{i=1}^{N}(P_{ei} - \hat{P}_{ei})^2 + \sum_{i=1}^{N}(I_i - \hat{I}_i)^2\right) \tag{2}$$

where δ_i is the ith sample of the rotor angle of the original system, $\hat{\delta}_i$ is the ith sample of the rotor angle of the estimated system, P_{ei} is the ith sample of the electrical power of the original system, $\hat{P}_{ei}$ is the ith sample of the electrical power of the estimated system, I_i is the ith sample of the stator current of the original system, $\hat{I}_i$ is the ith sample of the stator current of the estimated system.

As shown in Fig. 2, the original and the estimated systems are supplied with a same excitation input and their outputs are given as inputs to the fitness evaluator, where the fitness is calculated. The sum of squared error (SSE) for a number of samples shown as (2) is considered as fitness of estimated model. Then, as minimizing the fitness function, outputs of the estimated system approximates to the output of the original system and parameters of the estimated system converge to those of the original system.

4. Particle swarm optimization integrated with quantum operation

4.1. Overview of PSO and QPSO

By simulating social behavior such as bird flocking, fish schooling and swarm theory, PSO is firstly proposed by Kennedy and Eberhart in 1995. In PSO, each particle described by velocity and position represents a potential solution to the problem. The particles repeatedly update their velocity and position until the pre-specified number of generations G or the precision of solution is reached. The update law can be expressed as

$$v_{i,j}^{k+1} = w*v_{i,j}^{k} + c_1*rand*(pbest_{i,j}^{k} - x_{i,j}^{k}) + c_2*rand*(gbest - x_{i,j}^{k}) \tag{3}$$

$$x_{i,j}^{k+1} = x_{i,j}^{k} + v_{i,j}^{k+1}, \quad i = 1,2,\ldots,popsize, \quad j = 1,2,\ldots,p, \quad k = 1,2,\ldots,G \tag{4}$$

where $x_{i,j}^{k}$ is the jth dimension of the ith particle position in kth iteration, $v_{i,j}^{k}$ is the jth dimension of the ith particle velocity in kth iteration,