Frequency Domain Parameter Estimation of a Synchronous Generator Using Bi-objective Genetic Algorithms

P. PAO-LA-OR*, T. KULWORAWANICHPONG, and A. OONSIVILAI
Power and Energy Research Unit, School of Electrical Engineering
Institute of Engineering, Suranaree University of Technology
111 University Avenue, Muang District, Nakhon Ratchasima, 30000
THAILAND
*corresponding author: padej@sut.ac.th

Abstract: - This paper presents a way to obtain parameters of a direct-axis equivalent circuit of a synchronous generator from frequency response data using bi-objective genetic algorithms. The genetic algorithms is capable of finding a global minimum within a given search interval. The sum square error of magnitude and phase of the d-axis equivalent circuit transfer function to formulate a bi-objective optimization problem is minimized to best fit the measured data extracted from the frequency response test of the machine. As a result, exploitation of the bi-objective optimization based on Genetic Algorithms gives very good results than those of using either the magnitude or the phase as a single objective.

Key-Words: - Parameter Estimation, Genetic Algorithms, Bi-objective Optimization, Synchronous Generator, Frequency Response

1 Introduction

To date under deregulated power market environment electric utility has become increasingly much more complex that the past. Apart from economic view point, stability problems are equally important to operate electric power system in real time. To handle any stability-related problems accurate parameter estimation of a synchronous generator is concerned in both direct and quadrature models. Several kinds of tests are used to determine the direct-axis equivalent circuit parameters. These include on-line tests [1], standstill frequency response (SSFR) [2,3,4] and time domain [5] testing. From literature, the frequency response test has become one of the most popular approaches to obtain the synchronous transfer function parameters. With this method, the problem is reduced to find location of suitable poles and zeros of the machine transfer function. To complete this task, an efficient intelligent search method can be employed. Genetic algorithm (GA) is a searching method based on two natural processes: selections and genetics. It is considered as an evolutionary computation which has been proved to be a very powerful optimization method in an artificial intelligence area of interest. There have been various researches and applications of GA covering in most fields of studies. Therefore, it would be good for solving this problem based on the Genetic Algorithms.

This paper illustrates the way to apply the Genetic Algorithms to solve a bi-objective optimization problem in order to estimate a d-axis transfer function of a synchronous generator, which is explained in detail in section 2. Section 3 gives a brief of the step-by-step intelligent parameter estimation based on the Genetic Algorithms. Section 4 shows test results and discussion. The last section is the conclusion.

2 Direct-Axis Model Structure of a Synchronous Machine

The direct-axis of a synchronous machine includes two terminal ports. These correspond to the direct-axis equivalent armature winding and the field winding. The complete direct-axis equivalent circuit which second order model referred to the stator is shown in Fig.1 [6]

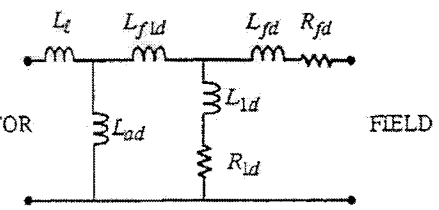

Fig. 1. Direct-axis equivalent

…, where
L_l = armature leakage inductance
L_{ad} = stator to rotor mutual inductance

L_{f1d} = mutual inductance between field winding and damper winding

L_{1d} = damper winding leakage inductance

R_{1d} = damper winding resistance

L_{fd} = field winding leakage inductance

R_{fd} = field winding resistance

The direct-axis specifically operational inductance (OI) transfer function $L_d(s)$ of synchronous machine has the form given below [7,8]. It is the Laplace transform of the ratio of the direct-axis armature flux linkages to the direct-axis current, with the field winding short-circuited.

$$L_d(s) = \mathrm{L_d}\frac{(1+T_1s)(1+T_2s)}{(1+T_3s)(1+T_4s)} \quad (1)$$

$L_d(s)$ is often expressed in terms of transient and subtransient quantities used [9],

$$L_d(s) = \mathrm{L_d}\frac{\left[1+\left(\tau'_{\mathrm{do}}\frac{\mathrm{L'_d}}{\mathrm{L_d}}\right)s\right]\left[1+\left(\tau''_{\mathrm{do}}\frac{\mathrm{L''_d}}{\mathrm{L'_d}}\right)s\right]}{\left(1+\tau'_{\mathrm{do}}s\right)\left(1+\tau''_{\mathrm{do}}s\right)} \quad (2)$$

..., where

$\mathrm{L_d}$ = synchronous inductance (p.u.)

$\mathrm{L'_d}$ = transient inductance (p.u.)

$\mathrm{L''_d}$ = subtransient inductance (p.u.)

τ'_{do} = transient open-circuit time constant (secs)

τ''_{do} = subtransient open-circuit time constant (secs)

3 Bi-objective Intelligent Parameter Estimation Based on Genetic Algorithms

There exist many different approaches to identify synchronous generator's parameters. For the GA is not new anymore. There exist a hundred of works employing GA technique. GA is a stochastic search technique that leads a population of solutions using the principles of genetic evolution and natural selection, called genetic operators e.g. crossover, mutation, etc. With successive updating new generation, a set of updated solution gradually converges to the real solution. Because the Genetic Algorithms is very popular and widely used in most research areas where an intelligent search technique is applied, it can be summarized briefly as follows [10,11].

1. Initialization: Randomly initialize populations or chromosomes and set them as a search space and then evaluate their corresponding fitness value via the objective function.
2. Evolution: Apply the genetic operators to create an offspring population as the sequence below,
   a. Selection: Form a set of mating pool with the same number of the population size by using a random procedure, e.g. the roulette-wheel or tournament schemes, with the assumption that each chromosome has a different chance. The higher the fitness value, the higher the chance or probability.
   b. Crossover: This operation is applied to a subset of the mating pool by taking a pair of chromosomes called the parents. The parents will yield a pair of offspring chromosomes. This operation involves exchanging sub-string of the parent chromosomes. It is performed by choosing a random position in the string and then swapping either the left or right sub-strings of this position (one-point crossover) with its chromosome mate.
   c. Mutation: For the chromosome to be mutated, the values of a few positions in the string are randomly modified. To prevent complete loss of the genetic information carried through the selection and crossover processes, mutation (if use at all) is limited to typically 2.5% of the population.
3. Fitness Test: Evaluate the fitness value for the generated offspring population.
4. Convergence Check: Check for violation of all termination criteria. If not satisfied, repeat the evolution process.

In this paper, the Genetic Algorithms is selected to build up an algorithm to identify such parameters. Briefly, the procedure to perform the proposed identification is described as follows. First, frequency responses of magnitude and phase based on SSFR test data of a synchronous generator are measured. Second, the Genetic Algorithms is employed to generate a set of initial random parameters. With the searching process, the parameters are adjusted to give response best fitting close to the test data. To perform the searching properly, a bi-objective function is the key. In this paper, the sum of squared errors (SSE) [12] is used as shown in the following equation.

$$\mathrm{SSE} = \sum_{i=1}^{N}\left(\frac{\mathrm{y_{measured}} - \mathrm{y_{simulated}}}{\mathrm{y_{measured,max}}}\right)^2 \quad (3)$$

with the bi-objective function

$$f_{\text{bi-obj}} = (W_{\text{mag}}) \cdot SSE_{\text{mag}} + (W_{\text{phase}}) \cdot SSE_{\text{phase}} \quad (4)$$

and

$$(W_{\text{mag}}) + (W_{\text{phase}}) = 1.0 \quad (5)$$

..., where

$f_{\text{bi-obj}}$ is the bi-objective function

W is the weighted SSE of magnitude or phase on frequency response characteristics

y_{measured} is the measured magnitude or phase on frequency response characteristics

$y_{\text{simulated}}$ is the simulated magnitude or phase on frequency response characteristics

4 Results and Discussion

The followings describe parameter setting for the Genetic Algorithms used in this paper.

GA:
Number of population = 50
Crossover probability = 70 %
Mutation probability = 1.4 %

Variable search spaces:

$L_d \in [0.50, 4.00]$

$L'_d \in [0.05, 1.00]$

$L''_d \in [0.01, 0.50]$

$\tau'_{do} \in [1.00, 8.00]$

$\tau''_{do} \in [0.01, 0.10]$

Termination criteria:
Maximum error allowance = 0.01 (SSE)
Maximum number of iteration = 1500

Table 1 also shows the parameters of turbine generator, 555 MVA/24 kV/60 Hz/0.9 pf [13] obtained by using the experimental and the Genetic Algorithms with bi-objective by various weighted SSE. The values appeared in this table is the best of 30 trials.

Comparing with the experimental results and the effectiveness and the accuracy of each Genetic Algorithms with bi-objective by weighted SSE are revealed as shown in Fig.2 - Fig.6.

Table 1. Comparison among obtained parameters

Parameters / Methods	L_d (p.u.)	L'_d (p.u.)	L''_d (p.u.)	τ'_{do} (secs)	τ''_{do} (secs)
Experimental	1.9700	0.2700	0.1270	4.3000	0.0310
GA, mag1.00-phase0.00	2.1273	0.2845	0.1477	4.3111	0.0427
GA, mag0.75-phase0.25	2.0991	0.2917	0.1428	4.4120	0.0355
GA, mag0.50-phase0.50	1.8957	0.2530	0.1183	4.3265	0.0284
GA, mag0.25-phase0.75	1.9803	0.2785	0.1295	4.4444	0.0315
GA, mag0.00-phase0.10	2.2632	0.3082	0.1449	4.2615	0.0327

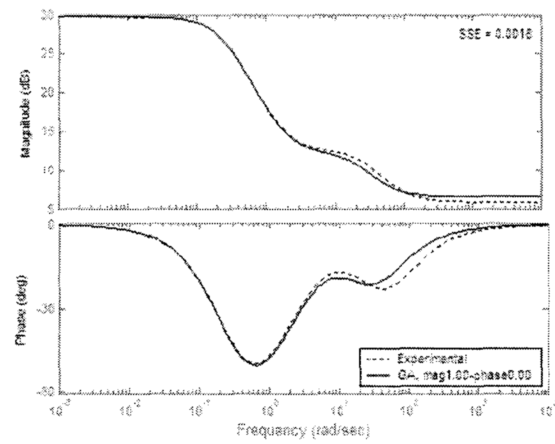

Fig. 2. Frequency response characteristics of the experiment and the Genetic Algorithms with bi-objective by weighted SSE (magnitude=1.00 and phase=0.00)

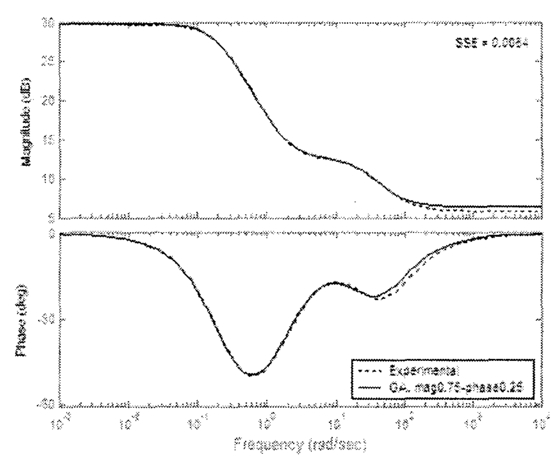

Fig. 3. Frequency response characteristics of the experiment and the Genetic Algorithms with bi-objective by weighted SSE (magnitude=0.75 and phase=0.25)

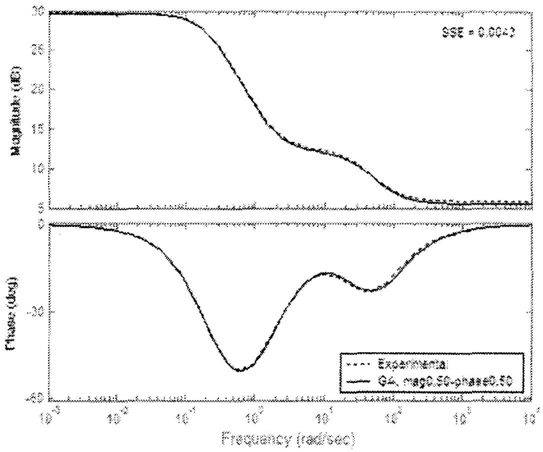

Fig. 4. Frequency response characteristics of the experiment and the Genetic Algorithms with bi-objective by weighted SSE (magnitude=0.50 and phase=0.50)

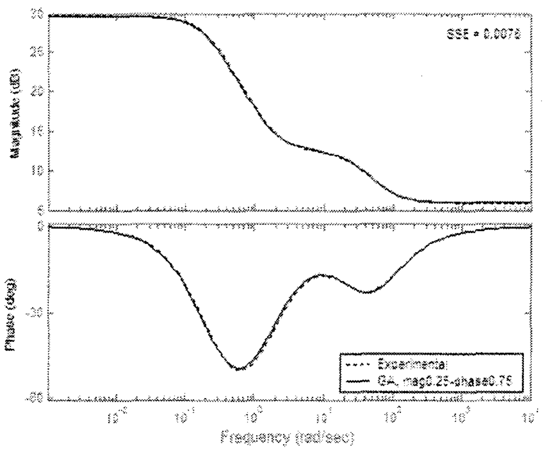

Fig. 5. Frequency response characteristics of the experiment and the Genetic Algorithms with bi-objective by weighted SSE (magnitude=0.25 and phase=0.75)

As can be seen, the results simulated by using the parameters obtained from the bi-objective Genetic Algorithms are satisfactory and very much better than those estimated by using a single objective function because in frequency domain magnitude and phase are equally essential characteristics that cannot be ignored.

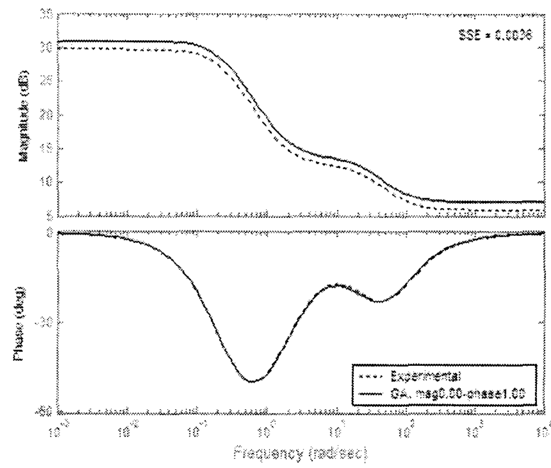

Fig. 6. Frequency response characteristics of the experiment and the Genetic Algorithms with bi-objective by weighted SSE (magnitude=0.00 and phase=1.00)

5 Conclusion

This paper illustrates the bi-objective genetic algorithms to estimate parameters of a direct-axis equivalent circuit transfer function of a synchronous generator. As a result, magnitude and phase of its frequency response characteristics simulated from the proposed method look good and rather fit to those obtained from the test data. However, to utilize the bi-objective optimization is crucial due to the difficulty of selecting weighted factors. It is problem-dependent and system designers must experience how to choose the weighted factors themselves in order to gain most advantages from the parameter estimation proposed in this paper.

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