The induction motor parameter estimation through an adaptive genetic algorithm

Xiaoyao ZHOU Haozhong CHENG

Department of Electrical Engineering, Shanghai Jiaotong University, 200030, Shanghai, China

Haifeng Wang

Department of Electrical Engineering, University of BATH, UK

Abstract: **This paper presents a new adaptive genetic algorithm for third-order induction motor model parameter estimation. The crossover and mutation probability of adaptive genetic algorithm change according to the fitness statistics of population at each generation. The proposed algorithm can enhance the convergence performance of GA and prevent premature problem. This algorithm is successfully applied to the third-order induction motor model parameter estimation.**

I. INTRODUCTION

To represent the inherent nonlinearity of electric loads, several nonlinear dynamic models have been developed[1,2,3]. Among them the induction motor models have been long studied and widely applied[1]. How to estimate the model parameters is a important problem, and now there are three kinds of approaches: optimization based approach[4,5], analytical approach[6] and stochastic approach[7]. The optimization based approach is to search the best parameters, which minimizes an errors function between the measured output variables and simulated ones. Traditional search algorithms have been applied in these kinds of approaches. Generally speaking, this sort of approach is based upon the assumption of a smooth parameter search space with ever present derivatives. When initial values of the parameters are far away from their real values, the estimation procedures may converge to local optimal values or even diverge. The analytical approaches derive parameters determinately according to the test results. This kind of approach can be used in a special test such as step test. Usually, it is sensitive to measurement error. The stochastic approach may be limited to the assumptions of noise.

Genetic algorithms is a search algorithm based on the principle of evolution and is used to search large, non-linear search spaces where traditional optimization techniques fall short. The basic principles of GAs were first designed by John Holland[7]. The genetic algorithm operates on a population of potential solutions (chromosome), each represent a possible solution to a given problem. Each chromosome is assigned a fitness value according to the result of the fitness function. Highly fit chromosomes are given more opportunities to reproduce and the offspring share features taken from their parents. These feature contribute to a genetic algorithm's robustness and increase the likelihood of finding the global optimal solution. Genetic algorithm has been applied to many fields of power system,[8,9,10] in [14] ordinary genetic algorithm(OGA) has been applied to some nonlinear load model parameter estimation, in this paper an adaptive genetic algorithm(AGA) is proposed and applied to induction-motor parameters estimation.

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In section II the third-order induction motor model is introduced and basic procedure of an optimization based parameter estimation method is given. Section III provides an adaptive genetic algorithm based approach for parameter estimation of induction motor model. Section IV studies the results of motor parameter estimation by AGA and OGA.

II. MATHEMATICAL FORMULATION OF INDUCTION MOTOR PARAMETER ESTIMATION

A. The induction motor model

The induction motor load is an important component of power system dynamic loads and has significant effect on transient voltage stability. By neglecting the stator transients, a third-order induction model can be derived from the detailed fifth-order model [10]. The equations of the third-order models are:

$$T_0'\frac{dE'}{dt} = -\frac{X}{X'}E' + \frac{X-X'}{X'}.V.\cos\delta \quad (1)$$

$$\frac{d\delta}{dt} = \omega - \omega_s - \frac{X-X'}{X'}.\frac{V.\sin\delta}{T_0'.E'} \quad (2)$$

$$M\frac{d\omega}{dt} = -\frac{V.E'.\sin\delta}{X'} - T_m \quad (3)$$

$$P = -(VE'/X').\sin\delta \quad (4)$$

$$Q = V(V - E'.\cos\delta)/X' \quad (5)$$

where

E', δ voltages magnitude and angle behind transient reactance

ω_0, ω_s angular velocity of stator and rotor [rad/s]

X_m, X_s, X_r magnetizing, stator and rotor reactance

$X' = X_s + X_m X_r /(X_m + X_r)$ transient reactance

$X = X_s + X_m$

$T_0' = (X_r + X_m)/\omega_0 R_r$ transient open-circuit time constant

R_s, R_r stator and rotor resistances

M motor inertia

T_m load torque constant

P, Q induction motor active and reactive power

let $T' = T_0'.X'/X$, $C = (X - X')/X$ the induction motor model can be rewritten as

$$\begin{cases} T'\dfrac{dE'}{dt} = -E' + CV.\cos\delta \\ \dfrac{d\delta}{dt} = \omega - \omega_v - \dfrac{CV}{T'E'}\sin\delta \\ M\dfrac{d\omega}{dt} = -\dfrac{VE'}{X'}\sin\delta - T_m \end{cases} \quad (6)$$

B. The major procedure of an optimization based parameter estimation method

The major procedure of an optimization based parameter estimation method is to search the best (or optimal) parameter vector Z^*, which minimizes an error function E

$$E = \underset{Z=Z^* Z\in S}{\text{minimize}}\, E(Z) \quad (7)$$

Where S a set of admissible parameters

The error function E is usually taken as a nonnegative and monotonously increasing function of output error

$$E = \int_{t_0}^{T} F(\|Y_m(t) - Y_c(t)\|)dt \quad (continuous\ time) \quad (8)$$

$$E = \sum_{k=0}^{N} F(\|Y_m(k) - Y_c(k)\|) \quad (discrete\ time) \quad (9)$$

Where, $[t_0, T]$ --- time region of observation

$\| \ \|$ --- norm

$F(e)$ Monotonously increasing function

k --- k^{th} Time sample

N ---Number of all samples

Y_m ---Measured (or desired) values of output vector

Y_c ---Computed values of output vector

For the third-induction motor model

$Y = [P, Q]^T$

$Z = [M,\ T',\ C,\ X',\ T_m, X\ ]^T$

C. GA based parameter estimation

It is obvious that better parameters usually result in less error function. In GA, large fitness would reproduce more off-springs. This will most likely contribute to better parameter estimation. Noting that the error function is always positive fitness is chosen as inverse of error function.

$$J = 1/E \quad (10)$$

So the procedure of searching minimum error function equivalent to searching maximum fitness function

$$\underset{Z=Z^* Z\in S}{\text{minimize}}\, E(Z) \Leftrightarrow \underset{Z=Z^* Z\in S}{\text{maximize}}\, J(Z) \quad (11)$$

The binary codes in GA should converted into decimal parameters used in model and fitness computations. At first the decimal integer $Z^{(10)}$ corresponding to a binary code $Z^{(2)}$ with length L can be obtained

$$Z^{(2)} = a_1\ a_2\ \cdots a_L, \qquad Z^{(10)} = \sum_{l=0}^{L} a_l 2^l$$

Where, a_l --- a single binary feature or detector

The maximum values are

$$Z^{(2)}_{\max} = 1\ 1 \cdots 1, \qquad Z^{(10)}_{\max} = 2^L - 1$$

Then, the decimal integer can be converted into the decimal parameter by

$$Z_j = Z_{j\min} + (Z_{j\max} - Z_{j\min})(Z_j^{(10)}/Z_{\max}^{(10)})$$

Where parameter, $Z_j \cdots j^{th}$ parameter

$[Z_{j\min}, Z_{j\max}]$ - Search range of Z_j

III. AN ADAPTIVE GENETIC ALGORITHM

There are usually there operators in a typical genetic algorithm, the first is the production operator which makes one or more copies of any individual that posses a high fitness value; otherwise the individual is eliminated from the solution pool the second operator is the crossover operator. This operator select two individual within the generation and a crossover site and carries out a swapping operation of the string bits to the right hand side of the crossover side on both individuals. Crossover operations synthesize bits of knowledge gained from both parents exhibiting better than average performance. Thus the probability of a better performing of offspring is greatly enhanced. The third operator is the mutation operator which introduces occasional change of a random string position with a specified mutation probability.

The influence of crossover probability p_c and mutation probability p_m on controlling GA performance has been acknowledged and many methods of setting the optimal values has been reported[9-13]. In this paper we improve the AGA (adaptive genetic algorithm) first proposed by Srinivas[13].

The key idea of the AGA is changing p_c, p_m according to the fitness statistics of population at each generation. It is has been observed that the difference between the maximum fitness and the average fitness of the generation decrease when the GA converges to the optimum solution. So the p_c , p_m should be changed according to the $f_{\max} - \bar{f}$. On the other hand if are the same p_c, p_m for all the chromosome of one generation, it means that solutions with high fitness and solutions with low fitness have the same value to do crossover and mutation, this will influence the effectiveness of GAs. So the adaptive strategy for updating has been proposed in [13].

$$p_c = \begin{cases} k_1(f_{\max} - f_i)/(f_{\max} - \bar{f}), f_i > \bar{f} \\ k_3, f_i \le \bar{f} \end{cases} \quad (12)$$

and

$$p_m = \begin{cases} k_2(f_{\max} - f_i)/(f_{\max} - \bar{f}), f_i > \bar{f} \\ k_4, f_i \le \bar{f} \end{cases} \quad (13)$$

Where $k_1, k_2, k_3, k_4 \in (0,1)$ to ensure $p_c, p_m \in [0,1]$

p_c is the large of fitness values of the individual selected for crossover and p_m is the fitness of the chromosome to which the mutation is applied.

When GA converges, the fitness differences be:

$$C(f_i) = \sum_{j=1}^{n} |f_i - f_j|, i \ne j \quad (14)$$

the normalized fitness is defined as:

$$\widetilde{C}(f_i) = \frac{\sum_{j=1}^{n} |f_i - f_j|}{(n-1)\max_j |f_i - f_j|}, i \ne j \quad (15)$$

in this paper it is found that when employ $\widetilde{C}(f)$ to regulate the crossover operation and mutation operator, it will highly enhance the GA convergence performance. That is:

(16)

$$p_c = \begin{cases} k_1(f_{\max} - f_c)\overline{C}(f_i)/(f_{\max} - \bar{f}), f_i > \bar{f} \\ k_3, f_i \le \bar{f} \end{cases} \quad (16)$$

$$p_m = \begin{cases} k_2(f_{\max} - f_i)\widetilde{C}(f_i)/(f_{\max} - \bar{f}), f_i > \bar{f} \\ k_4, f_i \le \bar{f} \end{cases} \quad (17)$$

IV. SIMULATION RESULTS

The OGA and AGA-based parameter estimation algorithms have been implemented to third-order induction motor based on the flowchart shown in Figure 1. The original motor parameters and search ranges are shown in table 1.

The adopted parameters in the algorithms are given in Table2:

Table 1 motor parameters and search range

	M	T_m	T'	C	X'	X
Real value	3.2	1.0	0.00685	0.9685	0.1344	3.72
Search range(max)	1	0.2	0.01	0.5	0.05	1
Search range (min)	8	1.8	2	1	0.5	5

Table 2. Parameter values for AGA and OGA

	No. Of variables	Length of chrom	Population size	No. Of iteration	p_c	p_m	k_1	k_2	k_3	k_4
AGA	5	48	50	100	0.95	0.05				
OGA	5	48	50	100			0.86	0.5	1.0	0.05

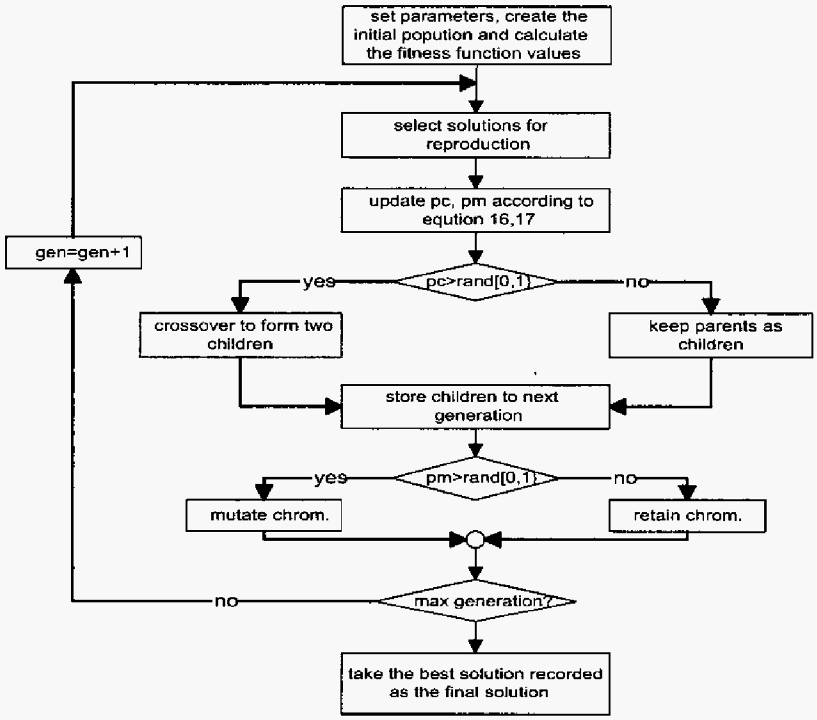

Fig 1. The flow chart of AGA

The input voltage changes from 1pu to 0.9pu at 10s then keep constants. The output variables active and reactive power are calculated according to the real value and estimation value. The objective function is chosen as inverse of output error function (equation 10).

The algorithms are executed 25 times when applied to the test system because of the randomness in GA approach. The best and worst results of parameter estimation and total error obtained by AGA and OGA are listed in table3 and table4 respectively. The results in Tables 3 and 4 show parameters determined by the AGA lead to lower error than that found by the OGA, which confirms that the AGA is well capable of determining the global or near-global parameter estimation. In addition, the results summarized in Table 5 show that the proposed AGA is about two times faster than OGA in speed.

Table 3. Simulation results obtained using AGA

	M	T_m	T'	C	X'	X	*Error*
Best	3.278	0.9894	0.0068	0.9631	0.1365	3.701	0.0185
Worst	3.335	0.9768	0.0076	0.9602	0.1413	3.552	0.2576
Average	3.30	0.9812	0.0073	0.962	0.1401	3.673	0.1583

Table 4. Simulation results obtained using OGA

	M	T_m	T'	C	X'	X	$Error$
Best	3.295	0.9801	0.0072	0.9639	0.1392	3.781	0.0856
Worst	2.98	0.9520	0.00856	0.9606	0.1568	3.984	1.2576
Average	3.30	0.9712	0.00838	0.9172	0.1491	3.897	0.5837

Table 5. Shortest and longest execution time by AGA and OGA

Method	Shortest execution time (s)	Longest execution time (s)	Average execution time (s)
AGA	15.12	16.74	15.53
CGA	27.46	35.65	30.49

V. CONCLUSION:

This paper presents a new adaptive genetic algorithm for third-order induction motor model parameter estimation. The crossover and mutation probability of adaptive genetic algorithm change according to the fitness statistics and normalized fitness distances between the solutions of population at each generation. This algorithm is successfully applied to the third-order induction motor model parameter estimation. The performance shows that the AGA is able to enhance the convergence performance of GA and prevent premature problem.

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