

Research Article

Parameter Estimation of Three-Phase Induction Motor Using Hybrid of Genetic Algorithm and Particle Swarm Optimization

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A cost effective off-line method for equivalent circuit parameter estimation of an induction motor using hybrid of genetic algorithm and particle swarm optimization (HGAPSO) is proposed. The HGAPSO inherits the advantages of both genetic algorithm (GA) and particle swarm optimization (PSO). The parameter estimation methodology describes a method for estimating the steady-state equivalent circuit parameters from the motor performance characteristics, which is normally available from the nameplate data or experimental tests. In this paper, the problem formulation uses the starting torque, the full load torque, the maximum torque, and the full load power factor which are normally available from the manufacturer data. The proposed method is used to estimate the stator and rotor resistances, the stator and rotor leakage reactances, and the magnetizing reactance in the steady-state equivalent circuit. The optimization problem is formulated to minimize an objective function containing the error between the estimated and the manufacturer data. The validity of the proposed method is demonstrated for a preset model of induction motor in MATLAB/Simulink. Also, the performance evaluation of the proposed method is carried out by comparison between the results of the HGAPSO, GA, and PSO.

1. Introduction

In most of the applications, induction motors are preferred to DC motors, because of their simple structure, easy operation, and also low cost maintenance and durability. Recently, advanced control techniques such as vector control and field-oriented control (FOC) make them compete with DC motors in many aspects [1]. The information regarding motor circuit parameters is very important for design, performance evaluation, and feasibility of these control techniques.

The conventional techniques for estimating the induction motor parameters are based on the locked-rotor and the no-load tests. However, these techniques cannot be implemented easily. The main disadvantage of these techniques is that the motor has to be locked mechanically. In the locked-rotor condition, the frequency of the rotor is equal to the supply frequency, but under operating condition, the rotor frequency is about 1–3 Hz. This incorrect rotor frequency will cause bad

results for the locked-rotor test. Besides, in the motors with high power, this test is impractical. These problems have encouraged the researchers to investigate alternative techniques for parameter estimation. The problem of induction motor parameter estimation has been addressed extensively by many researchers in the past. Deep bar motors were considered in [2] and parameter estimation was carried out with emphasis on leakage reactance in [3]. The method of finite element analysis was employed in [4]. Also, parameter estimation of an induction motor using some evolutionary algorithms is presented in [5–7].

Evolutionary algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO) seem to be a promising alternative to traditional techniques. The GA is a stochastic search procedure that mimics biological evolution by using genetic operators [8]. Like GA, the PSO is initialized with a population of random solutions. Compared with GA, PSO has some attractive properties. It has memory,

so that knowledge of good solutions is retained by all particles whereas in GA, previous knowledge of the problem is destroyed once the new population generates [5]. However, both methods have strengths and weaknesses. It seems that a hybrid of the GA and PSO models could lead to further advances. Therefore, in this paper, GA and PSO merge together to use the benefits of both methods. This algorithm is named as hybrid genetic algorithm and particle swarm optimization (HGAPSO). There have been many technical papers using evolutionary algorithm for parameter estimation, but parameter estimation of an induction motor using HGAPSO has never been presented by now.

This paper uses some nameplate or manufacturer data for problem formulation. By using the proposed method, the steady-state equivalent circuit of the motor can be estimated. In fact, the optimization problem is formulated so that the error between calculated data using the estimated parameters and manufacturer data is minimized.

In the next sections the set of equations for problem formulation is introduced. Also, a short description of GA and PSO and a more detailed explanation of HGAPSO are provided. The validity of the proposed method is tested by using a preset model of induction motor in MATLAB/Simulink. Also the performance evaluation of the proposed method is carried out by comparison between the results of the HGAPSO, GA, and PSO.

2. Problem Definition

An induction motor can be modeled by using a steady-state equivalent circuit. The parameter estimation problem is formulated as a least squares optimization problem so that the objective function is the minimization of the deviation between the estimated and the nameplate data. The problem formulation for a three-phase induction motor is described below.

The problem formulation uses the manufacturer data, such as the starting torque, the full load torque, the maximum torque, and the full load power factor. The proposed method is used to estimate the stator and rotor resistances, the stator and rotor leakage reactances, and the magnetizing reactance in the steady-state equivalent circuit of the motor. In Figure 1(a), the steady-state equivalent circuit model of a three-phase induction motor is shown. It should be noted that the rotor parameters have been referred to as the stator side. Also, it is assumed that the core-losses are negligible.

For problem formulation, Thévenin equivalent circuit proposed in IEEE standard 112 is used as shown in Figure 1(b). The problem formulation and objective function are as follows:

$$f_1 = \frac{K_t R'_r / s \left[(R_{th} + R'_r / s)^2 + (X_{th} + X'_r)^2 \right] - T_{fl}(\text{mf})}{T_{fl}(\text{mf})}$$

$$f_2 = \frac{K_t R'_r / s \left[(R_{th} + R'_r / s)^2 + (X_{th} + X'_r)^2 \right] - T_{st}(\text{mf})}{T_{st}(\text{mf})}$$

$$f_3 = \frac{K_t / 2 \left[R_{th} + \sqrt{R_{th}^2 + (X_{th} + X'_r)^2} \right] - T_{max}(\text{mf})}{T_{max}(\text{mf})}$$

$$f_4 = \frac{\cos \left(\tan^{-1} \left((X_{th} + X'_r) / (R_{th} + R'_r / s) \right) \right) - pf_{fl}(\text{mf})}{pf_{fl}(\text{mf})}, \quad (1)$$

where R_s is the stator resistance; R'_r is the rotor resistance which has been referred to as the stator side; X_s is the stator leakage reactance; X'_r is the rotor leakage reactance which has been referred to as the stator side; X_m is the magnetizing reactance; and s is the slip. Also, it is assumed that X_s is equal to X'_r . The other variables are introduced as follows:

$$V_{th} = \frac{V_{ph} X_m}{X_s + X_m}; \quad R_{th} = \frac{R_s X_m}{X_s + X_m}; \quad (2)$$

$$X_{th} = \frac{X_s X_m}{X_s + X_m}; \quad K_t = \frac{3V_{th}^2}{\omega_s},$$

where V_{ph} is input phase voltage; V_{th} is Thévenin voltage; R_{th} and X_{th} are Thévenin resistance and Thévenin reactance, respectively; ω_s is angular velocity; and K_t is the constant coefficient. Also, "mf" index is used for the manufacturer data so that $T_{st}(\text{mf})$, $T_{fl}(\text{mf})$, and $T_{max}(\text{mf})$ are the manufacturer values of the starting torque, full load torque, and maximum torque, respectively. Also, f_1 , f_2 , and f_3 are error between the calculated and manufacturer value of the full load torque, starting torque, and maximum torque, respectively. Also, f_4 is error between the calculated and manufacturer value of the full load power factor.

The objective function using aforementioned equations is defined as follows:

$$F = f_1^2 + f_2^2 + f_3^2 + f_4^2. \quad (3)$$

3. Evolutionary Methods

The proposed HGAPSO method is a combination of the GA and PSO to form a hybrid algorithm. This hybrid algorithm uses the benefits of the two well defined methods and produces the better results. In this section, basic concepts of the GA and PSO and also HGAPSO are introduced.

3.1. Genetic Algorithm. Genetic algorithm is a computational model and evolutionary process that solves optimization problems by imitating the behavior of populations during generations and based on the theory of evolution. It mimics biological evolution by using genetic operators [9]. It assumes that the solution of a problem is an individual and can be represented by a set of parameters. Genetic algorithm investigates the search space from the points it has to bias the search towards the best point. This algorithm is a stochastic search method and has shown that the answer is appropriate for problems where there are many global minimums or search space is extensive. A positive value, generally called fitness value, is used to measure the degree of "goodness"

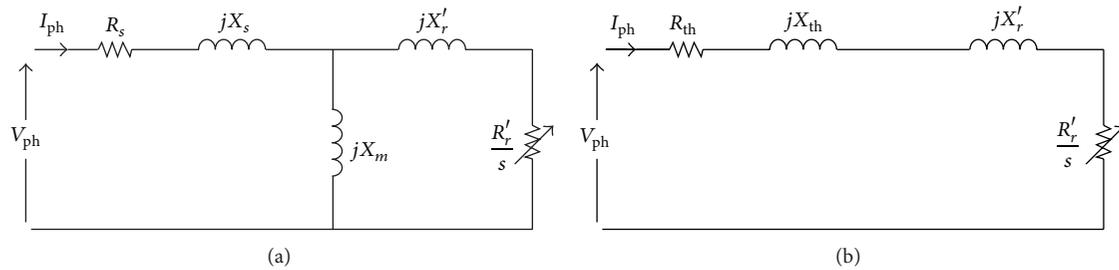


FIGURE 1: (a) One phase steady-state equivalent circuit model of a three-phase induction motor; (b) Thévenin equivalent circuit of induction motor.

of the chromosome for solving the problem, and this value is closely dependent on its objective value. The objective function of a problem is an important source providing the mechanism for evaluating the status of each chromosome. It takes the chromosome as input and produces a number or list of numbers such as objective value as a measure to the chromosome's performance. This is a main link between the algorithm and the system [10].

3.2. Particle Swarm Optimization. The PSO is a stochastic optimization method, which uses swarming behaviors observed in flock of birds. In fact, the PSO was inspired by the sociological behavior associated with swarms. The PSO was developed by Kennedy and Eberhart in 1995 as a new heuristic method [11]. Each particle in the PSO algorithm is a potential solution for the optimization problem and keeps track of its coordinates in the problem space and tries to search the best position through flying in a multidimensional space, which are associated with the best solution (called best fitness) it has achieved so far called "*pbest*." Another "*gbest*" value called "*gbest*" that is tracked by the global version of the particle swarm optimizer is the overall best value and its location is obtained so far by each particle in the swarm. Each particle is determined by two vectors in N -dimensional search space: the position vector and the velocity vector [12]. Each particle investigates its search space through previous experience, its present velocity, and the experience of the neighboring particles. The PSO concept is the change in the velocity of each particle toward its *pbest* and *gbest* positions in each iteration. In the PSO, acceleration of each particle is weighted by a random term [13]. The PSO is a history-based algorithm such that, in each iteration, particles use their own behavior associated with the previous iterations.

3.3. Hybrid of Genetic Algorithm and Particle Swarm Optimization. Since GA and PSO both work with a population of solutions, combining the searching abilities of both methods seems to be an excellent approach. PSO works based on social adaptation of knowledge and all particles are considered to be of the same generation. On the contrary, GA works based on evolution from generation to generation, so that the changes of individuals in a single generation are not considered. However, GA and PSO have strengths and weaknesses [14].

In comparison with GA, the information sharing mechanism in PSO is significantly different. In GA, chromosomes

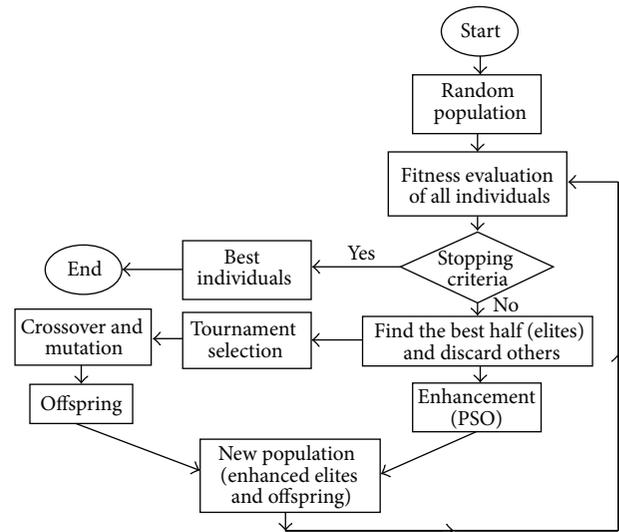


FIGURE 2: The block diagram of the HGAPSO algorithm.

share information with each other so that whole population moves like a one group towards an optimal area.

In PSO, only "*pbest*" and "*gbest*" give out the information to other particles. It is a one-way information sharing mechanism. However, PSO does not have genetic operators like crossover and mutation. On the contrary, in PSO, particles update themselves with the internal velocity. Also, they have memory which is important for the algorithm. By merging GA and PSO together, the produced algorithm has memory and genetic operators like crossover and mutation. Consequently, the new algorithm avoids the weaknesses of GA and PSO at the same time.

Therefore, in this paper, GA and PSO merge together to benefit from the advantages of both genetic algorithm and particle swarm optimization. This algorithm consists of four main operators: enhancement, selection, crossover, and mutation [15].

In Figure 2, the flowchart of the HGAPSO method is shown. In each iteration of the algorithm, the fitness values of all the individuals in the population are calculated. If the calculated fitness values are within the acceptable range, the algorithm can be stopped. Otherwise, the top-half best performing ones are marked and named as elites. Instead

TABLE 1: Original data of the test motor.

Capacity (HP)	5
Voltage (V)	460
Current (A)	4.9252
Frequency (Hz)	60
Number of poles	4
Full load slip	0.021
Starting torque (Nm)	119.2629
Maximum torque (Nm)	149.082
Full load torque (Nm)	19.6730
Starting current (A)	83.1818
Full load power factor	0.89

of reproducing these top individuals directly to the next generation as GA does, elites will be increased. The enhancement operation tries to imitate the maturing phenomenon in the nature, where individuals will become more suitable to the environment after learning knowledge from the society. Furthermore, by using these enhanced elites as parents, the generated offspring will achieve better efficiency than those bred by original elites [16].

In the HGAPSO, the GA operations are performed on the enhanced elites achieved using PSO. In order to select parents for the crossover operation in the HGAPSO, the selection scheme is used. Two enhanced elites are selected and their fitness values are compared together to select the one with better fitness as a parent [16].

In the next step, two offspring are created by applying crossover on the parent solutions. The final step in the genetic operator is mutation. This step can generate a new genetic descendant in the population to maintain the population's variety in the society. After performing the GA operators, the offspring and the enhanced elites from PSO, the new population, and their fitness values are evaluated and compared in order to select the elites for the next generation.

4. Simulation Results

To validate the proposed HGAPSO method for parameter estimation, this algorithm is tested on a 5 HP three-phase induction motor in MATLAB/Simulink preset models. The HGAPSO results are compared with the original parameters of the MATLAB model. The original data of the test motor are given in Table 1. Also, a comparative study between the results of the HGAPSO, GA, and PSO is done to verify the effectiveness of the proposed HGAPSO method. The errors between the calculated and original values of the starting torque, maximum torque, full load torque, and full load power factor in three methods are given in Table 2. The simulation results which are given in Table 2 show that the HGAPSO has lesser error than GA and PSO and thus the accuracy of the proposed HGAPSO method is better than GA and PSO.

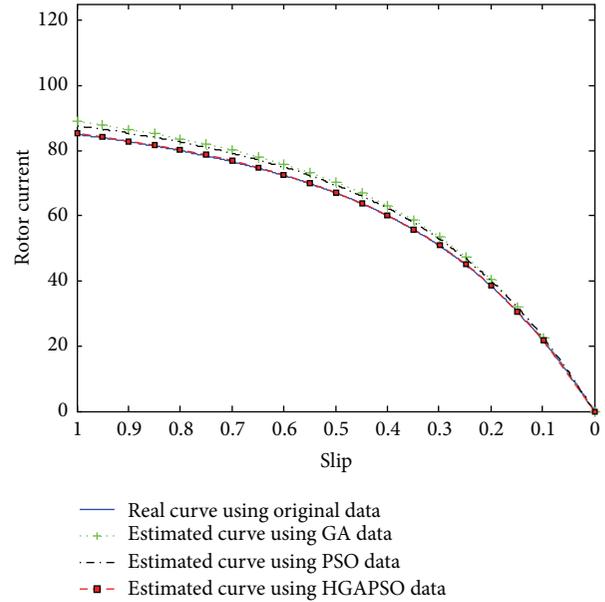


FIGURE 3: The rotor current versus slip curve using GA, PSO, and HGAPSO data.

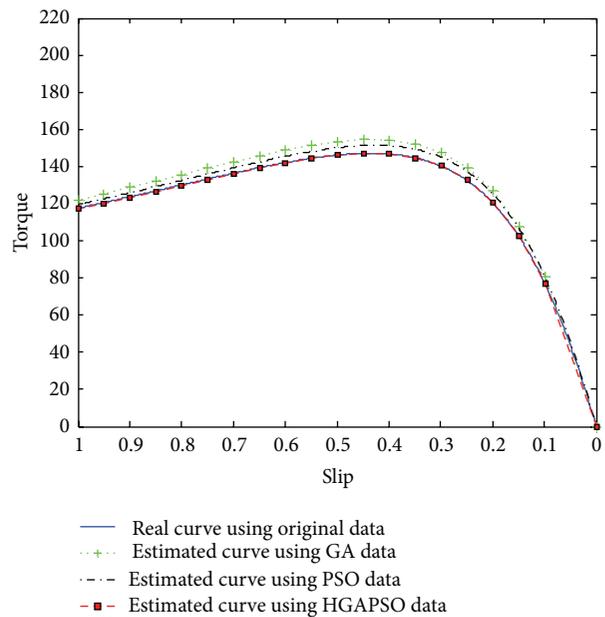


FIGURE 4: The torque versus slip curve using GA, PSO, and HGAPSO data.

The steady-state equivalent circuit parameters obtained using HGAPSO, GA, and PSO methods for the test motor are presented in Table 3. The results show that all of the parameters obtained using HGAPSO are closer to original parameters and the HGAPSO has lesser error than GA and PSO.

The rotor current characteristics versus slip using parameters obtained by the GA, PSO, and the HGAPSO are shown in Figure 3. It can be seen that estimated rotor current curve

TABLE 2: Starting torque, maximum torque, full load torque, and full load power factor calculated by GA, PSO, and HGAPSO.

Torque and power factor	Original value	GA		PSO		HGAPSO	
		Calculated data	Error (%)	Calculated data	Error (%)	Calculated data	Error (%)
T_{st}	119.2629	124.0018	3.97%	121.0186	1.47%	119.2300	-0.03%
T_{max}	149.082	154.0410	3.33%	151.1170	1.37%	149.1226	0.027%
T_{fl}	19.6730	19.8227	0.76%	19.8136	0.71%	19.7877	0.58%
PF_{fl}	0.89	0.91	2.25%	0.91	2.25%	0.90	1.12%

TABLE 3: The results of the parameter estimation by GA, PSO, and HGAPSO.

Parameters	Original value	GA		PSO		HGAPSO	
		Estimated data	Error (%)	Estimated data	Error (%)	Estimated data	Error (%)
R_s	1.115	1.0291	-7.7%	1.1029	-1.09%	1.1229	0.71%
R'_r	1.083	1.0304	-4.86%	1.0351	-4.42%	1.0741	-0.82%
X_s, X'_r	1.126	1.0739	-4.63%	1.0858	-3.57%	1.1169	-0.81%
X_m	38.4	20.4139	-46.84%	21.9514	-42.8%	36.8888	-3.94%

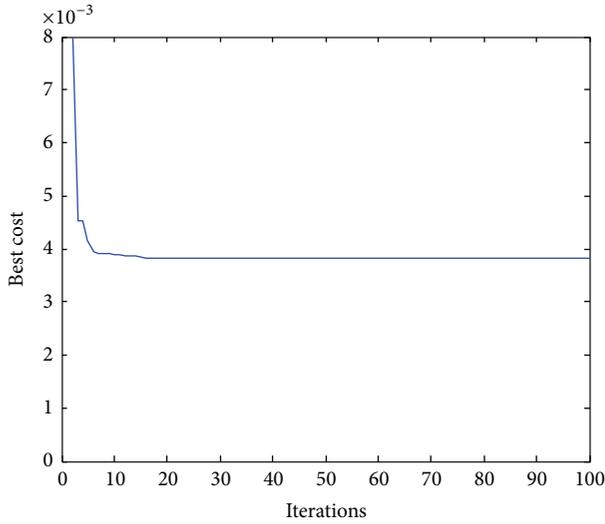


FIGURE 5: Convergence diagram of GA.

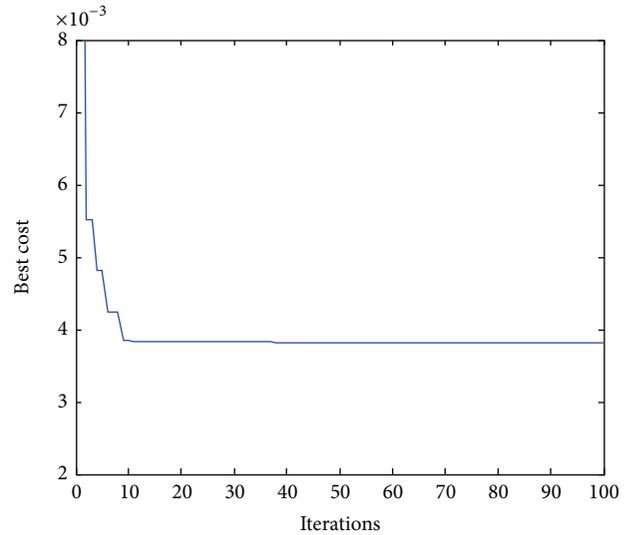


FIGURE 6: Convergence diagram of PSO.

using parameters obtained by GA and PSO has difference compared to the real curve, while estimated curve using parameters obtained by the HGAPSO is very close to the real curve. As shown in this figure, accuracy of the proposed HGAPSO method is excellent.

Also, torque characteristics versus slip using parameters obtained by the GA, PSO, and the HGAPSO are shown in Figure 4. It can be seen that estimated torque curve using parameters obtained by GA and PSO has a little difference compared to the real curve, while estimated curve using parameters obtained by the HGAPSO is very close to real curve.

The performance of the optimization method in terms of the fitness value for GA, PSO, and HGAPSO is shown in Figures 5, 6, and 7, respectively. It can be seen that the fitness value reduces over the iterations and converges to a minimum

value. It should be noted that the convergence speed of the HGAPSO is faster than GA and PSO.

5. Conclusion

In this paper, hybrid of genetic algorithm and particle swarm optimization method for parameter estimation of a three-phase induction motor using steady-state equivalent circuit model has been proposed. This problem is formulated as a nonlinear optimization problem. The feasibility of the proposed HGAPSO method is shown by evaluation on a 5 HP preset model of three-phase induction motor in MATLAB. By analyzing the parameter estimation results, it can be seen that the parameter estimation using HGAPSO gives better results than GA and PSO. The comparison between the HGAPSO, GA, and PSO results shows that the estimation errors using

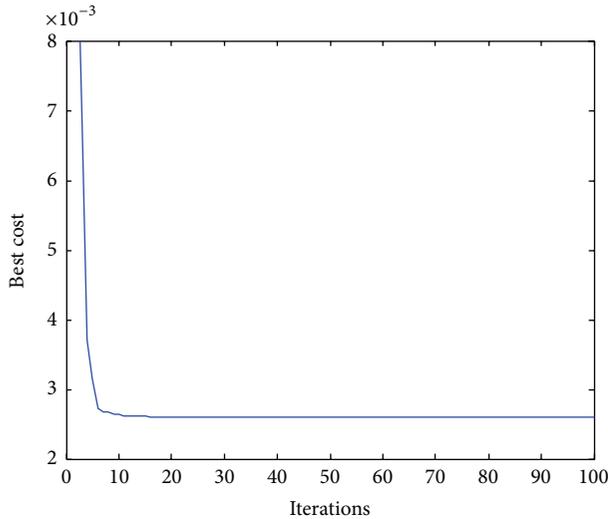


FIGURE 7: Convergence diagram of HGAPSO.

HGAPSO are comparatively lesser than those obtained using GA and PSO. Also, the convergence speed of the HGAPSO is faster than GA and PSO.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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