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Parameter Estimation of Induction Motor Using Shuffled Frog Leaping and Imperialistic Competitive Algorithms

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Abstract

This paper presents two methods based on Shuffled Frog Leaping Algorithm (SFLA) and Imperialistic Competitive Algorithm (ICA) for determining the values of the steady-state equivalent circuit parameters of an induction motor. The parameter estimation procedure is based on minimizing the error between some manufacturer's data and corresponding data calculated from proposed methods by determining proper objective functions. Proposed methods are applied to two different models of two distinct induction motors and the results are presented. Little errors between the manufacturer's data and the corresponding calculated data, and also small values reached for the objective functions confirms the exactness of the estimation processes.

1. Introduction

Induction machines models used in steady-state problems require equivalent circuit parameters. These parameters are the resistances and reactances representing the stator, rotor and magnetizing branches. As manufacturer data often does not include these parameters, it is necessary to obtain them from manufacturers data by using proper techniques. The conventional technique for determining the induction motor parameters is based on three tests: Direct Current Test (DCT), Blocked Rotor Test (BRT) and No Load Test (NLT). These tests can not implement easily. Besides, the locked-rotor test requires that the shaft of the motor be locked. In the locked-rotor conditions, the frequency of the rotor is too large compared to its normal frequency. This incorrect rotor frequency will give erroneous results for the locked-rotor test. To describe the performance of the induction machine more precisely and to reduce the differences between the estimated and real parameters, one must modify the parameters obtained from the classical tests [1].

The linear parameter estimation techniques have been used to determine the rotor resistance, rotor self-inductance and the stator leakage inductance of a three-phase induction machine. The problem has also been solved with more sophisticated approach for non-linear system identification. Several approaches have been presented for induction machine parameters identification based on data that are easily available from the manufacturer [2]–[5].

This paper presents two new methods for parameter estimation of induction motors. These methods are based on Shuffled Frog Leaping and Imperialistic Competitive optimization techniques. We use manufacturer data to estimate induction motor parameters (the resistances and reactances representing the stator, rotor and magnetizing branches). The goal is to minimize the error between manufacturer data and corresponding calculated data by precisely estimating the motor equivalent circuit parameters. For this aim, we use a multi-objective fitness function. The proposed methods have been applied to two induction motors and the ability of these methods in parameter estimation of induction machines is verified. The results are given and compared.

2. Induction Motor Model

Two models of Induction motor including approximate circuit model and exact circuit model are analyzed. The parameter estimation problem is formulated as a least squares optimization problem. The objective is the minimization of difference between the estimated and the manufacturer data. The problem formulation for the parameter estimation of two mentioned induction motor models is described below.

2.1. Approximate circuit model

Approximate circuit model of an induction motor is shown in Figure 1. In this model, R_1 is the stator winding resistance, $R_2^{'}$ is the rotor resistance referred to the stator side, X_1 is the combined stator and rotor leakage reactance, X_m is the magnetizing reactance referred to the stator side, I_1 is stator current, $I_2^{'}$ is rotor current referred to the stator side, V_{ph} is terminal voltage and s is the motor slip. The magnetizing reactance (X_m) can be eliminated from this model, because it has no effect on the rotor current and motor torque and power. Thus, the aim is to estimate R_1, $R_2^{'}$ and X_1 by using the starting torque, the maximum torque and the full load torque of the motor given by the manufacturer along with the motor slip and terminal voltage. Shuffled Frog Leaping Algorithm (SFLA) and Imperialistic Competitive Algorithm (ICA) are used for this propose. The objective function and associated constraints of the problem are formulated as follows:

2.1.1. Objective function

Using the approximate circuit model of an induction motor:

$$T_{fl}(cal) = \frac{K_t R_2^{'}}{s\left[\left(R_1+\frac{R_2^{'}}{s}\right)^2+X_1^2\right]} \quad (1)$$

$$T_{lr}(cal) = \frac{K_t R_2^{'}}{(R_1+R_2^{'})^2+X_1^2} \quad (2)$$

$$T_{max}(cal) = \frac{K_t}{2\left[R_1+\sqrt{R_1^2+X_1^2}\right]} \quad (3)$$

$$K_t = \frac{3V_{ph}^2}{\omega_s} \quad (4)$$

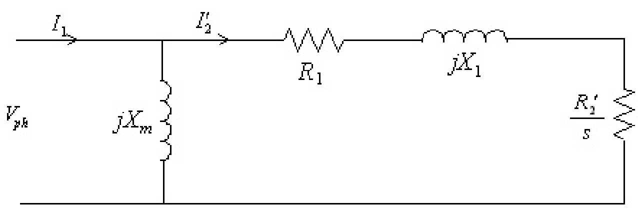

Figure 1. Approximate circuit model of an induction motor

where s, ω_s and V_{ph} are known (ω_s is the synchronous speed). $T_{fl}(cal)$, $T_{lr}(cal)$ and $T_{max}(cal)$ are full load torque, locked rotor torque and maximum torque respectively that are calculated by estimating R_1, $R_2^{'}$ and X_1. For this, we define an objective function as follows:

$$F = f_1^2 + f_2^2 + f_3^2 \quad (5)$$

where:

$$f_1 = \frac{T_{fl}(cal)-T_{fl}(mf)}{T_{fl}(mf)} \quad (6)$$

$$f_2 = \frac{T_{lr}(cal) - T_{lr}(mf)}{T_{lr}(mf)} \quad (7)$$

$$f_3 = \frac{T_{max}(cal) - T_{max}(mf)}{T_{max}(mf)} \quad (8)$$

where $T_{fl}(mf)$, $T_{lr}(mf)$ and $T_{max}(mf)$ are full load torque, locked rotor torque and maximum torque given by the manufacturer respectively. For the optimum estimation of unknown parameters, we should minimize the objective function "F".

2.1.2. Constraints

- Minimum and maximum limits of the parameters:

$$X_{i,min} \le X_i \le X_{i,max}$$

where $X_{i,min}$ and $X_{i,max}$ are the minimum and maximum values of the parameter X_i .

- Maximum torque constraint:

$$0.8 * T_{max}(mf) \le T_{max}(cal) \le 1.2 * T_{max}(mf)$$

2.2. Exact circuit model

Exact circuit model representing the steady-state operation of an induction motor is shown in Figure 2. At this model X_1 is stator leakage reactance and X_2' is rotor leakage reactance referred to the stator side. Other parameters of this model are the same as approximate circuit model.

In the conventional technique, by performing the direct current test, we can find each phase resistance of the stator winding (R_1). This test should be performed by the dc voltage supply because of preventing of the inductive effect in the stator winding. By performing the no-load test, $(X_1 + X_m)$ is found. This test performs under rated voltage and frequency. By the locked rotor test $(X_1 + X_2')$ and locked rotor resistance (R_{LR}) are found. This test performs by locking the rotor and under a voltage that is much less than rated value. By knowing $X_1 = X_2'$ and $R_{LR} = R_1 + R_2'$, the unknown parameters X_1 , X_2' , X_m and R_2' are obtained individually. These tests can not implement easily and they need dc voltage supply, the voltage supply with tunable voltage and frequency, voltmeters, ammeters, watt meters and external element for locking the rotor. Beside it takes much time. By formulation of the parameter estimation of induction motor, these parameters can be found easily with high accuracy. The problem formulation uses the starting torque, the maximum torque, the full load torque and the full load power factor given by the manufacturer along with motor slip and terminal voltage to estimate the stator

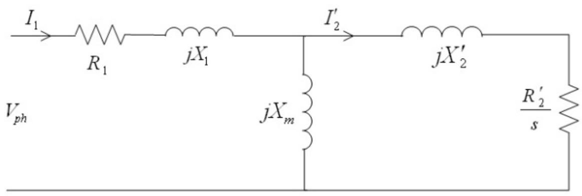

Figure 2. Exact circuit model of induction motor

resistance, the rotor resistance, the stator leakage reactance, the rotor leakage reactance and the magnetizing reactance by proposed methods. The objective function is as follows:

2.2.1. Objective function

At the exact circuit model of an induction motor:

$$T_{fl}(cal) = \frac{K_t R_2'}{s\left[\left(R_{th} + \frac{R_2'}{s}\right)^2 + X^2\right]} \quad (9)$$

$$T_{lr}(cal) = \frac{K_t R_2'}{(R_{th} + R_2')^2 + X^2} \quad (10)$$

$$T_{max}(cal) = \frac{K_t}{2\left[R_{th} + \sqrt{R_{th}^2 + X^2}\right]} \quad (11)$$

$$pf(cal) = \cos\left(\tan^{-1}\left(\frac{X}{R_{th} + \frac{R_2'}{s}}\right)\right) \quad (12)$$

$$K_t = \frac{3V_{th}^2}{\omega_s} , X = X_2' + X_{th} , X_{th} = X_1 \quad (13)$$

$$V_{th} = V_{ph}\left(\frac{X_m}{X_1+X_m}\right) \quad (14)$$

$$R_{th} = R_1\left(\frac{X_m}{X_1+X_m}\right)^2 \quad (15)$$

where s, ω_s and V_{ph} are known. $T_{fl}(cal)$, $T_{lr}(cal)$, $T_{max}(cal)$ and $pf(cal)$ are full load torque, locked rotor torque, maximum torque and power factor respectively that have to be calculate by estimating R_1, R_2', X_1, X_2' and X_m. Objective function is as follows:

$$F = f_1^2 + f_2^2 + f_3^2 + f_4^2 \quad (16)$$

where:

$$f_1 = \frac{T_{fl}(cal) - T_{fl}(mf)}{T_{fl}(mf)} \quad (17)$$

$$f_2 = \frac{T_{lr}(cal) - T_{lr}(mf)}{T_{lr}(mf)} \quad (18)$$

$$f_3 = \frac{T_{max}(cal) - T_{max}(mf)}{T_{max}(mf)} \quad (19)$$

$$f_4 = \frac{pf(cal) - pf(mf)}{pf(mf)} \quad (20)$$

For optimum estimation of unknown parameters, we should minimize the objective function "F".

2.2.2. Constraints

- Minimum and maximum limits of parameter:

$$X_{i,min} \le X_i \le X_{i,max}$$

where $X_{i,min}$ and $X_{i,max}$ are the minimum and maximum values of the parameter X_i .

- Maximum torque constraint:

$$0.8 * T_{max}(mf) \le T_{max}(cal) \le 1.2 * T_{max}(mf)$$

3. A Review of SFLA and ICA Algorithms

3.1. SFLA algorithm [6]

The shuffled frog leaping algorithm is a memetic meta-heuristic approach that is designed to seek a global optimal solution by performing a heuristic search. It is a population-based cooperative search inspired by natural behavior of a group of frogs when seeking for the location that has the maximum amount of available food. The algorithm contains elements of local search and global information exchange. At first an initial population of N frogs is created randomly. Then the frogs are sorted in a descending order according to their fitness. The whole population of frogs is then partitioned into "m" memeplexes. The SFLA then performs simultaneously an independent local search in each memeplex using a particle swarm optimization like method. Within each memeplex, the frogs with the best and worst fitness are identified. During each memeplex evolution, the worst frog leaps toward the best frog. The position of the worst frog in each memeplex is updated as follows:

$$D_i = r.(x_b - x_w) \quad (21)$$

$$x_w(new) = x_w + D_i \quad (22)$$

$$, (-D_{max} \le D_i \le D_{max})$$

where *"r"* is a random number between 0 and 1, x_b and x_w are position of the frogs with best and worst fitness respectively and D_{max} is the maximum allowed change in the frog's position. After a defined number of memeplex evolution steps, the virtual frogs are shuffled and reorganize into new memeplexes.

To provide the opportunity for random generation of improved information, random virtual frogs are generated and substituted in the population if the local search can not find better solutions. The flowchart of SFLA is shown in Figure 3.

3.2. ICA algorithm [7]

Imperialist competitive algorithm is an evolutionary algorithm for the optimization problems which is inspired by imperialistic competition of the countries of the world. Like other evolutionary algorithms, it starts with an initial population (countries of the world). Some of the best countries in the population are selected as the imperialists and the rest, forms the colonies of these imperialists. All the colonies are divided among the imperialists based on their power. Then these colonies start moving toward their relevant imperialist country by x units. x is a random variable with uniform (or any proper) distribution. Thus x is as follows:

$$x \sim U(0, \beta * d)$$

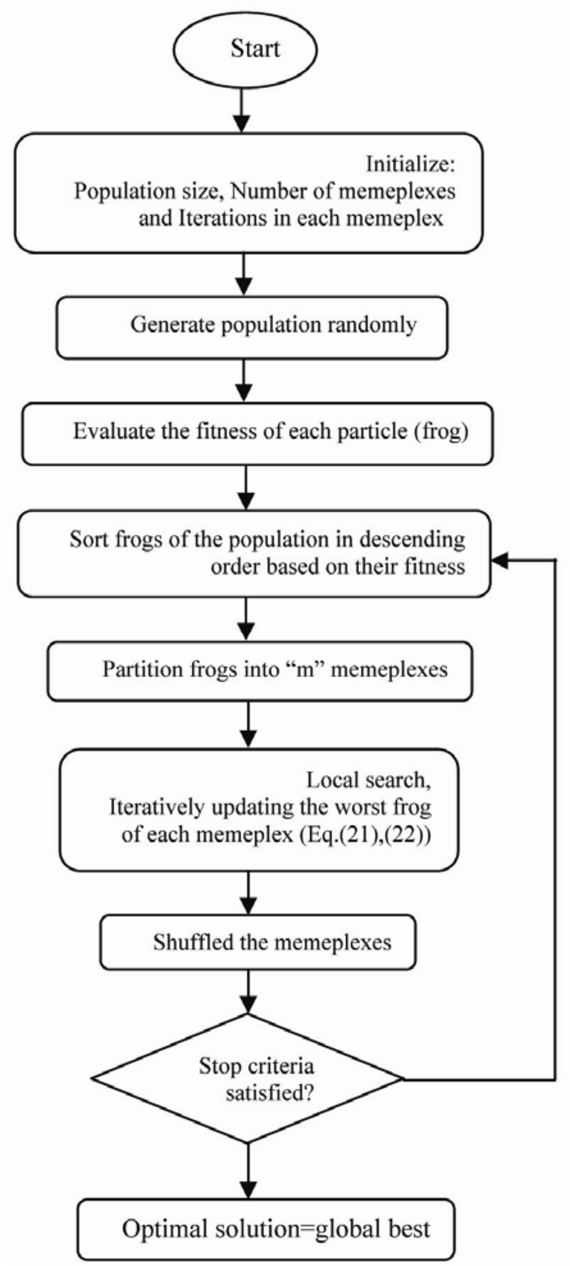

Fig.3. Flowchart of the SFLA algorithm

Where β is a number greater than 1 and *d* is the distance between colony and imperialist. The total power of an empire depends on both the power of the imperialist country and the power of its colonies. We will model this fact by defining the total power of an empire by the power of the imperialist country plus a percentage of mean power of its colonies. Then the imperialistic competition begins among all the empires. Any empire that is not able to succeed in this competition and can’t increase its power (or at least prevent decreasing that) will be eliminated from the competition. The imperialistic competition will gradually result in an increase in the power of powerful empires and a decrease in the power of weaker ones. Weak empires will lose their power and ultimately they will collapse.

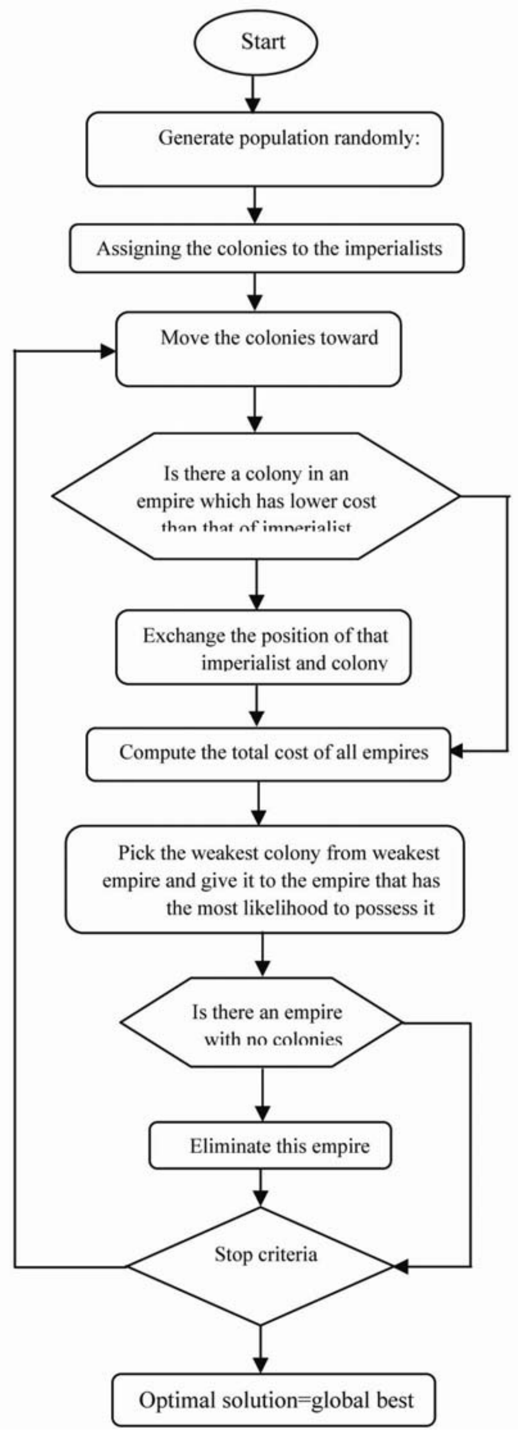

Fig.4. Flowchart of the ICA algorithm

The movement of colonies toward their relevant imperialists along with competition among empires and also the collapse mechanism will cause all the countries to converge to a state in which there exist just one empire in the world and all the other countries are colonies of that empire. In this ideal new world, colonies have the same position and power as the imperialist. The best country in this world is the optimum response. The flowchart of ICA is shown in Figure 4.

Total cost of an empire computes as follows:

$$T.C._n = \mathrm{Cost}(\mathrm{imperialist}_n) + \zeta * \mathrm{mean}\{\mathrm{Cost}(\mathrm{colonies\ of\ empire}_n)\} \quad (23)$$

Where $T.C._n$ is the total cost of n^{th} empire and ξ is a positive number which is considered to be less than 1. A little value for ξ causes the total power of the empire to be determined by just the imperialist and increasing it will increase the role of the colonies in determining the total power of an empire. In this paper the value of 0.1 for ξ is used. We model imperialistic competition by just picking some (usually one) of the weakest colonies of the weakest empires and giving them (that) to an empire that have most likelihood to possess these (this) colonies. Based on their total power, in this competition, each of empires will have a likelihood to taking possession of the mentioned colonies. To start the competition, first we find the possession probability of each empire based on its total power. The normalized total cost is simply obtained by Eq. (24):

$$N.T.C_n = T.C_n - \max\{T.C_i\} \quad (24)$$

where $T.C_n$ and $N.T.C_n$ are respectively total cost and normalized total cost of n^{th} empire. The possession probability of each empire is given by:

$$p_{p_n} = \left| \frac{N.T.C_n}{\sum_{i=1}^{N_{imp}} N.T.C._i} \right| \quad (25)$$

To divide the mentioned colonies among empires based on the possession probability of them, we form the vector P as follows:

$$P = [p_{p_1}, p_{p_2}, p_{p_3}, \ldots, p_{p_{N_{imp}}}] \quad (26)$$

Then we create a vector with the same size as P whose elements are uniformly distributed random numbers.

$$R = [r_1, r_2, r_3, \ldots, r_{N_{imp}}] \quad (27)$$

$$r_1, r_2, r_3, \ldots, r_{N_{imp}} \sim U(0,1)$$

Then we have D vector as follows:

$$D = P - R = [D_1, D_2, D_3, \ldots, D_{N_{imp}}] = [p_{p_1} - r_1, p_{p_2} - r_2, \ldots, p_{p_{N_{imp}}} - r_{N_{imp}}] \quad (28)$$

The mentioned colonies will give to an empire that its relevant index in D is maximum.

4. Estimation Results

The proposed SFLA and ICA algorithms for multi-objective parameter estimation of induction machines are tested on 5 and 40Hp motors using two different circuit models. Table 1 gives the manufacturer data of these test motors.

Table 1. Manufacturer data of the test motors

Specifications	Motor 1	Motor 2
Capacity (HP)	5	40
Voltage (V)	400	400
Current (A)	8	45
Frequency (Hz)	50	50
Number of Poles	4	4
Full load slip	0.07	0.09
Starting torque (Nm)	15	260
Maximum torque (Nm)	42	370
Starting Current (A)	22	180
Full load torque (Nm)	25	190

For estimating the unknown parameters of the approximate circuit model of these motors (R_1, X_1, R_2'), first the initial population of these parameters is generated randomly with uniform distribution in the proper range. Then equations 1-4 are used to calculate full load torque, locked rotor torque and maximum torque of the induction motor by substituting the randomly generated parameters in these equations. Afterwards equations 6-8 and then 5 are used along with the constraints to find the fitness functions value (F). This process is continuing until minimizing the value of fitness function and then satisfying stop criteria of the used algorithm. The final values of unknown parameters satisfying the stop criteria, are the estimated parameter. In the exact circuit model, unknown parameters are $(R_1, X_1, R_2', X_2', X_m)$. The same process as the approximate circuit model performs in this case, too. At this model, equations 9-15 are used for calculating the torques by the estimated parameters and equations 17-20 and then 16 together with the constraints are used to find the best fitness (minimum value) and the unknown parameters. Tables 2-5 give the results of induction motor parameter estimation in the two mentioned models (approximate model and exact model). Also Figures 5-6 show the fitness values reached in the parameter estimation processes.

Table 2.Comparison of SFLA and ICA torque results with manufacturer data for motor 1

Torque	Manufacturer value	SFLA				ICA			
		Model 1		Model 2		Model 1		Model 2	
		Estimated data	Error (%)	Estimated data	Error (%)	Estimated data	Error (%)	Estimated data	Error (%)
T_{st}	15	15.111	0.74	16.08	7.2	15.256	1.7	15.0437	0.29
T_{max}	42	40.467	3.65	40.995	2.39	40.333	3.97	40.358	3.91
T_{full}	25	25.97	3.88	27.174	8.7	25.508	2.03	25.837	3.348

Table 3.Comparison of SFLI and ICA torque results with manufacturer data for motor 2

Torque	Manufacturer value	SFLA				ICA			
		Model 1		Model 2		Model 1		Model 2	
		Estimated data	Error (%)	Estimated data	Error (%)	Estimated data	Error (%)	Estimated data	Error (%)
T_{st}	260	252.36	2.93	258.86	0.438	260	0	254.83	1.988
T_{max}	370	363.7	1.7	375.51	1.49	370	0	377.16	1.935
T_{full}	190	190.618	0.325	188.54	0.768	190	0	189.94	0.0315

Table 4.Approximate circuit model parameters estimated for motors 1 and 2

Parameters	Motor 1		Motor 2	
	SFLA	ICA	SFLA	ICA
R_1	0.169	$\simeq 0$	0.289	0.278213
R_2'	7.26	7.44	0.404	0.408495
X_1	37.585	37.88	1.07	1.062439

Table 5.Exact circuit model parameters estimated for motors 1 and 2

Parameters	Motor 1		Motor 2	
	SFLA	ICA	SFLA	ICA
R_1	3.198	≃0	0.215	0.18659
R_2'	5.134	6.52	0.395	0.38619
X_1, X_2'	13.28	16.86	0.5246	0.52422
X_m	102.126	283.314	15.683	11.223

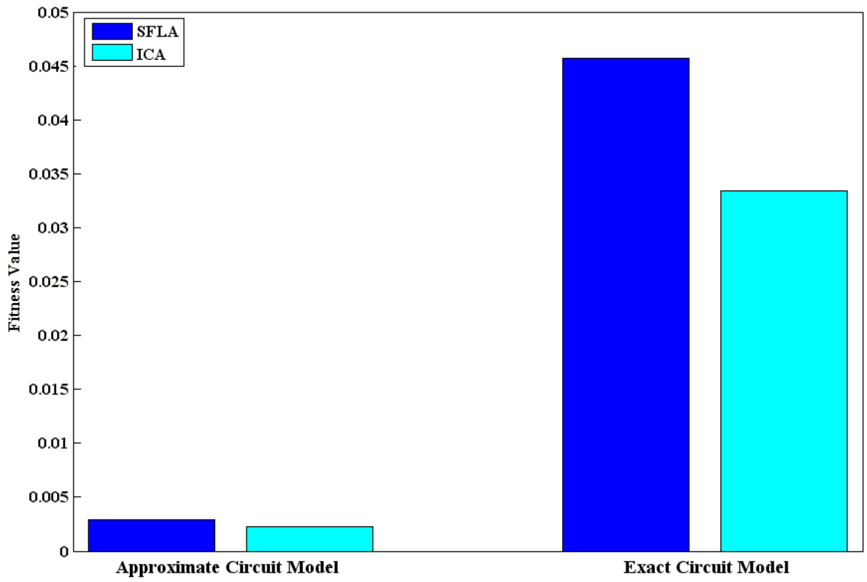

Fig.5. Comparison of the fitness values reached by SFLA and ICA for motor 1

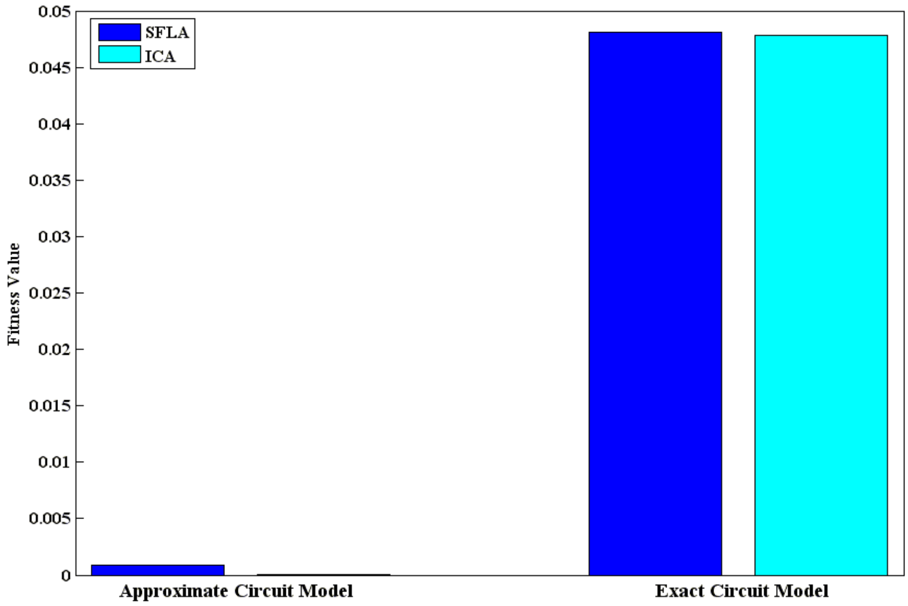

Fig.6. Comparison of the fitness values reached by SFLA and ICA for motor 2

The small errors between estimated and manufacturer torques in the Tables 2-3 and small values of the fitness function in Figures 5-6 show the ability of these two proposed methods in estimating the induction machines parameters, although, it seems that ICA is more reliable for such estimation problem.

5. Conclusion

This paper presents two methods for parameter estimation of induction machines using Shuffled Frog Leaping Algorithm (SFLA) and Imperialist Competitive Algorithm (ICA). These two methods are applied to 5 and 40Hp induction motors in the approximate circuit model and exact circuit model. The parameter estimation results are presented in various tables and figures. These results verify the ability of these two proposed methods in precisely estimation of the induction machines parameters.

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