

Comparison of Several Improved Versions of Particle Swarm Optimizer Algorithm for Parameter Estimation of Squirrel-Cage Induction Motors

**Mohammad Yazdani-Asrami*¹, *Mehran Taghipour Gorjikolaie*² and *S. Asghar Gholamian*¹

¹*Faculty of Electrical and Computer Engineering, Babol University of Technology, Babol, Iran*

²*Faculty of Electrical and Computer Engineering, University of Birjand, Birjand, Iran*

E-mail: yazdani@stu.nit.ac.ir

Abstract:

In this paper, three versions of Particle Swarm Optimization (PSO) are proposed to estimate the equivalent circuit parameters of squirrel cage induction motor. It is believed that how inertia weight changes during iterations can impact on final results. Constricted coefficients, linear model and exponential version are used as inertia weight, each of them presents different variations for inertia weight and consequently for particle movements and speed of such movements. In the linear version, particles start searching process with high speed and their speed will decrease by constant ramp, this kind of variation let to search all solution space in a short time and local search at the final iterations with low speed, also exponential version presents same treatment as linear version with non-linear variations in inertia weight and speed of movement. But, mathematical analysis shows that they trap into local minima and scientists presents constricted version to solve this problem. In order to evaluate proposed versions additional to make changing in PSO's version, sensitivity of proposed methods is analyzed using three sets of data. Results confirm the ability of proposed method which can estimate parameters with a possible least error.

Keywords: Equivalent circuit parameters, Induction motor, Parameter estimation, Particle Swarm Optimization

Introduction

Induction machines are extensively applied in all sectors of industrial power networks due to their low price and ruggedness. The presence or absence of a large induction machine or a combination of machines in power systems plays a significant role in their transient stability or security assessment. Accurate machine parameters are essential for systems behavior prediction. Machine parameters are also crucial in industrial system studies (Perez et al., 2012).

Electric drives using induction motors (IM) are one of the main fields of interest to the control systems and electrical engineering specialists. The quality and effective control of IM is based on their equivalent circuits. The necessity of knowing the equivalent circuit parameter of IM is constantly growing due to the following reasons (Kostov et al., 2009; Pillay et al., 1997; Leonhard, 2001):

1) Engineers and Students should get deeper, up-to-date and accurate knowledge in the physical processes

occurring in IM

- 2) Designed power converters should possess better quality indices in static and dynamic modes
- 3) Increasingly adequate models of IM are needed for their research and improvement.

Generally, estimation methods of induction motor parameter can be classified into five different categories, depending on what data is available, and what data is used for:

- 1) Parameter calculation from motor construction data: This method requires a detailed knowledge of the machine's construction, such as geometry and material parameters. On the one hand, it is the most accurate procedure, since it is most closely related to the physical reality. On the other hand, it is the most costly one since it is based on field calculation methods, such as the finite element method (Faiz and Ebrahimi, 2008; Lindenmeyer et al., 2001; Zhou et al., 1998; Ertan et al., 2003).

2) Parameter estimation based on steady-state motor models:

The methods in this category use iterative solutions based on induction motor steady-state network equations and given manufacturer data (Hung and Dommel, 1996). This is the most common type of parameter estimation for system studies since the data needed for it is usually available.

3) Frequency-domain parameter estimation:

The frequency response method is based on measurements that are performed at standstill. The motor parameters are estimated from the resulting transfer function (Willis et al., 1989). The major advantage of this method is its accuracy. However, stand-still tests are not common industry practice, and this method can therefore not be used very often.

4) Time-domain parameter estimation:

For this type of method, time-domain motor measurements are performed and model parameters are adjusted to match the measurements (Ju et al., 1996; Moon and Keyhani, 1994). Since not all parameters can be observed using measurable quantities, the motor models need to be simplified (Ju et al., 1996). The method is costly, and the required data is usually not available.

5) Real-time parameter estimation:

This type of parameter estimation is used to tune the controllers of induction motor drive systems. This requires real-time parameter estimation techniques, using simplified induction motor models, which are fast enough to continuously update the motor parameters and therefore prevent the detuning of induction machine controllers (Willis et al., 1989; Zaremba and Pavlov, 2002).

The newest class of the estimation methods is heuristic based methods, applied in the present paper. The survey of the methods for equivalent circuit parameters estimation shows, that adjustable, cost and accuracy are the major considerations when selecting a method for determining IM parameters. Users prefer a cheap and low adjustable method providing good accuracy. The evolutionary algorithm (Nangsue et al., 1999), genetic algorithm (GA) (Bishop and Richards, 1990; Rahimpour et al., 2007; Huang et al., 2001; Orłowska Kowalska et al., 2006), adaptive GA (Abdelhadi et al., 2004), artificial neural network (ANN) (Michael and Ronald, 1995; Bae, 1997) and differential evolution (DE) (Ursem and Vadstrup, 2003) have been used for parameter determination of induction motor.

The conventional method for estimation of IM equivalent circuit parameters is based on the no-load and blocked rotor tests which are a time-consuming

task, especially if the motor is already coupled to driving equipment. This paper presents a more sophisticated approach for determining the equivalent circuit parameters of induction motors. The approach is based on only a set of measured or analytically obtained data such as stator voltage, current, power factor and slip. Particle swarm optimization (PSO) algorithm models for determining the parameters are synthesized that enables the simultaneous satisfaction of steady-state stator current and power factor by defining an objective function. The results obtained by the synthesized model are compared with analytical data. An analysis is performed that proves the validity and adequacy of such models in IM control systems.

In the rest of the paper, overview of three versions of PSO has been presented in section 2. How can PSO be used for parameter estimation is stated in section 3 and obtained results are discussed in section 4. And finally, section 5 includes conclusion of the paper.

Overview of Particle Swarm Optimization

Particle Swarm Optimization: A Basic Version

Swarm Intelligence (SI) is one of the Artificial Life (AL) research branches. The Particle Swarm (PS) concept originated as a simulation of simplified social system. The original intent is to graphically simulate the choreography of bird of a bird flock or fish school. Particle Swarm Optimization (PSO) follows the special scenario: suppose that a group of birds are randomly searching food in an area. Suddenly one of them finds a piece of food. Other birds don't know where the food is, but they know which finds the food and how far from it. So, the best strategy is to follow the bird which is nearest to the food. Using this scenario, PSO can be used to solve optimization problems. In PSO, each single solution is a "bird" in the search space. Here, it is called as "particle". For all of the particles fitness value has been calculated, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. The particles are "flown" through the problem space by following the current optimum particles. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In each iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called "Pbest". Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best which is called "Gbest". After finding the two best values, the particle updates its velocity and positions based on following Equations:

$$V_{t+1} = W \times V_t + C_1 \times r \times (P_{pb} - X_{cs}) + C_2 \times r \times (P_{gb} - X_{cs}) \quad (1)$$

$$X_{t+1} = X_t + V_{t+1} \quad (2)$$

Where W is the inertia weight, V_{t+1} is the particle velocity, X_{cs} is the current particle (solution) of each particle, P_{pb} and P_{gb} are Pbest and Gbest, r is a random number between $[0,1]$ and C_1, C_2 are learning factors.

PSO versions: from topology point of view

The main PSO categorized into two major topologies: global PSO and local. Several tests show that global version has a worse search space coverage than the local PSO, also in global version particles' movement are more concentrated around one solution and therefore can more quickly find the best solution. An inappropriate problem may occur for global version is very susceptible to local minima. In general, global version is the better choice when solution space is not very scattered, because of its speed and accuracy (Clerc and Kennedy, 2002; Zahiri, 2010).

Following code shows global PSO algorithm's pseudo code:

```

For each particle
    Initialize particle
End
Do
    For each particle
        Evaluate objective function and calculate fitness value
        If the fitness value is better than the best fitness value Pbest in history
            Set current value as the new Pbest
        End
    Choose the particle with the best fitness value of all the particles as the Gbest
    For each particle
        Update particle's velocity according Equation (1)
        Update Particle's position according Equation (2)
    End
While maximum iteration or minimum error criteria is not attained
    
```

PSO versions: from inertia weight point of view

Inertia weight is the other factor that its changes can make new versions of PSO. In this case, amount of momentum that a particle carries between iteration can be controlled by a parameter w that multiplied by the particle's current velocity, as it can be seen in Equation (1). Indeed, this control parameter influences the particle's area of exploration. So, the amount of this parameter can play an important role in searching process. Using a high constant value of inertia weight

(e.g. more than unit) although can cover more area, but often PSO trap in local minima and can't find best solution. In the other hand, a lower value of this parameter will lead to particles concentrating on small search space and PSO losses the other possible solution spaces. In this paper, using different equations for inertia weight, three version of PSO is presented and used for parameter estimation of induction motor. As mentioned before, using not proper constant value for this control parameter may result in not suitable results, so one idea is using an equation for inertia weight that depends on the number of pass iterations so that decreases during search process. Using high value of inertia weight in initialization step can help PSO to search all area of the solution space, by spending time and increase of the number of iteration, inertia weight decreases; this can help PSO to present good local search at the final iterations. Equations (3) and (4) show the inertia weights of first and second used PSO in this paper, respectively.

$$W = w_{max} - \left(\frac{w_{max} - w_{min}}{T} \times t \right) \quad (3)$$

Where, w_{max} and w_{min} are the maximum and minimum values of inertia weight, respectively. T is the maximum iteration and t is the current iteration. As it can be seen in Equation (3), PSO search process is stated by a value less than w_{max} and when it wants to be finished inertia weight is equal to w_{min} . Several testes in this work show that best interval for w_{max} is 0.9 to 1.1 and for w_{min} is 0.01 to 0.1.

The other formula for inertia weight can be exponential format, as shown in Equation (4). Using this equation, PSO starts by a given value and decreases exponentially to near zero.

$$W = w_{max} e^{-\alpha \frac{t}{T}} \quad (4)$$

Where, w_{max} is the maximum values of inertia weight. Coefficient α is a positive constant that amount of it can control ramp, slope and bend of variations. Figure 1 shows the typical variations of proposed versions of PSO.

The other version of PSO is presented in (Clerc and Kennedy, 2002). This version uses constant value for inertia weight but this constant is calculated based on Equation (5). It is not a simple equation, while it is obtained by analytical and algebraic analysis that uses constriction property. Constriction coefficients can prevent explosion; further, these coefficients can induce particles to converge on local optima. In addition in this version Equation (1) has a significant change that can be seen Equation (6).

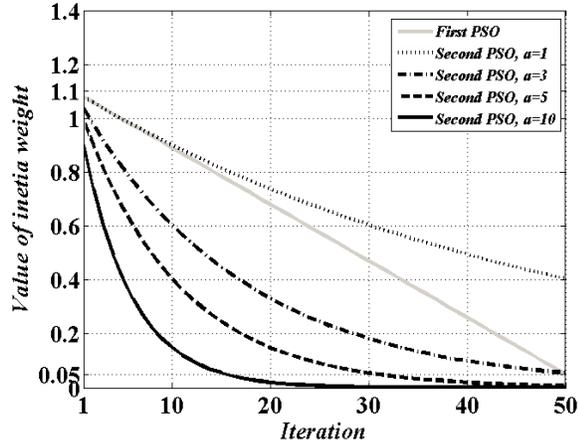


Figure 1: Typical variations of proposed versions of PSO: w_{max} and w_{min} are 1.1 and 0.05, and also in order to show the influence of coefficient α , it is changed from 1 to 10.

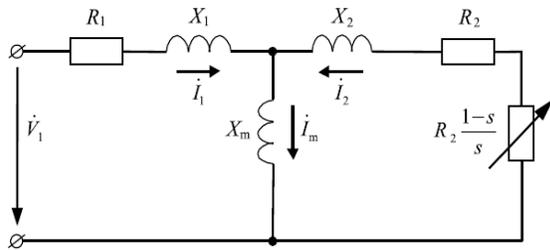


Figure 2: T-shape induction motor equivalent circuit without considering the steel losses

$$\chi = \begin{cases} \frac{2\kappa}{\varphi - 2 + \sqrt{\varphi^2 - 4\varphi}} & \text{for } \varphi > 4 \\ k & \text{else} \end{cases} \quad (5)$$

$$V_{t+1} = \chi \times (V_t + \varphi_1 \times (P_{pb} - X_{cs}) + \varphi_2 \times (P_{gb} - X_{cs})) \quad (6)$$

Where, coefficient χ is constriction coefficient which is used as inertia weight. Coefficients φ_1 and φ_2 are random numbers uniformly distributed in the range (0, $\varphi/2$). We set $k=1$, meaning that the space thoroughly searched before the swarm collapses into a point (Zahiri, 2010).

Application of Proposed Methods

As you know, one of the main applications of PSO is its powerful optimizing ability. In this paper, using this ability of PSO our purpose to estimate parameters of induction motor has been satisfied. As usual, PSO is

used for optimizing (minimizing) a designed objective function. It is worth noting that this optimization is the skin and output layer of the problem, indeed by utilizing this ability when designed objective function is minimized, the constructing parameters of this function obtain their optimum value. So, something which is important here and is the main part of the proposed method is objective function.

Designed objective function

In order to estimate parameters of induction motor, two sets of quantities are necessary; measured quantities and calculated quantities. So, objective function of this problem should be developed based on these values. According to Figure 2, T-shape induction motor equivalent circuit which steel losses are not considered equations of objective function is developed.

As it can be seen in Figure 2, five parameters are unknowns that should be estimated that descriptions of these parameters are shown in Table 1. So, one particle of PSO can be as Figure 3. Also, in addition to these parameters that should be calculated and estimated, some quantities that can be measured are shown in Table 2.

$$P_i = (P_{i1}, P_{i2}, P_{i3}, P_{i4}, P_{i5})$$

R₁	X₁	R₂	X₂	X_m
P _{i1}	P _{i2}	P _{i3}	P _{i4}	P _{i5}

Figure 3: a typical particle of PSO

Table 1: descriptions of unknown parameters which should be estimated

Unknown parameters of induction motor	Descriptions
R_1	<i>Stator resistance</i>
X_1	<i>Stator leakage reactance</i>
R_2	<i>Rotor resistance</i>
X_2	<i>Rotor leakage reactance</i>
X_m	<i>Magnetizing reactance</i>

Table 2: descriptions of known parameters which should be measured

Known parameters of induction motor	Descriptions
V_1	Input voltage that equals to rated value
I_1	Input current
$\text{Cos } \varphi$	Power factor
S	Slips

Table 3: set of data used for sensitive analysis

No.	Stator current (A)	Slip	Power factor
1	1.86	0.06	0.62
2	2.39	0.10	0.74
3	3.07	0.15	0.78

Stator current and power factor can be calculated by Equations (7) and (8) which can be derivated from Figure 2.

$$I_1 = \frac{\dot{V}_1}{Z_{eq}} = \frac{\dot{V}_1}{R_{eq} + jX_{eq}} \quad (7)$$

$$\text{cos } \varphi = \cos \left(\tan^{-1} \frac{X_{eq}}{R_{eq}} \right) \quad (8)$$

Where, Z_{eq} is the equivalent circuit impedance. Also, the equivalent circuit resistance (R_{eq}) and reactance (X_{eq}) can be computed by Equations (9) and (10), respectively.

Therefore, the objective function can be considered as Equation (11) that is the average error in the power factor and input current for various load points.

$$R_{eq} = R_1 + \frac{X_m^2 R_2}{S \left(\left(\frac{R_2}{S} \right)^2 + (X_2 + X_m)^2 \right)} \quad (9)$$

$$X_{eq} = X_1 + \frac{\left(\frac{R_2}{S} \right)^2 X_m + X_2 X_m (X_2 + X_m)}{\left(\frac{R_2}{S} \right)^2 + (X_2 + X_m)^2} \quad (10)$$

$$F_{obj} = \sum_{i=1}^n \left(\frac{\text{Cos } \varphi_{c,i}}{\text{Cos } \varphi_{m,i}} - 1 \right)^2 + \sum_{i=1}^n \left(\frac{I_{1c,i}}{I_{1m,i}} - 1 \right)^2 \quad (11)$$

Where, $I_{1c,i}$ and $\text{Cos } \varphi_{c,i}$ are the values computed by Equations (7) and (8). $I_{1m,i}$ and $\text{Cos } \varphi_{m,i}$ are measured or analytical values. Also, the variable n varies from 1 to the number of states. It is worth noting that the sensitivity of the approach is investigated in three states of data presented in Table 3.

Results and Discussion

As mentioned before, to do this estimation problem and choose best method three versions of PSO are used. Also, obtained results are compared to presented results in (Kostov et al., 2009). Proposed method is applied to a three-phase induction motor with the following data: 0.75 KW output power, 380 V phase-to-phase voltage, 50 Hz frequency and 2 poles.

In order to present trusty results, each estimation process is done for 50 times run and average value of obtained results for each parameter is reported. Also the configuration of the PC which simulation is done by it is: 2.53 GHz, Intel ® Core ™2 Duo CPU with 3GB RAM.

Each optimization process is done for 50 iterations. Table 4 illustrates amount of control parameters for simulation process. Figure 4 shows the typical convergence curve of objective function value for used PSOs. Estimated parameters of induction motor using proposed PSO-based methods as compared to GA-based method are presented in Table 5. In addition, errors of estimated values are calculated as Equation (12).

$$\text{Error} = \left| \frac{\text{Estimated value} - \text{Analytical value}}{\text{Analytical value}} \right| \times 100 \quad (12)$$

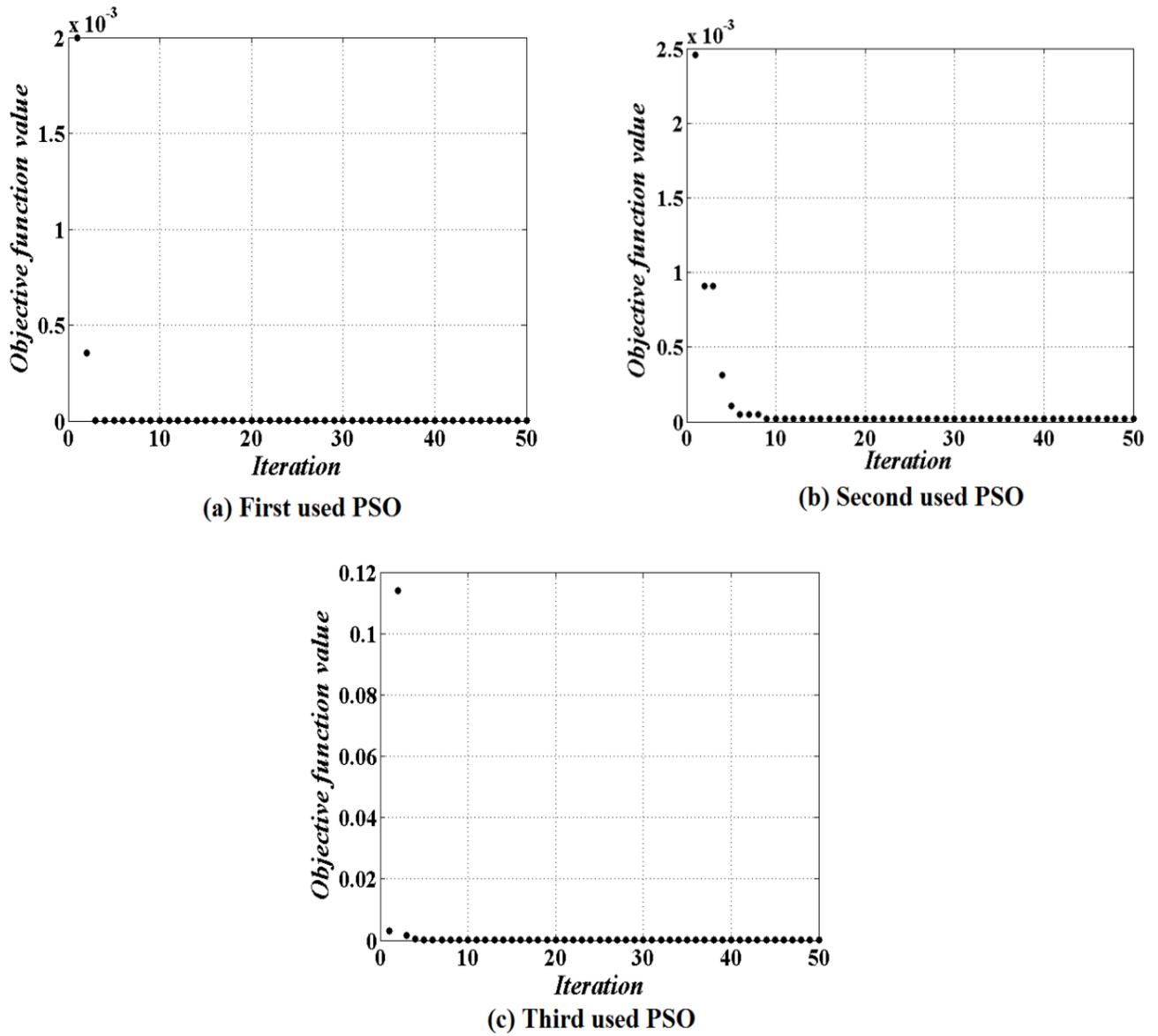


Figure 4: Convergence curve of objective function values for three used versions of PSO

Table 4: Control parameters of used PSOs

<i>PSO version</i>	<i>K</i>	φ	w_{max}	w_{min}	α	<i>T</i>	<i>Number of population</i>	C_1	C_2
<i>1st PSO</i>	-	-	0.9	0.05	-	50	500	2.8	1.2
<i>2nd PSO</i>	-	-	1	-	10	50	500	2.8	1.2
<i>3rd PSO</i>	1	6	-	-	-	50	500	-	-

Table 5: Estimated parameters of induction motor using proposed PSO-based methods as compared to GA-based method

Parameter of induction motor	Analytical value (Ω)	Proposed method	Estimated, one data set		Estimated, two data sets		Estimated, three data sets	
			Estimated value (Ω)	Error # (%)	Estimated value (Ω)	Error (%)	Estimated value (Ω)	Error (%)
R_1	10.20	<i>1st PSO</i>	10.28	0.78	9.95	2.45	10.17	0.29
		<i>2nd PSO</i>	10.19	0.09	10.02	1.70	10.11	0.88
		<i>3rd PSO</i>	8.9	12.74	9.97	2.25	10.11	0.80
		<i>GA</i>	62.56	513.30	10.54	3.30	10.28	0.80
X_1	8.17	<i>1st PSO</i>	7.62	6.73	7.33	10.28	8.03	1.71
		<i>2nd PSO</i>	7.53	7.80	7.45	8.80	7.96	2.50
		<i>3rd PSO</i>	7.16	12.36	7.61	6.85	8.18	0.12
		<i>GA</i>	43.49	432.30	8.24	0.90	8.19	0.20
R_2	10.52	<i>1st PSO</i>	10.53	0.09	10.56	0.38	10.44	0.76
		<i>2nd PSO</i>	10.54	0.19	10.54	0.19	10.45	0.66
		<i>3rd PSO</i>	8.4	20.15	10.52	0	10.42	0.95
		<i>GA</i>	11.02	4.80	10.47	0.50	10.48	0.40
X_2	19.16	<i>1st PSO</i>	19.13	0.15	18.90	1.35	19.32	0.83
		<i>2nd PSO</i>	18.95	1.09	18.94	1.10	19.26	0.52
		<i>3rd PSO</i>	19.47	1.61	18.51	3.39	19.09	0.36
		<i>GA</i>	101.98	432.20	19.32	0.80	19.21	0.30
X_m	143.57	<i>1st PSO</i>	142.95	0.43	143.49	0.05	143.47	0.06
		<i>2nd PSO</i>	143.03	0.37	143.40	0.11	143.53	0.02
		<i>3rd PSO</i>	141.11	1.71	143.11	0.32	143.42	0.10
		<i>GA</i>	58.77	59.10	142.73	0.60	143.17	0.30

Table 6: Some extra obtained results of this work; optimum range of parameters of used PSO

<i>PSO version</i>	K	φ	w_{max}	w_{min}	α	C_1	C_2	ATVOF	AT (second)
<i>1st PSO</i>	-	-	0.8-1.1	0.02-0.1	-	2-3	1-1.5	1.776603e-005	3.025
<i>2nd PSO</i>	-	-	0.9-1	-	7-12	2.5-3	0.9-1.5	1.776973e-005	3.015
<i>3rd PSO</i>	0.95-1.1	4.75-6.5	-	-	-	-	-	1.776601e-005	3.6

As it can be seen in Table 5, proposed methods can estimate parameters of induction motor by less than 0.2% error. Bold values in Table 5 shows the least error in each part. Additional to these results, some extra results are listed in Table 6; optimum range of control parameters, the average of terminates value of objective function (ATVOF) and average time of simulation (AT) for each estimating process. It is worth noting that although the average of terminates value of objective function is about $1.7e-005$ but maximum terminates value of objective function is about $8.5e-005$ and minimum terminates value of objective function is about $1.5e-010$.

In this paper, three versions of PSO based on their inertia weight have been used for solving our estimation problem. According to estimated values and calculated errors, third PSO estimates the parameters of studied induction motor more accurate, but in other hand, based on average time of simulation second version of PSO do the simulation faster than others. Therefore, we should consider a reasonable tradeoff between time and accuracy of estimation. In this work, because accuracy is more important third version of PSO can be best choice. Although depend on application of parameter estimation process, this tradeoff can be changed. For example, when parameter estimation is used to detect electrical or mechanical faults [26], faster method with acceptable accuracy is needed, but when it is just used to estimate structural parameters in order to manufacturing purpose and optimization design, using more accurate method with acceptable speed is reasonable.

Conclusions

As mentioned before, estimation of important parameters of electrical machines can help engineers to find out essential information about machine. In this paper, three versions of PSO have been proposed to estimate parameters of the equivalent circuit parameters of squirrel cage induction motor. Obtained results show the abilities of proposed methods that can estimate equivalent parameters with less than 0.2% error; also this procedure is done only in less than 4 seconds. So, proposed methods present accuracy along with speed in decision making. These two important factors hope us to use these useful methods in other parameter estimation applications and problems. In addition, it is worth noting that equivalent parameters estimation has been only done by three electrical input data; voltage, current and power factor and slip of the motor.

References

- Abdelhadi B., Benoudjit A., Nait Said N., (2004). Identification of Induction Machine Parameters Using an Adaptive Genetic Algorithm. *Electric Power Components and Systems*. Vol. 32, pp. 767-784.
- Bae D., (1997). Determination of Induction Motor Parameters by Using Neural Network Based on FEM Results. *IEEE Transactions on Magnetics*, Vol. 33, pp. 1924-1927.
- Bishop R. R., Richards G. G., (1990). Identifying Induction Machine Parameters Using a Genetic Optimization Algorithm. *In Proceedings of IEEE Southeastcon*. Vol. 2, pp. 476-479.
- Clerc M., Kennedy J., (2002). The Particle Swarm—Explosion, Stability, and Convergence in a Multidimensional Complex Space. *IEEE Transactions on Evolutionary Computation*, Vol. 6, No. 1, pp. 58-73.
- Ertan H. B., Leblebicioglu K., Avenoglu B., Ercan B., (2003). Identification of parameters of an induction motor from field solution. *In Proceedings of 6th International Conference on Electrical Machines and Systems*, Vol. 1, No. 1, pp. 1-6.
- Faiz J., Ebrahimi B. M., (2007). Influence of Magnetic Saturation upon Performance of Induction Motor Using Time Stepping Finite Element Method. *Electric Power Components and Systems*, Vol. 35, No. 5, pp. 505-524.
- Hung R., Dommel H. W., (1996). Synchronous machine models for simulation of induction motor transients. *IEEE Transactions on Power Systems*, Vol. 11, No. 2, pp. 833-841.
- Huang K. S., Kent W., Wu Q. H., Turner D. R., (2001). Parameter Identification for Induction Motors Using Genetic Algorithm with Improved Mathematical Model. *Electric Power Components and Systems*. Vol. 29, No. 3, pp. 247-258.
- Ju P., Handschin E., Wei Z. N., Schluecking U., (1996). Sequential parameter estimation of a simplified induction motor load model. *IEEE Transactions on Energy Conversion*, Vol. 11, No. 1, pp. 319-324.
- Kostov I., Spasov V., Rangelova V., (2009). Application of Genetic Algorithms for Determining the Parameters of Induction Motors. *Technical Gazette*, Vol. 16, No. 2, pp. 49-53.
- Leonhard W., (2001). Control of electrical drives, Springer Verlag.

Lindenmeyer D., Dommel H. W., Moshref A., Kundur P., (2001). An induction motor parameter estimation method. *Electrical Power and Energy Systems*, Vol. 23, No. 4, pp. 251-262.

Michael T. W., Ronald G. H., (1995). Identification and Control of Induction Machines Using Artificial Neural Networks. *IEEE Transactions on Industry Applications*, Vol. 31, No. 3, pp. 612-619.

Moon S. I., Keyhani A., (1994). Estimation of induction machine parameters from standstill time-domain data. *IEEE Transactions on Industry Applications*, Vol. 30, No. 6, pp. 1609-1615.

Nangsue P., Pillay P., Conry S., (1999). Evolutionary Algorithms for Induction Motor Parameter Determination. *IEEE Transactions on Energy Conversion*, Vol. 14, No. 3, pp. 447-453.

Orlowska Kowalska T., Lis J., Szabat K., (2006). Identification of the Induction Motor Parameters using Soft Computing Methods. *COMPEL*, Vol. 25, No. 1, pp. 181-192.

Perez I., Gomez-Gonzalez M., Jurado F., (2012). Estimation of induction motor parameters using shuffled frog-leaping algorithm. *Electrical Engineering*, Vol. 95, No. 3, pp. 267-275.

Pillay P., Sabur S., Haq M., (1997). A model for induction motor aggregation for power system studies. *Electric Power Systems Research*, Vol. 42, pp. 225-228.

Rahimpour E., Rashtchi V., Pesaran M., (2007). Parameter Identification of Deep-Bar Induction Motors Using Genetic Algorithm. *Electrical Engineering*. Vol. 89, pp. 547-552.

Ursem R. K., Vadstrup P., (2003). Parameter Identification of Induction Motors Using Differential Evolution. *The Congress on Evolutionary Computation*, Vol. 2, pp. 790-796.

Willis J. R., Brock G. J., Edmonds J. S., (1989). Derivation of induction motor models from standstill frequency response tests. *IEEE Transactions on Power Energy Conversion*, Vol. 4, No. 4, pp. 608-615.

Zahiri S. H., (2010). *Swarm Intelligence and Fuzzy Systems*, Nova Publisher, USA.

Zaremba A. T., Pavlov A. V., (2002). Real-Time Identification of an Induction Motor using Sinusoidal

PWM Voltage Signals. *In the Proceedings of the American Control Conference*, pp. 3082-3087.

Zhou P., Gilmore J., Badics Z., Cendes Z. J., (1998). Finite element analysis of induction motors based on computing detailed equivalent circuit parameters. *IEEE Transactions on Magnetics*. Vol. 34, No. 5, pp. 3499-3502.