International Journal of the Physical Sciences Vol. 6(19), pp. 4564-4570, 16 September, 2011
Available online at http://www.academicjournals.org/IJPS
DOI: 10.5897/IJPS11.890
ISSN 1992-1950 ©2011 Academic Journals

Full Length Research Paper

Investigation of induction motor parameter identification using particle swarm optimization-based RBF neural network (PSO-RBFNN)

Hassan Farhan Rashag[1], S. P. Koh[1], S. K. Tiong[1], K. H. Chong[1] and Ahmed N. Abdalla[2]*

[1]Department of Electronics and Communication Engineering, University Tenaga Nasional, Selangor 43009, Malaysia.
[2]Faculty of Electrical and Electronic Engineering, University of Technology, Pekan 26600, Malaysia.

Accepted 5 August, 2011

High dynamic performance of induction motor drives is required for accurate system information. From the actual parameters, it is possible to design high performance induction motor drive controllers. In this paper, improving the induction motor performance using intelligent parameter identification was proposed. First, machine model parameters were presented by a set of time-varying differential equations. Second, estimation of each parameter was achieved by minimizing the experimental response based on matching of the stator current, voltage and rotor speed. Finally, simulation results demonstrate the effectiveness of the proposed method and great improvement of induction motor performance.

Key words: Induction motor, particle swarm optimization (PSO), parameter identification, least square algorithm.

INTRODUCTION

Nowadays, parameter identification with good accuracy and general practicality is quite a significant tool for increasing the performance of induction motor controller. However, the intelligent parameters identification technique achieved through excellent performance with good exactness and universal practicality is very important in order to give fast dynamic response performance.

Many researchers have done a lot of research on parameters identification of the induction motor using offline identification methods of the induction motor (SeungMoon and Ali, 1994; ManueleBertoluzzo et al. 2001; Sonnaillon et al., 2007; Jul-Ki et al., 1997; Young-Su et al., 2009; Paolo and Andrea, 2005). Previous works have also discussed the parameters evaluation of the machine in standstill (Willis et al., 1989; Seok et al., 1997). These methods have good performance in practical. But these methods are not ideal in the online real time performance. Ribeiro et al. (1997) proposed effective estimation method under any mechanical load. Choi and Sul (1999) proposed a complicated calculation and hardware. Therefore, it is necessary to estimate these parameters before the operation, that is, offline parameter identification, and to track their variation during normal conditions. Fuzzy logic control is a feasible alternative to conventional control technique in situations where there are unidentified variations in the parameters of plant and structure (Gandomkara et al., 2011). Messaoudi et al. (2007) present a robust nonlinear observer for variables and parameters estimation in sensorless Indirect Field Oriented Control (IFOC) of induction motors (IM). A mismatch in parameters will create incorrect flux estimation and as a result incorrect torque estimations (Bose, 1986; Novotny and Lipo, 1996; Tajima, 2002). Azzolin et al. (2007) proposed the identification of all electrical parameters, using Recursive Least Square identification algorithms, without any previous tests. Particle swarm optimization (Picardi and Rogano, 2006; Noor et al., 2011; Mohammad et al., 2010), genetic algorithm (Ursem and Vadstrup, 2003; Huang et al., 2002) and differential evolution (Alonge et al., 1998) were used as a computational and optimization methods for estimating induction motor parameters. Surya et al. (2007) studied the analytical sensitivity expression for an indeterminate structural design optimization problem can

*Corresponding author. E-mail: dramaide@yahoo.com.

be factored into a simple determinate term and a complicated indeterminate component. Sensitivity can be approximated by retaining only the determinate term and setting the indeterminate factor to zero. Muhammad et al. (2010), focus on modified variation of parameters method, which is an elegant coupling of variation of parameters method and Adomian's decomposition method, for solving the solution system of nonlinear boundary value problems associated with obstacle, contact and unilateral problems. Hao and Pu (2011) present a hybrid approach which combined genetic algorithm and local optimization technique for simulation optimization problems. Through the combination of genetic algorithms and with the local optimization method, it can maximally use the good global property of random searching and the convergence rate of a local method. Lu Lu and XiuxiaQuan (2011) propose a learning genetic algorithm to solve the experimental parameters optimization problem. This method can not only enhance the efficiency of genetic algorithm through the pre-given user experience, but also improve the efficiency of genetic algorithm via learning the knowledge obtained from the optimization process.

In this paper, precise and fast method for evaluation of the parameters of the induction motor, using HPSO was proposed. First, induction motor model and experimental setup were explained in detail. The induction motor used for this test is a 2.2 kW, 4 pole. Second, the HPSO algorithm based on combination of RBFNN and PSO was used in induction motor identification system. Third, the proposed method is compared with least square algorithm (LSA) in terms of improving induction motor response. Finally, simulation and experimental results are presented to validate the viability and performance of the proposed methods.

THEORETICAL BACKGROUND

Model of Induction motor

The induction motor model can be expressed in the d-q fixed reference frame by the following Equations (1) to (6).

$$\bar{v}_{s,dq} = R_s \bar{i}_{s,dq} + \frac{d\bar{\psi}_{s,dq}}{dt} + j\omega_s \bar{\psi}_{s,dq} \quad (1)$$

$$0 = R_r \bar{i}_{r,dq} + \frac{d\bar{\psi}_{r,dq}}{dt} + j(\omega_s - \omega_r)\bar{\psi}_{r,dq} \quad (2)$$

$$\bar{\psi}_{s,dq} = L_s \bar{i}_{s,dq} + L_m \bar{i}_{r,dq} \text{ and } L_s = L_m + L_{ls} \quad (3)$$

$$\bar{\psi}_{r,dq} = L_r \bar{i}_{r,dq} + L_m \bar{i}_{s,dq} \text{ and } L_r = L_m + L_{lr} \quad (4)$$

$$T_e = \frac{3}{2} P(\psi_{ds} i_{qs} - \psi_{qs} i_{ds}) \quad (5)$$

$$T_e - T_L = J\frac{d\omega_m}{dt} + B\omega_m \quad (6)$$

where, dq ,βα: Axis of the generic reference system and axis of the system fixed to the stator; $\bar{v}_{s,dq}$, $\bar{i}_{s,dq}$, $\bar{\Psi}_{s,dq}$:stator voltage, current and flux vectors; $\bar{i}_{r,dq}$, $\bar{\Psi}_{r,dq}$: Rotor current and flux vectors; w_r, w_s, w_m,:Rotor electrical, slip and rotor mechanical speed. L_m,L_s, L_r, : Mutual, stator and rotor inductances. L_{ls},L_{lr}:Stator and rotor leakage inductances; R_s,R_r:Stator and rotor resistances; T_e,T_L:Motor and load torque; B, J:Friction coefficient and Inertia of the system. The equivalent circuit corresponding to these equations is illustrated in Figure 1.

PSO algorithm

Kennedy and Eberhart (2001) proposed particle swarm optimization (PSO) in 1995 as an adaptive algorithm based on a social-psychological metaphor; a population of individuals (referred to as particles) adapts by returning stochastically toward previously successful regions.

There are two primary operators; Position up date and velocity update. Each particle during each generation is accelerated toward the particles previous best position and the global best position. The evaluation of new velocity in each iteration for each particle is referred to its current velocity, the distance from its previous best position, and the distance from the global best position. The value of new velocity is used to compute the next position of the particle in the search space. This process is iterated as a set of number of times, or until lowest error is completed.

The algorithm of PSOIn D-dimensional space can be illustrates as follows: Let $X_i=(x_{1i},x_{2i},\ldots,x_{Di})$ is the "particle" current position and $V_i=(v_{1i},v_{2i},\ldots,v_{Di})$ its velocity. The local best location is denoted as $P_{best,i}=(p_{1i},p_{2i},\ldots,p_{Di})$. Let $P_{gbest}=(p_{g1},p_{g2},\ldots,p_{gd})$ represent the global best position of the whole particles. The velocity can be determined by the following equations:

$$v_{id}^{(k+1)} = h^{(k)} v_{id}^{(k)} + c_1 r_1 (p_{id}^{(k)} - x_{id}^{(k)}) + c_2 r_2 (p_{gd}^{(k)} - x_{id}^{(k)}) \quad (7)$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k)} \quad (8)$$

where, i=1,2,…n, d=1,2,…D; and D is the dimensions number for each particle, c_1, c_2 is constant of acceleration, k is the times of iterative,r_1, r_2 are the two random number with the range of [0,1], h is the inertia weighting factor.

RBF neural network

Radial basis function (RBF) neural network is embedded in a three layers neural network as shown in Figure 2, which is an input layer, a nonlinear hidden layer and a linear output layer. The input layer implements the data input to the network non-linearly. The output layer implements linearly a weighted sum of hidden unit outputs. There is a layer of processing units between the inputs and outputs which called hidden units. Each of them achieves a function of radial basis.

Pattern classification of RBF network shown in Figure 2 is based on the assumption that the set of training data is $X=[x_1,x_2,\ldots,x_m]^T$. The output is $Y=[y_1,y_2,\ldots,y_p]^T$. The Gaussian activation function is used as basis function which is given by:

$$\varphi(x_i, c_i) = \exp(-\|x_i - c_i\|/2\sigma_i^2) \quad (9)$$

where, $c_i$is is the center of the Gaussian activation function, and σ_t is the variance of Gaussian activation function.

The neural network is used as a pattern classification, which is shown in Figure 2. RBF neural network has to learn three parameters: the center of radial basis function, the variance of radial basis of function and the weight. The choice of the three

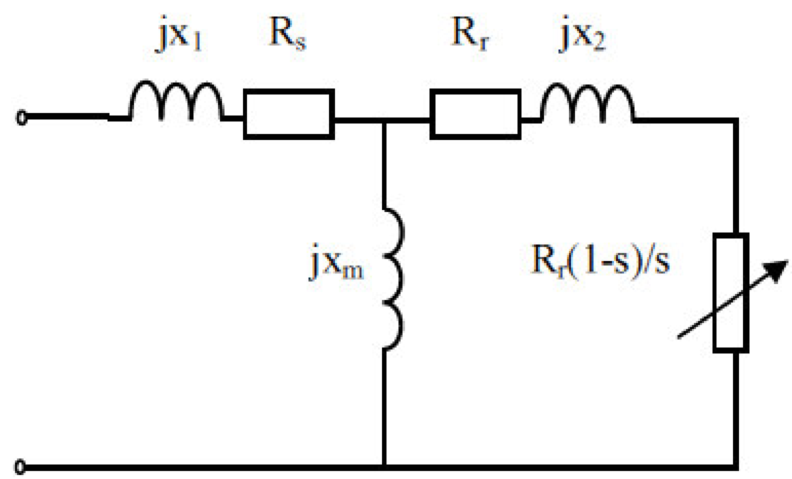

Figure 1. Equivalent circuit of induction motor.

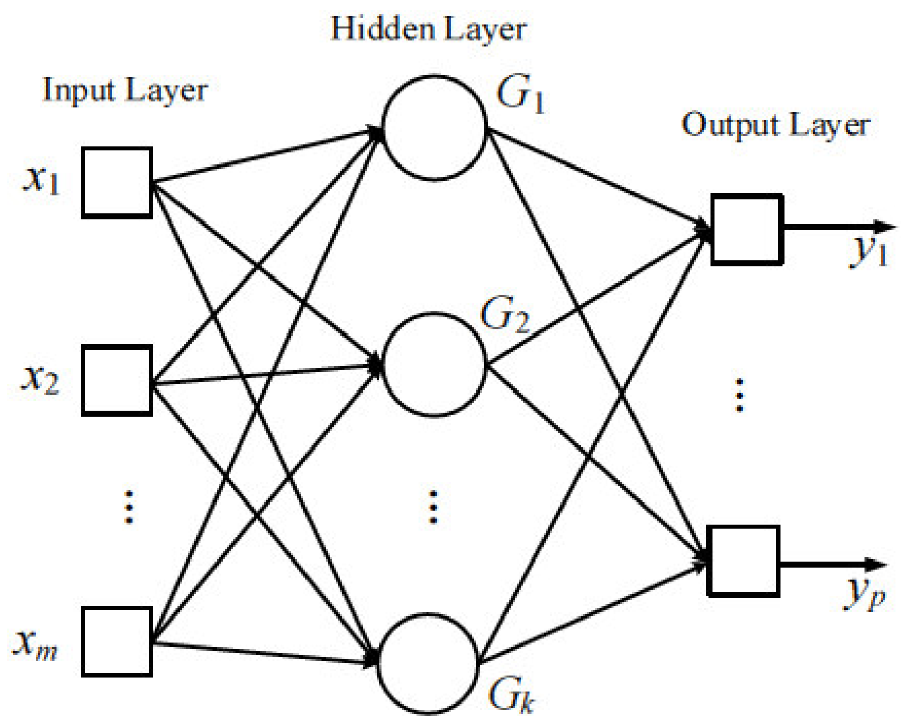

Figure 2. RBF network in pattern classification.

parameters has an important effect on the classification performance of RBF neural network.

PROPOSED METHOD

The estimation method in general may use the data that can become obtainable from the motor manufacturer, or are effortlessly measured, like the characteristic of slip-current, or the slip-torque characteristic, or the slip-power factor features. The procedure of parameter evaluation becomes very significant, when a slip-dependent parameter model is employed. In this case, the model coefficients of Equations (1) to (6) are hard of unfeasible to be calculated without employing an evaluation procedure. It can be noted that there is an obvious disparity between the simulation model and experimental responses representing a difference between estimated parameters and the experimental. The procedure of RBF and PSO proposed can be done by the following steps:

1. Initialize a group of particles, number of iterations, the random particle position and velocity. Each particle consists of the center of radial basis function.
2. Evaluate the fitness value of each particle used to measure the performance of the model with current parameters of RBF neural network;

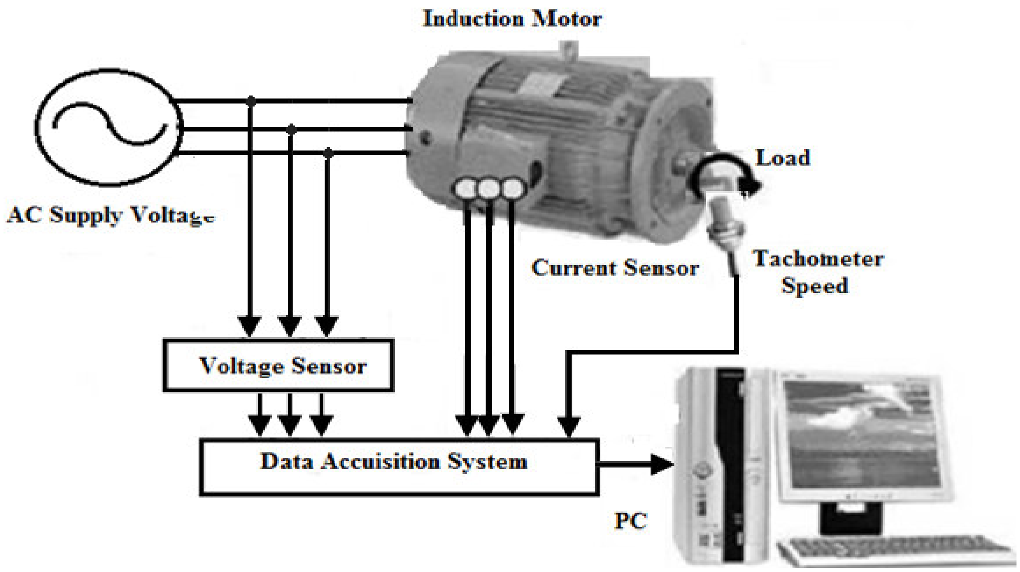

Figure 3. Experimental setup sensor.

Table 1. The value of identified parameter.

Element	Exact	PSO-RFFNN algorithm		LS algorithm	
		Parameter	Error (%)	Parameter	Error (%)
$R_s(\Omega)$	2.531	2.54352	0.01252	2.4162	0.0215
$R_r(\Omega)$	2.408	2.4860	0.0169	2.329	-0.079
L_s(H)	0.0025	0.0024	0.0001	0.01248	0.00998
L_r(H)	0.0025	0.0026	0.0001	0.002612	0.000112
L_m (H)	0.0847	0.0886	0.0039	0.081	-0.0037
		ME	0.01252		0.0215
		AAE	0.006704		0.022858

3. Compare the fitness value for each particle with its location position of experiencing the best comparison: P_{ibest} if better than P_{ibest}' then replace the P_{ibest} as the current position;
4. Compare the fitness value for each particle with the global position of experiencing the best: g_{ibest}' if better, then reset the index number of the g_{ibest} ;
5. According to the standard particle swarm optimization update each particle's velocity and position; its velocity and position are computed by equations (7) and (8), respectively.
6. If not achieve, the maximum number of iterations, then return to step 2;
7. The best location would be experienced by groups to get induction motor model parameters based on PSO-RBF neural network.

RESULTS AND DISCUSSION

In order to verify the accuracy and identification precision of presented parameter identification method, the method is tested on the IM whose Y-connected, P = 2.2 kW, U = 420 V, I = 5.2 A, 4 pole and the experiment setup is shown in Figure 3. The system consists of a three-phase supply, current and voltage sensors. Blocked–rotor, no–load and Dc tests have been used to find exact parameter of induction motor as shown in Table 1 and it gives the induction motor parameters identified by PSO-RBFNN algorithm. In addition, Table 1 shows the performance of optimization algorithm results with respect to average absolute error (AAE) and maximum error (ME) for both PSO-RBFNN and LSA. So, it is clear that the proposed algorithm is much better than LSA compared to experimental result.

The training error curves for PSO-RBFNN are shown in Figure 4. From this curve it can be inferred that the identification speed based on PSO-RBFNN can trace the real speed accurately.

To verify the accuracy of induction motor parameter in Table 1, a set of samples of the phase voltages, the phase currents and speed are calculated using PSO-RBFNN and compared with experimental data. From Figure 5, it can be concluded that the errors between the responses of the induction motor with the real parameters are quite small.

Finally, the proposed method is compared with least

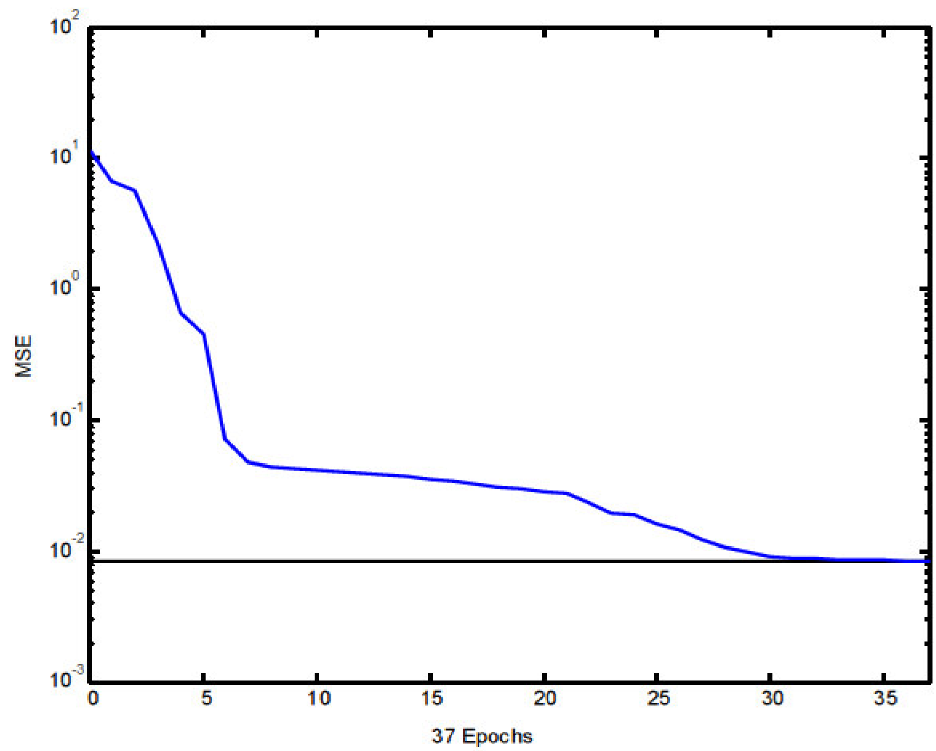

Figure 4. Training curve for PSO-RBFNN.

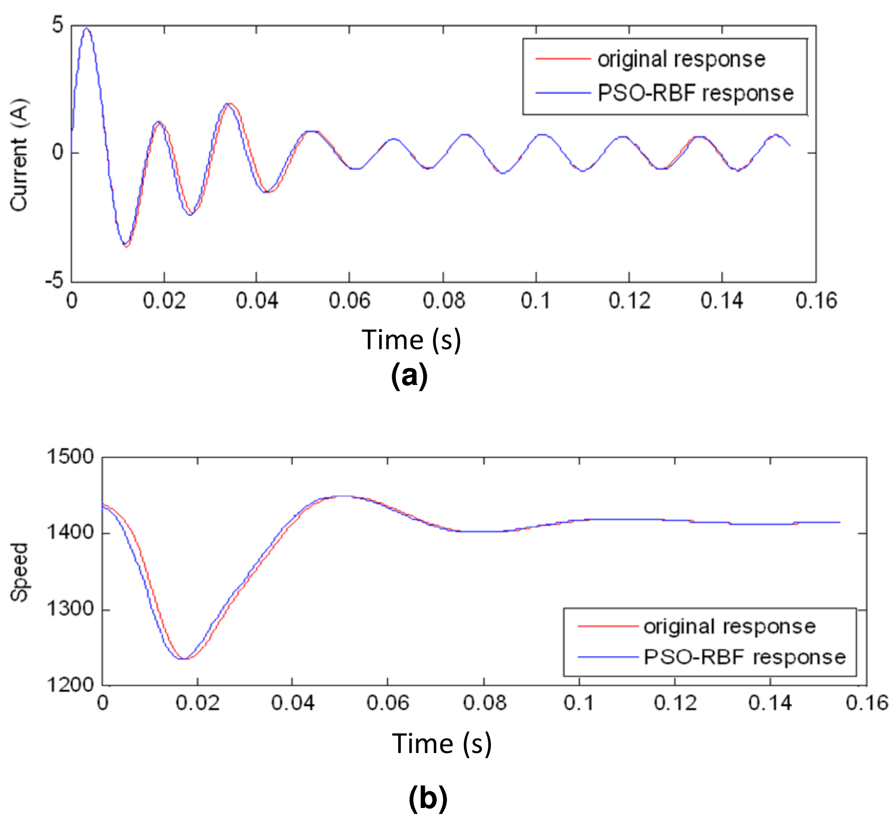

Figure 5. Induction motor response by real parameter and PSO-RBFNN identify parameter (a) stator line current, and (b) speed.

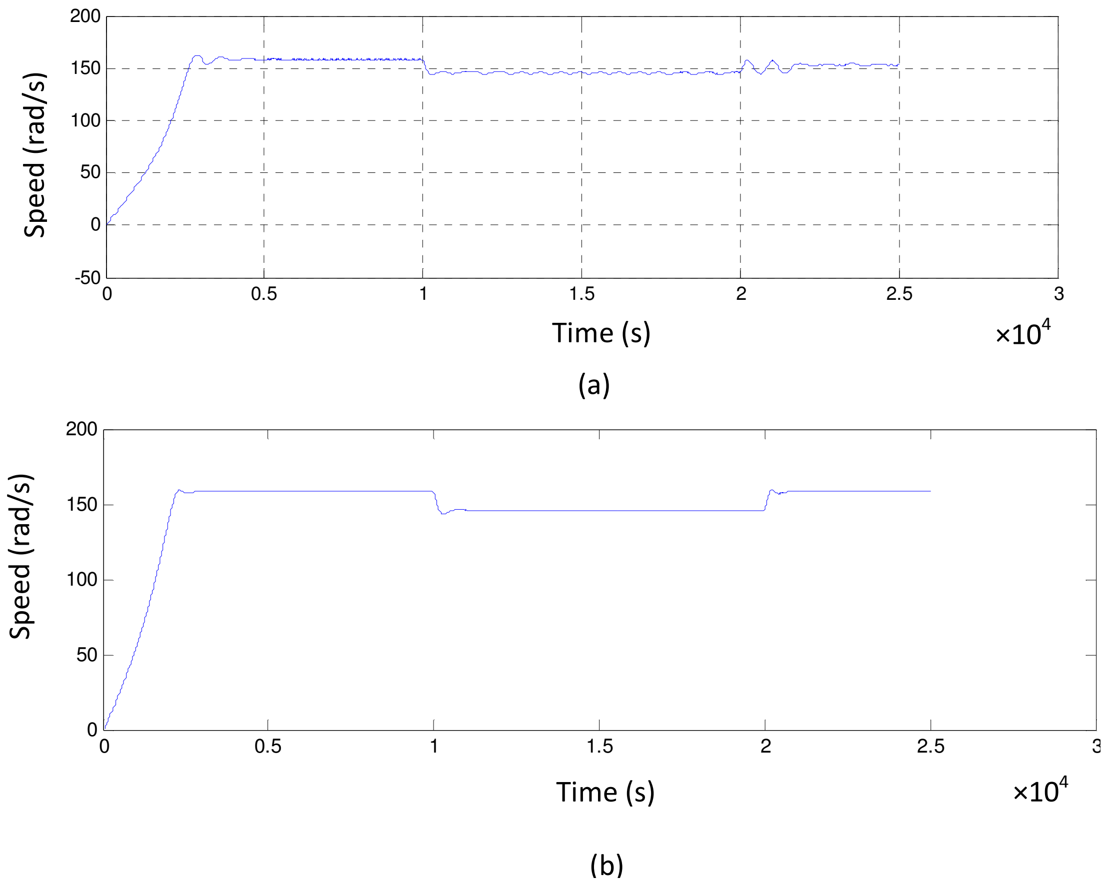

Figure 6. (a) Induction motor response using LSA parameter; (b) Induction motor response using PSO-RBF parameter.

squares algorithm (LSA) transform as shown in Figure 6a and b. It is clear that induction motor response is more stable using PSO-RBFF Parameter identification. In addition, PSO-RBFNN is much fast than LSA.

Conclusion

This paper describes a model parameter identification method of the induction motor based on PSO-RBF algorithm. It is compared with the results of simulation model and experimental transient measurements for any operating condition using PSO-RBFNN to obtain the main five electric parameters of the induction machines. The experimental results show that the proposed method can improve the induction motor performance accuracy. PSO is successfully used to optimize the RBF neural network parameters, reduce the impact from the interference factors in observation process and the structure is very simple.

Future researches should follow up on improving the performance of this proposed approach, and applying it to find induction motor with different drive system.

REFERENCES

Alonge F, Ippolito FD, Ferrante G, Raimondi FM (1998). Parameter identification of induction motor model using genetic algorithms. Proc.Inst. Elect. Eng. Contr. Theory Appl., 145(6): 587–593.

Azzolin RZ, Martins M, Michels L, Gründling HA (2007). Parameter estimator of an induction motorat standstill. COBEP, pp. 152-157.

Bose BK (1986). Power Electronics and AC Drives. Prentice Hall, New Jersey. 2: 40-45.

Choi HS, Sul SK (1999). Automatic commissioning for vector controlledac motors using Walsh functions. IEEE Ind. Appl. Soc. Annu. Meeting, pp. 1284-1289.

Gandomkar A, Mahmoudi A, Pirasteh H, Parastar A, Kahourzade S (2011). Improvement of direct torque control in high power induction motors. Int. J. Phys. Sci., 6(12): 2789-2798.

Hao Xu, Wan PU (2011). An improved genetic algorithm for solving simulation optimization problems. Int. J. Phys. Sci., 6(10): 2399-2404.

Huang KS, Wu QH, Turner DR (2002). Effective identification of induction motor parameters based on fewer measurements. IEEE Trans.Energy Convers., 17(1): 55–60.

Jul-Ki S, Seung M, SeungKi S (1997). Induction Machine Parameter Identification using PWM Inverter at Standstill. IEEE Trans. Energy Convers., 12(2): 127-132.

Kennedy J, Eberhart R (2001). Swarm Intelligence. Morgan Kaufmann Publishers, San Francisco, CA. pp. 207-212.

Lu Lu Xiuxia Q (2011). The experimental parameters optimization approach using a learning genetic algorithm. Int. J. Phys. Sci., 6(7): 1803-1807.

Messaoud M, Sbita IL, Abdelkrim MN (2007). A robust nonlinear observer for states and parameters estimation and on-line adaptation of rotor time constant in sensorless induction motor drives. Int. J. Phys. Sci., 2(8): 217-225.

Manuele B, Giuseppe SB, Roberto M (2001). Self-Commissioning of RFO IM Drives: One-Test Identification of the Magnetization Characteristic of the Motor. IEEE Trans. Ind. Appl., 37(6): 1801-1806.

Mohammad K, Ahmed EM, Raihan T (2010). Modified particle swarm optimization for probabilistic slope stability analysis. Int. J. Phys. Sci., 5(15): 2248-2258.

Muhammad AN, KhalidaInayat N, AsifWaheed ES (2010). Modified variation of parameters method for solving system of second-order nonlinear boundary value problem. Int. J. Phys. Sci., 5(16): 2426-2431.

Noor MM, Kadirgama K, Rahman MM (2011). Particle swarm optimisation prediction model for surface roughness. Int. J. Phys. Sci., 6(13): 3082 -3090.

Novotny DW, Lipo TA (1996). Vector Control and Dynamics of AC Drives. Clarendon, New York. pp. 1090–1095.

Paolo C, Andrea T (2005). Parameter Estimation of Induction Motor at Standstill with Magnetic Flux Monitoring. IEEE Trans. Control. Syst. Technol., 13(3): 386-400.

Picardi C, Rogano N (2006). Parameter identification of induction motor based on particle swarm optimization. In Proc. Int. Symp. Power Electron Electr. Drives, pp. 968–973.

Ribeiro LAS, Jacobina CB, Lima AMN (1997). The influence of the slip and the speed in the parameter estimation of induction machines. In Proc. PESC Conf. Rec. pp. 1068-1074.

Seok JK, Moon SI, Sul SK (1997). Induction parameter identification using pwm inverter at standstill. IEEE Trans. Energy Convers., 12: 127-132.

Seung M, Ali K (1994). Estimation of Induction Machine Parameters from Standstill Time-Domain Data. IEEE Trans. Indust Appl., 30(6): 1609-1161.

Sonnaillon MO, Bisheimer G, Angelo CD, García GO (2007). Automatic induction machine parameters measurement using standstill frequency-domain tests. IET Electr. Power Appl., 1(5): 833–838.

Surya NP, Shantaram SP, Dale AH (2007). Precision of sensitivity in the design optimization of indeterminate structures. Int. J. Phys. Sci., 2(1): 018-032.

Tajima H (2002). Consideration about problems and solutions of speed estimation method and parameter tuning for speed sensorless vector control of induction motor drives. IEEE Trans. Ind. Appl. 38: 1282–1289.

Ursem RK, Vadstrup P (2003). Parameter identification of induction motors using differential evolution. Congress Evol. Comput., 2: 790–796.

Willis JR, Brock GJ, Edmonds JS (1989). Derivation of induction motor models from standstill frequency response tests. IEEE Trans.Energy Convers., 4: 608-613.

Young-Su K, Jeong-Hum L, Sang-Ho M, Byung-Ki K, Chang-Ho C, Jul-Ki S (2009). Standstill Parameter Identification of Vector-Controlled Induction Motors Using the Frequency Characteristics of Rotor Bars. IEEE Trans. Indust. Appl., 45(5): 1610-1618.