Nonintrusive Efficiency Estimation of Induction Motors Using an Optimized EKF

Hong-xia Yu, Chuang Li, Yan-hong Wang, and Li Chen

Abstract In this paper, an intelligent optimal EKF (Extended Kalman Filter) algorithm was presented to overcome the defect of getting the noises covariance matrices of EKF by a trial and error method. In order to get optimal parameter of noises covariance matrices by intelligent method, an optimal model was established using the error of estimated speed and torque with measured, then solved by PSO. The efficiency was computed using the estimated speed and load torque by the optimized EKF. Experimental results demonstrated that the estimated efficiency using this method has higher estimated accuracy than EKF.

Keywords Efficiency estimation • Extended Kalman filter • Induction motor • Nonintrusive • PSO

1 Introduction

Electric machines are extensively used as driven equipment in industrial, agricultural and commercial domain etc. In industry, over two-thirds of the total electric energy consumed by motor [1, 2], Energy saving of induction motors are important for overall energy saving. This could be done replacing oversized motors [3] or applying more efficient control techniques [4]. When replacing oversized motors, the operating efficiency of the motor can be used to evaluate the energy efficiency of the motor and provide a reference for choosing a more suitable motor; when it comes to efficient control techniques, the efficiency of the motor can also evaluate the effect of energy-saving control.

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Therefore, a lot of methods are presented to estimate efficiency of motor, Engineers and scholars strive to implement nonintrusive efficiency estimation that is to estimate the efficiency of induction motor does not interfere with the running of motor system in actual industrial field. Lu gives a summary of efficiency estimation methods [5]. The two main methods for non-intrusive efficiency estimated are equivalent circuit method [6, 7] and the air gap torque method [8]. In equivalent circuit method, the efficiency of the motor are calculated using the copper losses and iron loss of motor calculated in equivalent circuit, the mechanical and stray loss using approximation, the parameters of equivalent circuit are identified using stator current, voltage and estimated speed. The nonintrusive air gap torque method is implemented by introducing nonintrusive speed and stator resistance estimation into the air gap torque method, the mechanical and stray loss using approximation. So, these methods have the same problem that the mechanical and stray loss are assumed to be a percentage of the rated power in efficiency estimation.

In recent years, the sensorless motor's speed estimation methods using EKF (Extended Kalman Filter) was researched by many researchers [9–11] for its good dynamic performance and robustness. The EKF method can estimated motor speed accurately when the motor's model is imprecise for the motor parameter variation and signal measurement error are account to the noise in EKF Algorithm. But the key problem is that the estimation results of using EKF is greatly affected by the covariance matrices of noise, the improper covariance matrices of noise will make the result of estimation divergence or have large estimate error. The mostly used method of get covariance matrices of noise is to try and regulate according estimate error repeatedly, obviously it is a tedious procedure, Also getting the optimal covariance noise matrices is difficult by this method. To solve this problem, the covariance matrices of noise are got by optimization using GA in [12, 13], the covariance matrices of noise are got by optimization using SA in [14].

The PSO is swarm intelligence method based on the foraging behavior of birds and schools of fish developed by Kennedy and Eberhart, and was widely used in a variety of optimization problems [15, 16] for, its iterative process is relatively simple and faster convergence. In this paper, The noise covariance matrices of EKF was optimized through the particle swarm optimization (PSO). The optimization goal is to make the speed and torque estimation error is minimized, the potential solution of the parameter of noise covariance matrices consist of the search space of the particles. The algorithm avoid the tedious process of trial and error method to obtain the noise covariance matrix, and at the same time you can get a better noise covariance array, the estimation accuracy of EKF using optimized noise covariance matrix are improving effectively.

2 Model of Induction Motor

In the stator stationary frame, the mathematical model of induction motor can be expressed as formula (1).

$$\dot{x}(t) = \begin{bmatrix} \dot{i}_{s\alpha} \\ \dot{i}_{s\beta} \\ \dot{\psi}_{r\alpha} \\ \dot{\psi}_{r\beta} \end{bmatrix} = \begin{bmatrix} a_1 & 0 & \frac{a_2}{\tau_2} & a_2\omega \\ 0 & a_1 & -a_2\omega & \frac{a_2}{\tau_2} \\ \frac{L_m}{\tau_2} & 0 & -\frac{1}{\tau_2} & -\omega \\ 0 & \frac{L_m}{\tau_2} & \omega & -\frac{1}{\tau_2} \end{bmatrix} \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \\ \psi_{r\alpha} \\ \psi_{r\beta} \end{bmatrix} + \begin{bmatrix} \frac{1}{\sigma L_1} & 0 \\ 0 & \frac{1}{\sigma L_1} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_{s\alpha} \\ u_{s\beta} \end{bmatrix} \tag{1}$$

Where $\psi_{r\alpha}$ and $\psi_{r\beta}$ are rotor flux, $u_{s\alpha}$ and $u_{s\beta}$ are stator voltages, $i_{s\alpha}$ and $i_{s\beta}$ are stator current, ω is angular speed, $a_1 = -(R_1/\sigma L_1 + 1 - \sigma/\sigma\tau_2)$, $a_2 = L_m/\sigma L_1 L_2$, $\tau_2 = L_2/R_2$, $\sigma = 1 - L_m^2/L_1 L_2$, R_1 and L_1 are stator resistance and inductance, R_2 and L_2 are rotor resistance and inductance, L_m is mutual inductance.

The mechanical equation of induction motor can be expressed as formula (2).

$$\frac{d}{dt}\omega = -a_3 i_{s\alpha}\psi_{r\beta} + a_3 i_{s\beta}\psi_{r\alpha} - \frac{B}{J_l}\omega - \frac{p}{J_l}T_L \tag{2}$$

Where J_l is the total inertia of the IM and load, B is mechanical friction coefficient, T_L is load torque, $a_3 = p^2 L_m/JL_2$, p is the number of pole pairs.

In steady-state, the state equation of load torque can be expressed as formula (3).

$$\dot{T}_L = 0 \tag{3}$$

So the extended mathematical model of induction motor including state variables of the speed and load torque of induction motor can be expressed as (4).

$$\begin{cases} \dot{x}(t) = f(x(t), u(t)) = \begin{bmatrix} a_1 x_1 + \frac{a_2}{\tau_2}x_3 + a_2 x_4 x_5 + \frac{1}{\sigma L_1}u_{s\alpha} \\ a_1 x_2 - a_2 x_3 x_5 + \frac{a_2}{\tau_2}x_4 + \frac{1}{\sigma L_1}u_{s\beta} \\ \frac{L_m}{\tau_2}x_1 - \frac{1}{\tau_2}x_3 - x_4 x_5 \\ \frac{L_m}{\tau_2}x_2 + x_3 x_5 - \frac{1}{\tau_2}x_4 \\ -a_3 x_1 x_4 + a_3 x_2 x_3 - \frac{B}{J_l}x_5 - \frac{p}{J_l}x_6 \\ 0 \end{bmatrix} \\ y(t) = h(x(t), u(t)) = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \end{cases} \tag{4}$$

Where $x = \begin{bmatrix} i_{s\alpha} & i_{s\beta} & \psi_{r\alpha} & \psi_{r\beta} & \omega & T_L \end{bmatrix}^T$ is state vector and $y = \begin{bmatrix} i_{s\alpha} & i_{s\beta} \end{bmatrix}^T$ is output vector.

In actual system of induction motor, the process noise $w(t)$, the measuring noise $v(t)$ and the input noise $\zeta(t)$ are considered, so the stochastic model of induction motor can be expressed as formula (5).

$$\begin{cases} \dot{x}(t) = f\left(x(t), u(t) + \zeta(t)\right) + w(t) \\ y(t) = h\left(x(t), u(t) + \zeta(t)\right) + v(t) \end{cases} \tag{5}$$

Where, the noises are subject to the following distribution:

$$
\begin{aligned}
&p\,(\omega) \sim N\,(0, Q)\\
&p(v) \sim N\,(0, R)\\
&p\,(\zeta) \sim N\,(0, D)
\end{aligned}
\tag{6}
$$

3 Optimized EKF

3.1 Speed and Load Torque Estimation Using EKF

When the speed and load torque of induction motor are the state of system model and parameter of coefficient matrix, the model described by (4) became a nonlinear model, however the EKF (Extended Kalman Filter) is based on the linear model, so the nonlinear model must be transformed to linear model by linearization, the linear model of induction motor can be expressed as formula (7).

$$
\begin{cases}
\delta x(t) = F\,(x(t))\,\delta x(t) + B\,(u(t) + \zeta(t)) + w(t) \\
\qquad = \dfrac{\partial f}{\partial x}\,(x(t), u(t), 0)\,\delta x(t) + \dfrac{\partial f}{\partial u}\,(x(t), u(t), 0)\,(u(t) + \zeta(t)) + w(t) \\
y(t) = H\delta x(t) + v(t) \\
\qquad = \dfrac{\partial h}{\partial x}\,(x(t), u(t), 0)\,\delta x(t) + v(t)
\end{cases}
\tag{7}
$$

The computer implementation of EKF algorithm is based on discretization system model, when the sample time is T_s, the linear system model (7) of induction motor are discretized to be the following linear discretization model (8).

$$
\begin{cases}
\delta x(k) = \Phi_k \delta x(k) + M_k\,(u(k) + \zeta(k)) + W_k w(k) \\
y(k) = H\delta x(k) + v(k)
\end{cases}
\tag{8}
$$

Where

$$\Phi_k = \exp\,(F_k T_s) \tag{9}$$

$$W_k = \int_0^T \Phi(k)dt \tag{10}$$

$$M_k = \int_0^T B\Phi(k)dt \tag{11}$$

When assumed that the n sampling data is estimated, the implementation process of EKF algorithm based on linear discretization (8) model is as follows:

1. Initialization $X_0, \delta X_0, P_0, Q, R, D$
2. Begin sampling, k = 1
3. State prediction

$$\widehat{X}_k^- = f\left(\widehat{X}_{k-1}, u_k, 0\right) \approx \Phi_{k-1}\widehat{X}_{k-1} + M_{k-1}u_k \tag{12}$$

$$\widehat{Y}_k^- = h\left(\widehat{X}_k^-, 0\right) \approx H_k\widehat{X}_k^- \tag{13}$$

$$\delta\widehat{X}_k^- = \Phi_{k-1}\delta X_{k-1} \tag{14}$$

$$P_{k/k-1} = \Phi_{k-1}P_{k-1}\Phi_{k-1}^T + M_{k-1}D_{k-1}{M_{k-1}}^T + W_{k-1}Q_{k-1}{W_{k-1}}^T \tag{15}$$

4. State update

$$K_k = P_{k/k-1}H_k^T\left(H_kP_{k/k-1}H_k^T + R_k\right)^{-1} \tag{16}$$

$$\delta\widehat{X}_k = \delta\widehat{X}_k^- + K_k\left(\delta Y_k - H_k\delta\widehat{X}_k^-\right) \tag{17}$$

$$\delta Y_k = Y_k - \widehat{Y}_k^- \tag{18}$$

$$P_{k/k} = (I - K_kH_k)\,P_{k/k-1} \tag{19}$$

$$\widehat{X}_k = \widehat{X}_k^- + \delta\widehat{X}_k \tag{20}$$

5. If k < n, then k = k + 1, go to step(3)
6. End

The noise covariance matrix (D, R and Q) can be got by trial and error. The form of the noise covariance matrices are:

$$\begin{cases} D = diag\begin{bmatrix}\xi & \xi\end{bmatrix} \\ R = diag\begin{bmatrix}\lambda & \lambda\end{bmatrix} \\ Q = diag\begin{bmatrix}\alpha & \alpha & \varsigma & \varsigma & \beta & \gamma\end{bmatrix}\end{cases} \tag{21}$$

3.2 Optimized Noise Covariance Matrices

The potential solution of the problem constitutes the search space of particles in particle swarm when the optimization problem was solved by PSO algorithm. According to form of noise covariance matrix D, R and Q, the parameters of the noise covariance matrix needed to be optimized are $\xi, \lambda, \alpha, \varsigma, \beta, \gamma$. So the potential solution space of the problem is 6, whereby the dimension of the particles of the search space can be determined as 6, each dimension of the particles correspond to the parameters of the noise covariance matrix, the i-th particle of particle group can be expressed as:

$$\begin{aligned} X_i &= \begin{bmatrix} x_{i1} & x_{i2} & x_{i3} & x_{i4} & x_{i5} & x_{i6} \end{bmatrix} \\ &= \begin{bmatrix} \xi & \lambda & \alpha & \varsigma & \beta & \gamma \end{bmatrix} \end{aligned}$$

For the optimal goal of PSO is to improve the estimation accuracy of EKF, the objective function is defined using speed load torque estimated by EKF and measured,

$$J = \frac{1}{N}\left(\sum_{i=1}^{N}(n_i - \widehat{n}_i)^2 + \sum_{i=1}^{N}\left(T_{Li} - \widehat{T}_{Li}\right)^2\right) \tag{22}$$

Where, n_i and T_{Li} are measured speed and load torque of motor, $\widehat{n}_i$ and $\widehat{T}_{Li}$ are estimated speed and load torque by EKF.

When the optimal problem is solved by PSO, the PSO method initially has a population of random selective solutions. Each potential solution is called a particle. Each particle is given random position and velocity, then flown towards the target to find the optimal solution of the problem through the problem space. Particle swarm algorithm is widely used in a variety of optimization problems [6, 7] for its iterative process is relatively simple and faster convergence.

Accordance with the objective function, the main steps to optimize the parameters of the noise covariance matrix in the particle swarm optimization are described as follows:

1. Initialize a population of particles. Initialization number of populations is M, and the population is initialized by random positions $x_i(0)$ and velocities $v_i(0)$ in 6 dimensions of the problem space. The optimization algebra is $iter\_\max$, the target of the objective function value is $J_{\min}$;
2. Evaluate the fitness $J(x_i(0))$ of each particle in the swarm. The particle initial value is set to the optimum position of the particles themselves $p_i(0) = x_i(0)$, and to find the optimum position p_g according to Eq. (23) for all particles.

$$J\left(p_g\right) = \min\left\{J\left(x_i(0)\right)\right\}, i = 1, 2, 3, \cdots, M \tag{23}$$

3. Change the velocity $v_i(v_{i1},v_{i2},v_{i3},v_{i4},v_{i5},v_{i6})$ and position of the particle $x_i(x_{i1},x_{i2},x_{i3},x_{i4},x_{i5},x_{i6})$ according to Eqs. (24) and (25) respectively.

$$v_{id}(k) = wv_{id}(k-1) + c_1r_1(p_{id} - x_{id}(k-1)) + c_2r_1\left(p_{gd} - x_{id}(k-1)\right) \tag{24}$$

$$x_{id}(k) = x_{id}(k-1) + v_{id}(k) \tag{25}$$

Where: v_{id} and x_{id} represent the velocity and position of the ith particle with d dimensions respectively. r_1 and r_2 are two uniform random number, and w is the inertia weight, c1 and c2 are learn factor.

4. Update the optimal location of the particle itself p_i. For every iterations, the optimal location obtained by compare each particle's fitness with its previous best fitness.

$$p_i(k+1) = \begin{cases} p_i(k) & J(x_i(k+1)) >= J(p_i(k)) \\ x_i(k+1) & J(x_i(k+1)) < J(p_i(k)) \end{cases} \tag{26}$$

5. Update best location of all particles p_g. Compare best fitness of particles with each other and update the swarm global best location p_g.

$$J\left(p_g\right) = \min\{J(x_i(k))\}, i = 1, 2, 3, \cdots, M \tag{27}$$

6. If $J(p_g(k)) < J_{\min}$, then go step (8);
7. If $k < iter\_\max$, then $k = k + 1$, turn to step (3);
8. The optimization results is given, the end.

4 Nonintrusive Efficiency Estimation

After speed and load torque are estimated using PSOEKF, The efficiency estimation value can be calculated by formula (28) through substituting T_L and n with the steady-state mean value of the estimated speed $\widehat{n}_i$ and load torque $\widehat{T}_{Li}$, the steady-state mean of speed and load torque are defined as formula (30) and (31).

$$\eta = \frac{P_{out}}{P_{in}} = \frac{30}{pi} \cdot \frac{T_L{}^* n}{P_{in}} \tag{28}$$

Where input power can be calculated as follows:

$$P_{in} = \frac{\int_0^T (v_a i_a + v_b i_b + v_c i_c)\, dt}{T} = \frac{\int_0^T (v_{ab} i_a - v_{bc} i_c)\, dt}{T} \tag{29}$$

$$\overline{\hat{n}} = \frac{1}{2,048} \sum_{i=2,049}^{4,096} \hat{n}_i \tag{30}$$

$$\overline{\hat{T}}_L = \frac{1}{2,048} \sum_{i=2,049}^{4,096} \hat{T}_{Li} \tag{31}$$

5 Experimental Results

Figure 1 shows the bench, an induction motor (Y100L2-4) drag a DC generator (Z_2-42), a precision torque meter and the voltage and current sensors are equipped in bench. The nameplate parameter of induction motor and DC generator are given in Table 1. The induction motor parameters are $p = 2$, $R_s = 2.0713\ \Omega$, $L_s = 0.241929H$, $R_r = 1.7148\ \Omega$, $L_r = 0.242007H$, $L_m = 0.232559H$, $J_l = 0.02\ \text{kg}\cdot\text{m}^2$, $B = 0$.

The load of induction motor are changed by changing the excited voltage of the generator, and stator instantaneous line voltage(v_{ab}, v_{bc}), instantaneous phase current (i_a, i_b, i_c), speed (n) and load torque (T_L) are collected at different excitation voltage(EV), The sampling period is 1/4,096 s, Acquisition time is 1 s. The calculated data using measured value by formula (28), (29), (30), and (31) at different load are shown in Table 2.

Fig. 1 Bench of induction motor

Table 1 Nameplate data of motor

Motor	P_N (Kw)	I_N (A)	n_N (rpm)	η_N (%)	cos φ_N	λ
Y100L2-4	3	6.8	1,420	82.5	0.81	2.3
Z_2-42	4	220	22.3	1,500		

Table 2 Calculated values using measured value at different excited voltage

EV (V)	$\overline{n}$ (rpm)	$\overline{T}_L$ (Nm)	P_{in} (W)	η (%)
0	1,495.7	0.76	392.04	30.35
25	1,488.1	2.52	634.02	61.90
50	1,474.3	6.15	1,242.72	76.35
75	1,463.1	9.92	1,917.08	79.24
100	1,455.1	13.03	2,469.88	80.39
125	1,445.2	15.59	2,912.19	80.97
150	1,435.0	17.72	3,269.54	81.4
175	1,428.1	19.25	3,560.91	80.8
200	1,421.1	21.01	3,871.67	80.71

Table 3 Optimized parameters of noise covariance matrix

EV (V)	ξ	λ	α	ς	β	γ
0	6.06e-06	5.52e-07	7.21e-04	0.9754	0.6395	9.4995
25	9.43e-07	4.69e-07	2.75e-03	0.8401	0.9371	9.8133
50	6.07e-06	7.30e-07	1.53e-03	1.2973	0.6362	0.2992
75	9.81e-06	7.98e-07	2.70e-04	1.3754	0.0017	0.3763
100	4.39e-06	6.29e-07	9.99e-04	0.9.695	0.4093	9.9535
125	6.85e-06	6.20e-07	7.47e-04	0.7271	0.5396	1.5550
150	7.86e-06	1.37e-06	8.00e-04	1.1800	0.2578	1.8857
175	3.84e-06	4.92e-07	2.90e-03	0.4064	0.2533	5.9555
200	2.71e-06	4.61e-06	5.23e-04	1.8459	0.5864	1.4846

In experiment, the population number M is initialized 20, Optimization algebra is 2,000, the target of the objective function value is 0.00001, Inertial weight w is chosen 0.8. learn factor c1 changes adaptively in the formula (32) with an initial value of 2, and c2 is set a constant 2.

$$c_1 = 2\,(1 - iter/iter - \max) \tag{32}$$

The initial value is selected as follows in EKF:

$$x(0) = \begin{bmatrix} 0\ 0\ 0\ 0\ 0\ 0 \end{bmatrix}$$

$$P(0) = diag\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \cdot 1e^{-10}$$

Table 3 give the optimized parameters of noise covariance matrix using PSO, Fig. 2 give the estimate results of speed and load using PSOEKF at different excited voltage. Table 4 give the estimate error of speed and load torque at different excited voltage, the error is computed according to the formula (33) and (34). From Table 4, the PSOEKF has higher precision than EKF.

$$e\overline{\widehat{n}} = \overline{n} - \overline{\widehat{n}} \tag{33}$$

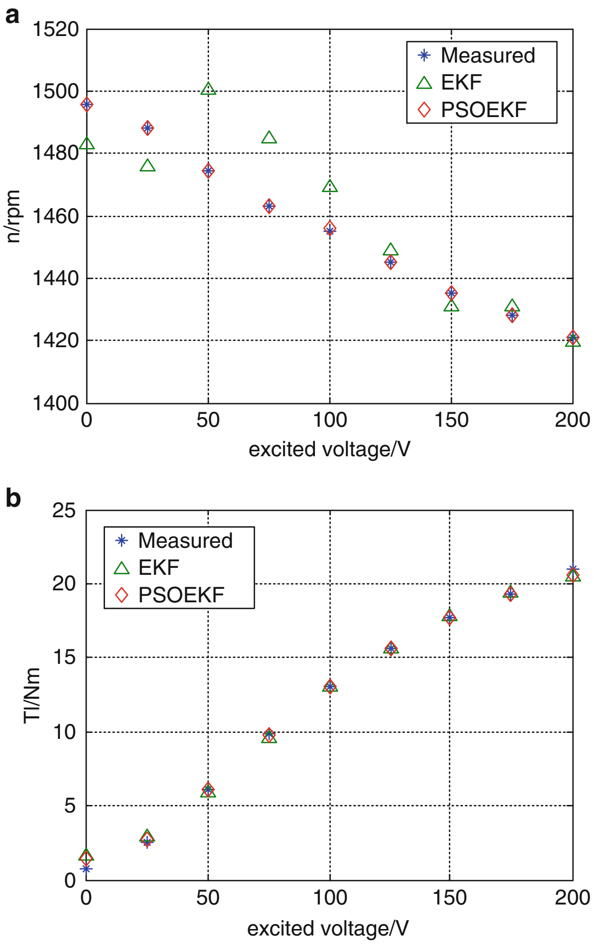

Fig. 2 Comparison of estimate results at different excited voltage. (**a**) Comparison of speed. (**b**) Comparison of load torque

$$e\overline{\widehat{T}}_L = \overline{T}_L - \overline{\widehat{T}}_L \tag{34}$$

The efficiency was computed using estimated speed and load torque according formula (28), (29), (30), and (31). Figure 3 gives the estimate results comparison of efficiency using PSOEKF at different excited voltage. Table 5 give the efficiency estimation error at different excited voltage, in table 5 efficiency error is defined as formula (35). Table 5 show the proposed PSOEKF method higher precision than EKF.

$$e\widehat{\eta} = \eta - \widehat{\eta} \tag{35}$$

Table 4 Estimate error of speed and load torque at different excited voltage

	EKF		PSOEKF	
EV (V)	$e\overline{\hat{n}}$ (rpm)	$e\overline{\hat{T}}_L$ (Nm)	$e\overline{\hat{n}}$ (rpm)	$e\overline{\hat{T}}_L$ (Nm)
0	12.7	−0.84	−0.28	−0.66
25	12.1	−0.4	0	−0.2
50	−25.88	0.26	0	0.04
75	−21.86	0.35	0	0.11
100	−13.16	−0.01	−0.05	−0.02
125	−3.55	0	0.2	−0.01
150	4.13	−0.1	0	−0.03
175	−2.92	−0.11	0.13	0
200	1.55	0.55	0.14	0.44

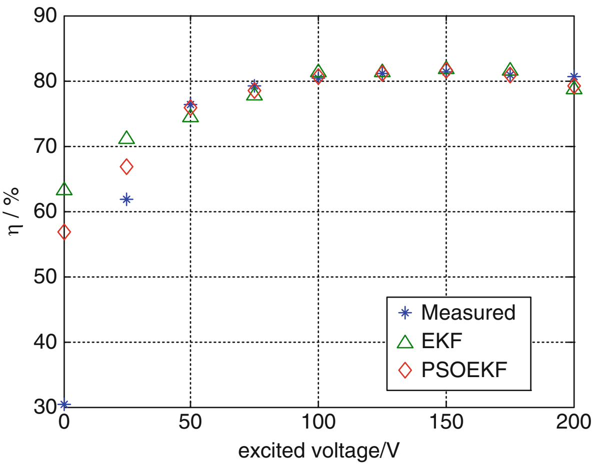

Fig. 3 Comparison of estimate results of efficiency at different excited voltage

Table 5 Estimate results of efficiency at different excited voltage

	$e\hat{\eta}$ (%)	
EV (V)	EKF	PSOEKF
0	−32.95	−26.53
25	−9.18	−4.91
50	1.88	0.45
75	1.57	0.87
100	−0.83	−0.15
125	−0.23	−0.09
150	−0.27	−0.17
175	−0.66	−0.05
200	2.13	1.65

6 Conclusion

This paper presents a nonintrusive efficiency estimation method of induction motor based on PSOEKF. The nonintrusive efficiency estimation of motor is implemented by estimating the speed and the load torque of the motor using PSOEKF. The PSOEKF get the optimized noise covariance matrices by minimizing the objective function that defined using speed load torque estimated by EKF and measured using PSO. The proposed method avoid using approximate value of stray loss in the conventional efficiency estimation method, and overcome the defects of getting the noise covariance matrices by trial and error in EKF method, The experimental results show that PSOEKF with the optimized noise covariance matrix has higher estimation accuracy.

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