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Tuning of Extended Kalman Filter using Self-adaptive Differential Evolution Algorithm for Sensorless Permanent Magnet Synchronous Motor Drive

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ABSTRACT

In this paper, a novel method based on a combination of Extended Kalman Filter (EKF) with Self-adaptive Differential Evolution (SaDE) algorithm to estimate rotor position, speed and machine states for a Permanent Magnet Synchronous Motor (PMSM) is proposed. In the proposed method, as a first step SaDE algorithm is used to tune the noise covariance matrices of state noise and measurement noise in off-line. In the second step, the optimized values of above covariance matrices are injected into EKF in order to estimate the rotor speed on-line. The estimated speed is fed back to the PI controller and to minimize the speed error, parameters of PI controller are tuned again using SaDE algorithm. The simulation results show that the tuned covariance matrices Q and R improve convergence of estimation process, quality of estimated states and PI controller improves the settling time and stability of the system.

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1. INTRODUCTION

The PMSM is widely used in industrial drive systems due to its compactness, superior power density, high torque density, high efficiency, high power factor and low maintenance cost. They are appropriate for computerized numerical control (CNC) machines and submarine propulsion due to their wide speed ranges. In PMSM, rotor losses are eliminated due to the absence of slip rings for field excitation, which make them ideal for robotic and automatic production systems [1, 2]. In most drive systems, closed loop control is based on the speed or position measurement using optical encoders or Hall Effect sensors. Use of such sensors will increase the complexity and weight of the system, resulting in increased cost and reduced overall reliability of the system [3]. In most applications, due to harsh environmental conditions or excessive wire lengths, it is difficult to get the actual speed/position information from the sensors to the controller. Sensorless speed control drive system reduces complexity, weight and cost and improves reliability and dynamic performance of the system [4].

Various control algorithms have been proposed to eliminate the speed and position sensors. Among them, Luenberger observer [5] and Kalman filter [6] are used for linear systems. However, these methods are not applicable for state estimation of non-linear systems. To surmount this, many methods are proposed in literature; such as reduced order observer [7], full order observer [8], Sliding Mode Observer (SMO) [9], Extended Kalman Filter (EKF) [10, 11], Model Reference Adaptive Systems (MRAS) [12], based observers.

For stochastic non-linear systems, EKF is one of the widely used observers for state estimation of PMSM drive over the last decade. The EKF provides a quick and accurate estimation of the variables with rapid convergence and improvement in transient performance of the system. Therefore, it is the best method for the estimation of rotor position, speed and machine states of a PMSM drive. The EKF estimation process is greatly influenced by the values of system parameters and error covariance matrices Q and R. As the order of the system

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increases the manual tuning of these matrices *Q* & *R* becomes hard as the computational time increases. To overcome this problem several algorithms are proposed in literature; such as Genetic algorithm (GA) [13], particle swarm optimization (PSO) [14], Differential evolution (DE) [15], Self-adaptive Differential Evolution (SaDE) [16] and so on. DE is one of the recent powerful population based stochastic search technique, which is an efficient and effective continuous search method proposed by Storn and Price [17]. The DE has been successfully applied in diverse fields and sensitivity of DE depends on population (NP), crossover rate (CR) and scale factor (F). In DE, for setting the best control parameter values, a trial and error method is used; which takes more computational time for setting the best values. To avoid these problems an advanced DE named Self-adaptive Differential Evolution (SaDE) algorithm is employed. In this algorithm, trial vector generation strategies and associated parameter values are self adapted by learning from their previous generating values.

The main objective of this paper is to tune the parameters of covariance matrices *Q* and *R* using SaDE algorithm. In the proposed scheme *Q* and *R* values are formulated in off-line manner and these values are injected in the corresponding matrices, to estimate the rotor position, speed and machine states in on-line. For closed loop operation, estimated speed is given as feedback and hence the performance of EKF becomes a part of the speed control. The speed error is given to the PI controller and by tuning the parameters of controller; the performance of overall system is improved. The parameters of PI controller can be tuned using Zieglar-Nichols method [18], Particle Swarm optimization (PSO) [19], Differential evolution (DE) [17], Self-adaptive Differential Evolution (SaDE) [20]. In this work, SaDE algorithm is also used for tuning K_p and K_i values of PI controller effectively. Finally the optimum values of PI controller are obtained and these values are injected into the controller, to get the better results.

2. MODELLING OF PMSM

The voltage equations for a PMSM in the rotor reference frame can be expressed as follows:

$$V_d = R_s i_d + L_d p i_d - \omega_e L_q i_q \quad (1)$$

$$V_q = R_s i_q + L_q p i_q + \omega_e L_d i_d + \omega_e \psi_f \quad (2)$$

Where, V_d , V_q are d & q axes stator voltages, i_d , i_q are d & q axes stator currents, R_s is stator phase resistance, L_d , L_q are d & q axes stator inductances, ψ_f is Rotor flux (Permanent magnet flux), ω_e is electrical speed in rad/sec.

The electromagnetic torque of PMSM is:

$$T_e = \left[\frac{3}{2} P_n i_q \left(\psi_f - \left(L_q - L_d \right) i_d \right) \right] \quad (3)$$

Where, P_n = number of pole pairs

The mechanical equation of the system is:

$$J \frac{d\omega_r}{dt} + B\omega_r + T_l = T_e \quad (4)$$

Where, J= moment of inertia, B= friction coefficient and T_l = Load torque

Finally, the above equations are mentioned in the form of state equations as follows:

$$\frac{di_d}{dt} = \frac{1}{L_d} \left[-R_s i_d + \omega_e L_q i_q \right] + \frac{V_d}{L_d} \quad (5)$$

$$\frac{diq}{dt} = \frac{1}{L_q} \left[-R_s i_q - \omega_e L_d i_d - \omega_e \psi_f \right] + \frac{V_q}{L_q} \quad (6)$$

$$\frac{d\omega_r}{dt} = \frac{1}{J} \left[\frac{3}{2} P_n i_q \left(\psi_f - \left(L_q - L_d \right) i_d \right) \right] - \frac{B}{J} \omega_r - \frac{T_l}{J} \quad (7)$$

$$\frac{d\theta_e}{dt} = P_n \omega_r \quad (8)$$

$$\frac{dT_l}{dt} \quad (9)$$

3. DESIGN OF EXTENDED KALMAN FILTER

The Extended Kalman filter algorithm is an optimal recursive estimation algorithm for non-linear systems. This method can be used to estimate the rotor position, machine parameters and speed. Motor state variables are estimated by means of measurements of stator line voltages and currents. Due to its rapid delivery, precise and accurate estimation, it is used in research and applications. The feedback gain used in EKF [21] achieves quick convergence and provides stability for the observer. Due to its various feasibilities, EKF is widely used in various sensorless speed control methods.

In this paper, to find the best linear estimation of the state vector x_k of PMSM, the discrete-time non-linear dynamics is:

$$x_{k+1} = f_k(x_k, u_k, w_k) \quad (10)$$

$$y_k = h_k(x_k, u_k, v_k) \quad (11)$$

where:

$$f_k(x_k, u_k, w_k) = A_d x_k + B_d u_k + w_k$$

$$A_d = I + AT_s$$

$$B_d = BT_s$$

$$h_k(x_k, u_k, v_k) = C_d x_k + v_k$$

$$C_d = C$$

x_k is system state vector, u_k is input vector, w_k is process noise, v_k measurement noise T_s is sampling time.

3. 1. Algorithm of EKF

Step-1: Initialize the state vector and covariance matrices x(0), P, Q and R.

Step-2: compute the Jacobian matrices for f_k,h_k

$$F = \frac{\partial f_k}{\partial x_k} \tag{12}$$

$$H = \frac{\partial h_k}{\partial x_k} \tag{13}$$

Step-3: Prediction state (time update)

To perform the time updating of state estimate and estimation of error covariance

$$X = f_k(x_k, u_k) + x(0) \tag{14}$$

$$P_1 = FPF^T + Q \tag{15}$$

Step-4: Correction state (measurement update)

To perform the measurement updating of state estimate and estimation of error covariance by using Kalman gain

Kalman gain matrix $K = P_1 H^T / \left(HP_1H^T + R\right)$ (16)

Update state prediction $X_1 = X + K\left(y - y_1\right)$ (17)

where $y_1 = Hx_k$

Estimation of error covariance matrix:

$$P = \left(I - KH\right)P_1 \tag{18}$$

4. TUNING OF PI CONTROLLER AND FILTER VARIABLES BY USING SaDE ALGORITHM

SaDE algorithm was proposed by A. K. Qin and P. N. Suganthan. In this algorithm choice of learning strategies and two control variables F and CR are need not be pre-specified. During the evolution process, these values are gradually self adapted by previous experience. SaDE could be used to minimize non-linear and non-differentiable continuous space functions, which gives better global search and convergence.

4. 1. SaDE Algorithm

i. Initialization Randomly initialize the population (NP), Generation counts (G), Dimension of number of tuning variables (D) and also choose the upper and lower bounds of tuning parameters.

Population for generation, G is given by:

$$x_{i,G}^j = x_{lower}^j + rand(\text{NP}, \text{D})\left\{x_{upper}^j - x_{lower}^j\right\} \tag{19}$$

Where, j=0, 1, 2,………………, D

ii. Trial Vector Generation Strategies To generate promising and optimum solutions at each generation with respect to each target vector in the present population, one strategy will be chosen among the available trial vector generations.

iii. Generate a new population by using trial vector generation and control parameters (F&CR).

Iv. If any control variable is outside the limits, then reinitialize the trial vector.

v. Selection The trial vector is compared with corresponding target vector in the current population. If the trial vector is less or equal to target vector, the trial vector will be replaced by the target vector value for the next generation. Otherwise, target vector will remain in the population for the next generation.

vi. Increase the generation count G=G+1

vii. Termination When the generation count reached to its maximum value, it will be terminated.

4. 2. Tuning of EKF Parameters Using SaDE

The choice of elements of the covariance matrices *P*,*Q* and *R* is important in the design of Kalman filter since it effects the performance, convergence and stability of the system. The initial state error covariance matrix (*P*) is a diagonal matrix, which may cause initial disturbances due to randomly chosen values. But when the algorithm converges, these disturbances will be disappeared. The higher noise and parameter uncertainties in the model indicates the higher values of parameters in *Q* which tends to increase of Kalman gain; results in faster filter dynamics but, leads to poorer steady-state performance. Measurement noise depends upon the matrix *R*. Whenever there is an increase in the value of the elements of *R*; current measurements are more affected by noise and thus less reliable. This results in the decrease of filter gain, yielding poor transient response. The error covariance matrices Q, R are manually tuned for EKF, so it is a time consuming process. As an alternative to this, Self adaptive evolutionary algorithm is used to tune the error covariance matrices *Q* & *R*. These matrices are tuned using the SaDE algorithm in order to obtain the optimum values at a time after maximum number of iterations. This improves both the transient and steady state stability of the system by eliminating the noise.

In this proposed scheme, set the *Q* & *R* matrices dimensions as 5 × 5 and 2 × 2, which are assumed as:

$$Q = diagonal \;\; of \left[q_1 \quad q_2 \quad q_3 \quad q_4 \quad q_5 \right]$$

$$R = diagonal \;\; of \left[r_1 \quad r_2 \right]$$

The objective function:

$$F = w_1 e_1 + w_2 e_2 + w_3 e_3 + w_4 e_4 + w_5 e_5 \tag{20}$$

where w_1, w_2, w_3, w_4, w_5 are weights of the corresponding state variables of error covariance matrices *Q* & *R*, e_1 is integral square error of measured and estimated values of i_d, e_2 is integral square error of measured and estimated values of i_q, e_3 is Integral square error of actual and estimated values of ω_r, e_4 is Integral square error of actual and estimated values of θ_e and e_5 is Integral square error of actual and estimated values of T_l.

Integral square error (ISE) integrates the square of the error over time. But the square of the larger errors will have

higher magnitude when compared to the smaller one. So the errors with higher magnitude are easily identified and eliminated quickly while the smaller ones persist for longer duration. Therefore, in order to get relatively the same magnitude of the error, each error should be multiplied by weights corresponding to their error magnitudes.

i.e. $ISE = \int |u|^2 dt$ (21)

The selection of weights plays a vital role in tuning of these parameters. Improper selection of these weights leads to estimated values of these parameters doesn't track the actual values precisely. So the weights are chosen as w_1=1, w_2=0.5, w_3=0.02, w_4=0.0027, w_5=0.2.
Also initialize
Population size (NP) =50,
Initial generation (G) =0,
Dimension (D) =7 and number of strategies = 4
Learning generation = 50
Number of evolutions = n*D where n = integer
randomly choose the upper & lower bounds for variable:

$$X_{lower} = \left\{ x_l^1 \; x_l^2 \; x_l^3 \ldots\ldots\ldots x_l^D \right\} = \left\{ 1e^{-3} \; 1e^{-3} \; 1e^{-3} \; 1e^{-3} \; 1e^{-3} \; 1e^{-3} \; 1e^{-3} \right\}$$

$$X_{upper} = \left\{ x_u^1 \; x_u^2 \; x_u^3 \ldots\ldots\ldots x_u^D \right\} = \left\{ 20 \; 20 \; 50 \; 50 \; 10 \; 100 \; 100 \right\}$$

control parameters F= [0.3 0.5] and CR = [0 1].
The optimum value of objective function is obtained by selecting proper values of Q & R matrices by using SaDE algorithm.

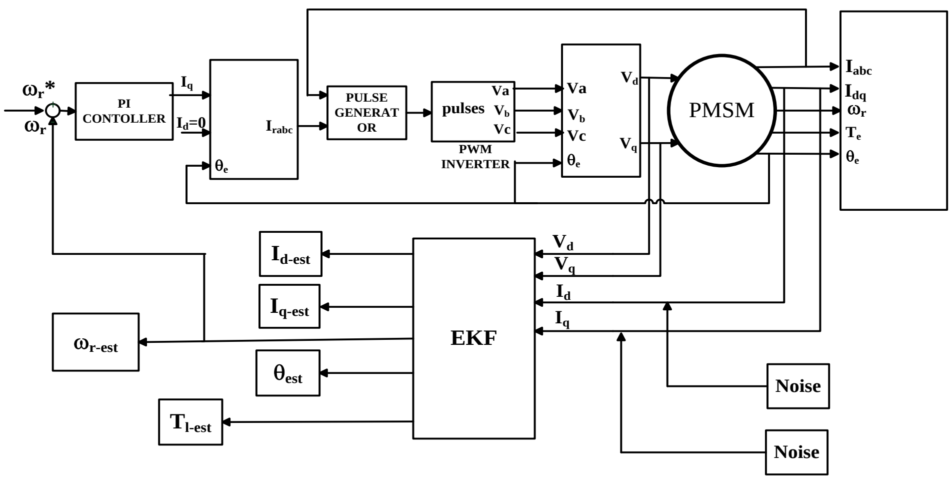

Figure 1. EKF based sensorless speed control of PMSM

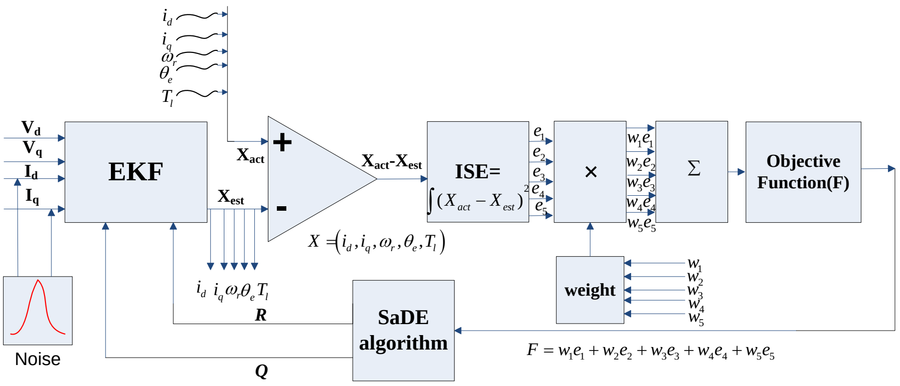

Figure 2. Block-diagram of SaDE-EKF estimation system

TABLE 1. Simulated values of matrices Q & R using SaDE

Numberof iterations	Diagonal elementsof *Q*	Diagonal elementsof *R*	ISE
100	[8.89 0.29 6.67 3.25 7.51]	[6.96 8.38]	$2.184e^4$
700	[5.18 8.75 8.55 2.14 0.03]	[7.96 8.49]	$2.173e^4$
1050	[16.84 0.24 12.25 3.01 2.64]	[43.83 84.72]	$2.179e^4$
1400	[16.94 0.08 9.50 6.78 0.004]	[30.07 37.221]	$2.008e^4$

4. 3. Tuning of PI Controller Parameters Using SaDE Algorithm After preset number of iterations of SaDE algorithm, optimum parameter values of diagonal elements Q and R matrices are obtained. Finally these optimum values are injected into EKF, and from that the estimated values of state variables are obtained. If the estimated speed is given as feedback, then speed error is given to the PI controller and the parameters of PI controller are obtained by tuning with SaDE algorithm:

Objective function $F = \int \left| \omega_{ref} - \omega_{est} \right|^2 dt$ (20)

Let population size (NP) =50, Initial generation G=0, dimension (D) =2 and randomly choose the upper & lower bounds for variables as:

$X_{lower} = \{1e^{-3} \;\; 1e^{-3}\}$ & $X_{upper} = \{100 \;\; 100\}$

So here the PI controller minimizes the settling time and also reduces the steady state error.

5. RESULTS AND DISCUSSIONS

The non-linear equations of motor in d-q model given by Equations (1), (2) & (3) are simulated using MATLAB/SIMULINK software with motor parameters as presented in Appendix-A to demonstrate the performance of the proposed drive system. Along with this the discrete-time EKF algorithm has been implemented using embedded MATLAB function by using dynamic state equations given in section 2, with sampling period 2×10^{-5} sec The embedded MATLAB function block contains v_d, v_q, i_d and i_q as the input signals for EKF and the state variables are estimated at each iteration using EKF algorithm. In order to imitate the condition of real systems, Gaussian noise of 3×10^{-6} added to measured variables i_d & i_q. For the simulation process, initialize the states and error covariance matrices as *x*(0)=(0,0,0,0,0), P(0) = diagonal of (1,1,1,1,1). The values of covariance matrices Q and R taken form SaDE algorithm as given in the following Table 1.

Better objective function value is obtained by EKF algorithm at 1400 iterations. The corresponding Q and R values for the above obective function are injected into the EKF and run in online to estimate the rotor position , speed and machines states. These results compared with those of trial and error method using optimum Q and R values,

$$Q = diagonal\ of\ [0.4 \quad 4 \quad 1 \quad 2 \quad 0.2]$$

$$R = diagonal\ of\ [2 \quad 2]$$

Case-1: SaDE Tuning of EKF Parameters (estimated) for PMSM Drive Figures 3-7 show the estimated values of state variables i_d, i_q, ω_r, θ_e and T_l respectively. Figures 3 and 4 show the estimated currents i_d & i_q using SaDE algorithm has less initial overshoots and converges fastly when compared to trial and error method. From Figure 4 it is clear that the estimated speed using trial and error method fluctuates between -500rpm to 1000rpm, where as using SaDE algorithm the speed settles at 0.01 sec only. Figure 8 shows the estimated value of load torque using SaDE algorithm has less initial overshoots and converges fastly when compared to trial and error method. The measured and estimated waveforms of i_d and i_q are shown in Figures 8 and 9 respectively. The measured value of i_d fluctuates between 1.7A to -1.7A and i_q steps from 0A to 10A, fluctuates between 7.5A to 11.5A to generate the required torque to the system. The estimated value of i_d and i_q strictly converges with the measured values and reduces the noise in the measured value. The estimated values of currents having large deviations due to convergence problem of state error covariance matrix at the beginning. After 0.05 sec both the state variables converges and settles. Figure 10 shows the actual & estimated values of rotor position for PMSM drive. The actual rotor angle starts from 0.01 sec, while the estimated rotor angle started from 0.001 sec. In the steady state there is an error between actual and estimated rotor positions due to usage of terminal voltages instead of reference voltages. In Figure 11 the actual and estimated speeds are compared and the reference speed is given as 500 rpm. The estimated speed is tracks the actual speed at 0.001 sec only, so estimated speed is quickly converges due to precise values of matrices Q & R chosen by SaDE algorithm.

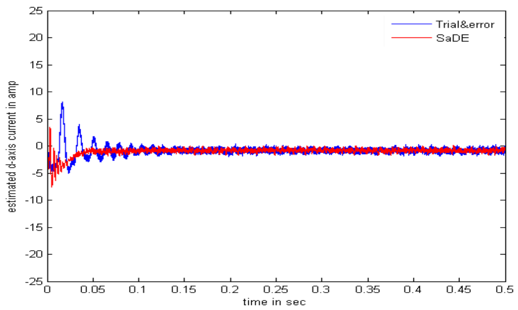

Figure 3. Estimated d-axis currents of Trial & error and SaDE methods

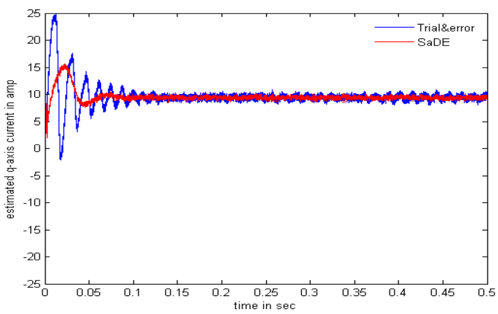

Figure 4. Estimated q-axis currents of Trial & error and SaDE methods

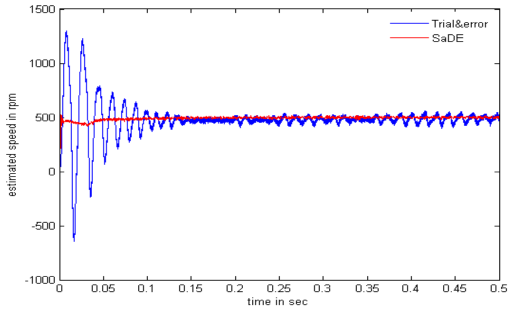

Figure 5. Estimated speed of Trial and error and SaDE methods

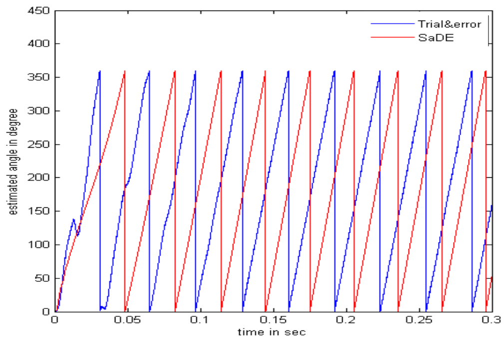

Figure 6. Estimated rotor angle of Trial and error and SaDE methods

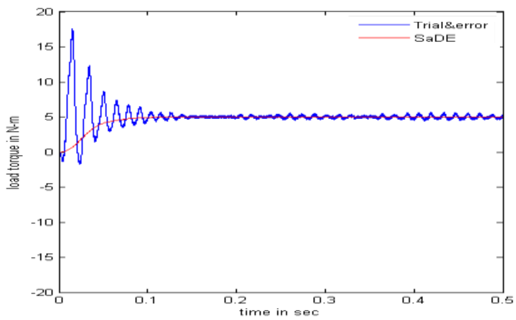

Figure 7. Estimated load torques of Trial & error and SaDE methods

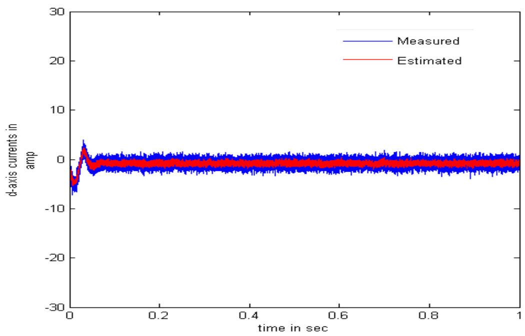

Figure 8. Measured & estimated waveforms of i_d

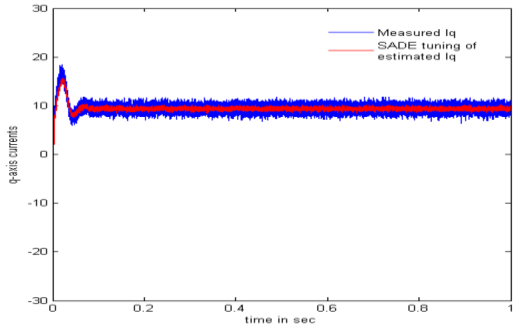

Figure 9. Measured & Estimated waveforms of i_q

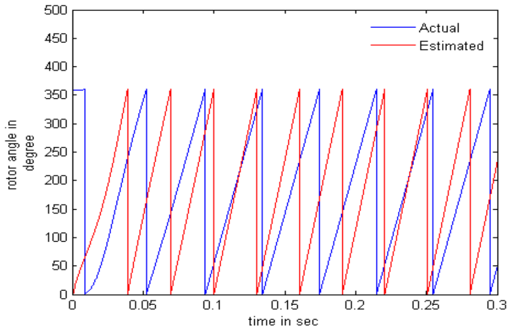

Figure 10. Actual & Estimated wave forms of rotor angle

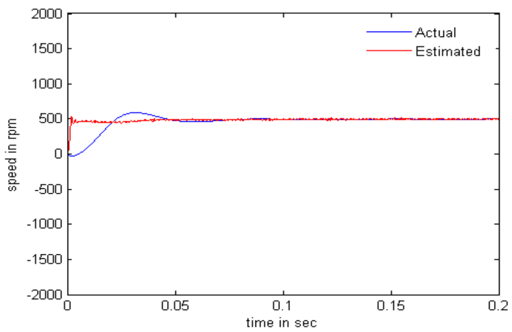

Figure 11. Actual & Estimated waveforms of rotor speed

Case 2: SaDE Tuning of PI Controller After tuning with SaDE algorithm the below values are obtained in Table 2. The better values of the table is selected and injected into PI controller and run online. These results compared with those of trial and error method using optimum K_p and K_i values i.e. K_p=7 and K_i =16.

TABLE 2. Simulated values of K_p and K_i using SaDE

No. of Iterations	K_p	K_i	ISE
1400	59.10885	33.82371	18.3194
2000	4.960035	99.15802	12.7781

Figures 12 and 13 show the rotor speed and electromagnetic torque. From Figure 12, it is clear that actual rotor speed having large number of ripples initially due to improper selection of K_p and K_i values in trial & error method, where as the SaDE algorithm, gives optimum gain values of controller and hence ripples are greatly reduced and speed is quickly converged i.e. at 0.001 sec. From Figure 13, it is clear that the electromagnetic torque has initial overshoot in trial & error method; where as initial overshoots are greatly reduced and achieves steady state quickly in SaDE algorithm.

From the Figures 14 and 15, it is observed that even for a 10% and 20% change in both mechanical and electrical parameters, the EKF is robust towards parameter variations.

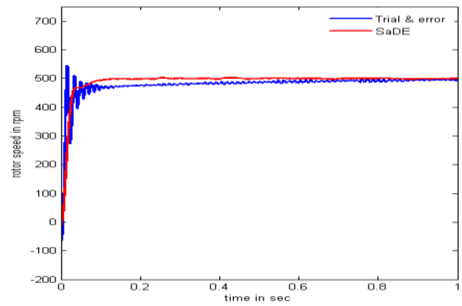

Figure 12. Actual rotor speed

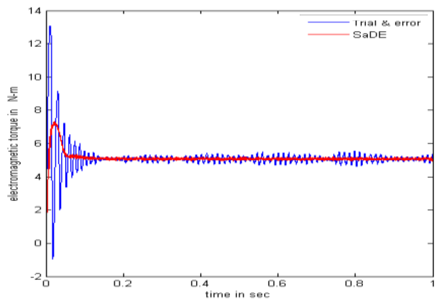

Figure 13. Electromagnetic Torque

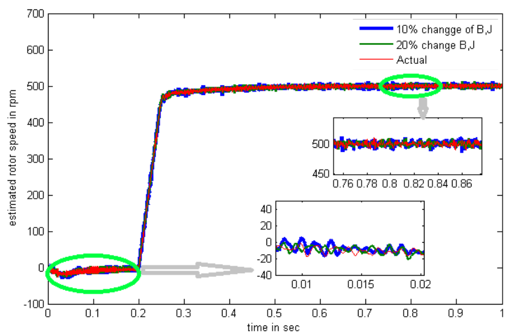

Figure 14. Estimated rotor speed under mechanical parameter variations

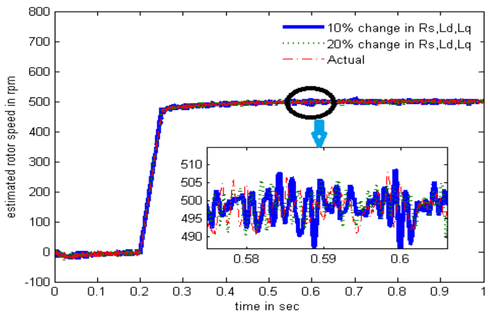

Figure 15. Estimated rotor speed under electrical parameter variations

6. CONCLUSION

In this paper, a novel approach of combining EKF with SaDE algorithm to achieve high performance and accurate rotor speed, machine states and rotor position estimation in PMSM drive has been presented. The proposed SaDE algorithm enables the noise covariance matrices *Q* and *R* on which the EKF performance critically depends, to be suitably selected. Since the selection of parameters of PI controller plays a dominant role on the performance of the closed loop system, these parameters are tuned using SaDE algorithm. The performance of basic differential evolution is enhanced using SaDE by adopting the learning strategies and control parameters. In this algorithm learning strategies and control parameters are self adapted by its previous experience. The SaDE tuned EKF is used to estimate the states of PMSM including rotor speed. The simulation results of EKF based sensorless speed control of PMSM shows superior performance in terms of noise reduction, settling time, initial overshoots and overall system stability when compared with the trial and error method.

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Appendix A: Machine Ratings and Parameters of PMSM

Parameters	Symbol	Numerical value
Resistance of stator	R_s	0.675 ohm
Direct axis inductance of stator	L_d	0.0085 H
Quadrature axis inductance of stator	L_q	0.0085 H
Flux linkages	ψ_f	0.12 Wb
Inertia of rotor	J	0.0011 Kg/m^2
friction coefficient	B	0.0014 Nm/s^2
Pair of poles	P_n	3
Rated speed	N	1000 rpm

Tuning of Extended Kalman Filter using Self-adaptive Differential Evolution Algorithm for Sensorless Permanent Magnet Synchronous Motor Drive

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چکیده

در این مقاله روشی نوین بر مبنای فیلتر کالمن (EKF)گسترش یافته با الگوریتم تکاملی تفاضلی خود تطبیق (SaDE) برای تخمین موقعیت روتور، سرعت و حالت های ماشین برای یک موتور سنکرون با مغناطیس دائم (PMSM) ارائه شده است. در روش ارائه شده در مرحله اول الگوریتم SaDE بکار گرفته شده تا ماتریس های کوواریانس نویز مربوط به حالت نویز و اندازه گیری نویز در حالت خارج ازخط را تنظیم کند. در مرحله دوم مقادیر ماتریس کوواریانس بهینه شده بالا به EKF اعمال شده تا سرعت روتور را به صورت بر–خط تخمین بزند.سرعت تخمین زده شده به کنترل کنندهPI باز خور می شود و برای کمینه کردن خطای سرعت پارامتر های کنترل کننده PI دوباره با الگوریتم SaDE تنظیم می شود. نتایج شبیه سازی نشان می دهد که ماتریس های کوواریانس تنظیم شده Q وR همگرایی فرآیند تخمین و کیفیت حالت های تخمین زده شده را بهبود می بخشد و کنترل کننده PI زمان استقرار و پایداری سیستم را بهبود می دهد

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