ONLINE PARAMETER ESTIMATION OF PERMANENT MAGNET SYNCHRONOUS MOTOR BY ACTIVE IDENTIFICATION

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ABSTRACT: *Online active identification method is used for parameter estimation due to fast variations of parameters in permanent magnet synchronous motor (PMSM). This method has the ability to estimate the parameters in a certain range of time. In order to implement the estimator, linear regression form is heuristically obtained by non-linear model of discrete mode. The proposed method is then compared to recursive least squares estimator for evaluation. The results show superiority of the proposed method in terms of speed and accuracy*.

Keywords: Active identification, Orthogonal projection algorithm, Non-linear model of Permanent Magnet Synchronous Motor, Linear regression form, Parameters estimation

Nomenclature

Constant

R : stator resistance

p : pole-pairs

Φ_f : magnet flux linkage

J : Inertia coefficient

L_d : direct and quadrature inductances of Park transformation

L_q : direct and quadrature inductances of Park transformation

θ_1 : parameter vector form 1

θ_2 : parameter vector form 2

Variables

i_q : Park transformation currents

i_d : Park transformation currents

Ω : Rotor angular speed

δ : rotor angular position

i_m : nominal current

ϕ_1 :estimator vector Form 1

ϕ_2 : estimator vector Form 2

y_1 : output Form1

y_2 :output Form 2

p : covariance Matrix

L_2 : second norm of parameter estimation error vector

J : normalized residue

Indices

k : step sample time in discrete time

t : time(sec)

1 . INTRODUCTION

Regarding the increase in complexity of power systems, there is a need for more accurate model to achieve physical parameters. In recent years, permanent magnet synchronous motors are widely used in industrial applications. Such kind of motor has gained too much attention due to some excellent features like high efficiency, compact structure, robust construction, high power, high torque to inertia ratio, high torque density capability and simpler controller comparing to induction and DC motors [1-7]. Therefore, controling such motors is very important. Physical parameters of these non-linear time variable motors are affected by different factors like temperature, mechanical vibrations, loading conditions, longing of ageing and environmental factors [8-9]. These variations lead to parametric uncertainty in system and affect the selection of model and parameter estimation when one is going to design its controller [10-11]. Different methods have been used to estimate the parameters of PMSM. It is often tried to identify the parameters in online condition to better control the system. Some factors affect the parameter estimation like speed of convergence, accuracy, initial estimation of parameters and noise conditions. Every identification algorithms cover one or more superiority factors in parameter estimation with regards to their features.Extended Kalman filter and reference model which cover speed factor and convergence accuracy, neural networks with learning capability and , recursive least squares robust to noise are some of the methods illustrated in the control literatures.[12-19]

One of the online methods to identify and estimate the non-linear systems is the active identification method[30] which is used for identification of synchronous generator power system [20] and covers all the above mentioned factors. In this study, active identification method is applied to the non-linear model of PMSM without any simplification or linearization in order to estimate the physical parameters.

The proposed estimator is described in section 2. In section 3, the proper model of system and changing it into linear regression form for implementing the estimator is presented. After that, the results of the proposed estimator are compared with the results of least square estimator in simulation section. Finally, the paper is concluded in section 5.

2. Description of active identification method

One of the methods for parameter estimation is the orthogonal projection algorithm. This method tries to produce orthogonal estimator vectors by making a vector subspace that constitute the bases of this space in order to project the unknown parameter vector on this subspace [21]. The disadvantage of this algorithm is the uncertain time for completing the estimation subspace. In active identification, output is guided toward the way that these independent estimator vectors are produced by giving purposed input to the system in order to facilitate the estimation in a certain amount of time [22]. This estimator would be useful for a system like PMSM in which its parameters are varied by different factors.

Orthogonal projection algorithm is a linear equations method to linear regression form which is given in equation (1). y is the output of scalar, ϕ estimator vector, θ unknown parameter and e noise in the system.

$$y[t]=\phi^{T}[t]\hat{\theta}+e[t] \qquad (1)$$

Considering this equation, OPA is started by using equations (2) and with an initial estimation of parameters $\hat{\theta}_0$ and covariance identity matrix p_0 [23].

$$if\ \phi_{t-1}^{T}\,p_{t-1}\,\phi_{t-1}\neq 0 \ \Rightarrow \begin{cases} \hat{\theta}_t=\hat{\theta}_{t-1}+\dfrac{P_{t-1}\cdot\phi_{t-1}}{\phi_{t-1}^{T}.P_{t-1}.\phi_{t-1}}.\left[y[t]-\hat{\theta}_{t-1}^{T}.\phi_{t-1}\right] \\ P_t=P_{t-1}+\dfrac{P_{t-1}.\phi_{t-1}.\phi_{t-1}^{T}.P_{t-1}}{\phi_{t-1}^{\mathrm{T}}.P_{t-1}.\phi_{t-1}} \end{cases} \qquad (2)$$

$$if\ \phi_{t-1}^{T}\,P_{t-1}\,\phi_{t-1}=0 \ \Rightarrow\ \hat{\theta}_t=\hat{\theta}_{t-1}\ ,\ P_t=P_{t-1}$$

The two conditions in (2) investigate the orthogonal situation of estimator vector. If the estimator vector is independent and linear toward its previous, parameter estimation and covariance matrix are updated, otherwise previous values of covariance and parameters are maintained.

Active identification method is formed by adding input selection to the OPA, at first system is with rank n, then input is cut and output is sample. Estimator vector ϕ_t in each sample t is investigated. If it can form a basic vector for estimation subspace, the estimator performs a new estimation of the parameters then waits until the measurement of the next sample, otherwise previous values are kept. Then investigation process and pre-calculation of output (regarding the features of orthogonal projection) would continue until the sample (t+n). If an independent vector is formed based on dynamics of system until sample (t+n), we would wait, otherwise for producing independent estimator vectors in samples (t+n+1), an input is needed for system to produce an output in order to produce independent linear estimator vector with respect to previous vectors. This process would continue until completion of bases for estimation subspace. n samples are needed to do this. Finally, active identification algorithm ends at most with $2nr$. The stages of algorithm are described in detail as:

In active identification method, applying an input for speeding up the convergence of parameters is performed on several sampling time. Therefore, at first inputs are considered zero and if needed, purposed input is applied to the system.

Stage zero: initializing the parameters vectors $\hat{\theta}_0$, square matrix p_0 and iteration variable L=0

First stage: sampling is performed from input and output until t=n-1 and estimator vector ϕ is formed and up to this time it is considered $\hat{\theta}_t=\hat{\theta}_0$ and $p_t=p_0$

Second stage: forecast time tp is set to n-1

Third stage: vectors ϕ_{tp} are calculated and the orthogonal condition of estimator vector is investigated ($\phi_{tp}^{T}\,p_{t-1}\,\phi_{tp}\neq 0$), if condition is fulfilled, a step is added to tp (tp=tp+1), then initialize t=tp and going to the next stage, otherwise going to seventh stage

Fourth stage: performing the sampling of output y(t) at instant t

Fifth stage: updating the covariance matrix (p_t) and parameter vector ($\hat{\theta}_t$) based on equation (2) and L=L+1

Sixth stage: if L is equal to the dimension of parameters vector ($\dim(\theta)=L$), estimation is finished and $\hat{\theta}_t=\theta$ and covariance matrix is equal to zero, otherwise going to third stage

Seventh stage: output is pre-calculated at (tp+1) (to produce a new base for estimation subspace)

$$y(tp+1)=\phi_{t-1}{}^{T}\theta \qquad (3)$$

Eighth stage: one step is added to tp (tp=tp+1), if tp<t+n going to third stage otherwise going to next stage

Ninth stage: an accidental vector with the same dimension of the number of input for system for u(t) (to determine an input that goes y(t+n+1) toward a new base))

Tenth stage: if the condition is not met $\phi_{tp}^{T}\,p_{t-1}\,\phi_{tp}\neq 0$, returning to ninth stage, otherwise a step is added to tp (tp=tp+1) and t=tp and going to fourth stage.

3. Linear regression form of PMSM

The selected model for PMSM is a fourth rank model to be near to reality and considering the dynamics of the system [24-26].

$$\begin{aligned} \frac{d\delta}{dt}&=\Omega \\ \frac{d\Omega}{dt}&=\frac{p}{J}\Phi_f\, i_q-\frac{1}{J}T_e \\ \frac{di_q}{dt}&=-\frac{R}{L_q}i_q-p\Omega i_d-p\frac{1}{L_q}\Phi_f\Omega+\frac{1}{L_q}v_q \\ \frac{di_d}{dt}&=-\frac{R}{L_d}+p\Omega i_q+\frac{1}{L_d}v_d \end{aligned} \qquad (4)$$

δ is power angle, Ω angular velocity, i_d and i_q Park's transformation currents of state variables of the system, R stator resistance, L_d and L_q Parks' transformation inductance, p number of pole-pairs, Φ_f flux linkage, J inertia coefficient of physical parameters and T_e electromagnetic torque.

The aim of this part of the paper is to rewrite this non-linear model as linear regression form considering availability of power angle (δ) which this variable is selected as desired output for linear regression form. State space model will be according to equation (6) using equation (5) [27]and discretization based on $\left(\dot{x}=\left[x(t+T_s)-x(t)\right]/T_s\right)$where T_s is sampling time:

$$\begin{cases} i_d = i_m \cos(\delta) \\ i_q = i_m \sin(\delta) \end{cases} \Rightarrow\Rightarrow \begin{cases} i_d = i_m \cos(x_1) \\ i_q = i_m \sin(x_1) \end{cases}$$

$$T_e = 1.5\left(L_d - L_q\right) i_d\, i_q \tag{5}$$

$$\begin{cases} x_1[k+T_S] = x_1[k] + T_S\, x_2[k] \\ x_2[k+T_S] = x_2[k] + T_S\left(\dfrac{1.5P\Phi_f}{J}\right)x_3[k] + T_S\left(\dfrac{1.5(L_d - L_q)}{J}\right)x_3[k]x_4[k] \\ x_3[k+T_S] = T_S\left(\dfrac{-\Phi_f P}{L_q}\right)x_2[k] + T_S\left(\dfrac{-R}{L_q}\right)i_m \sin(x_1[k]) + T_S/L_q\, u_1[k] \\ \qquad + T_S\left(-p\dfrac{L_d}{L_q}\right)i_m \cos(x_1[k])x_2[k] + i_m \sin(x_1[t]) \\ x_4[t+T_S] = i_m \cos(x_1[k]) + T_S\left(\dfrac{-R}{L_d}\right)i_m \cos(x_1[k]) + \dfrac{T_S}{L_d}u_2 \\ \qquad + T_S\left(P\dfrac{L_q}{L_d}\right)i_m \sin(x_1[t])x_2[t] \end{cases} \tag{6}$$

In (6), all state variables are rewritten to linear regression form based on the first variable i.e. power angle x_1. Physical parameters are estimated as factors due to multiplying the physical parameters with another. At the end of estimation, to separate the physical parameters, complex non-linear equations have to be solved. Therefore, to avoid solving non-linear equations, equation (6) is rewritten into two linear regression forms based on variable (x_1) in order to obtain the parameters using simple mathematical relations.

3.1. First form

The second state variable of equation (6) can be rewritten by using equation (5) as below:

$$x_2[k+T_S] = x_2[k] + T_S\left(\frac{1.5P\Phi_f}{J}\right)x_3[k] + T_S\left(\frac{1.5(L_d - L_q)}{J}\right)\frac{i_m^{\,2}}{2}\sin 2(x_1[k]) \tag{7}$$

By shifting forward in equation (7) and putting $x_3[k+1]$ in it from equation (6) and substituting $T_s = 1$:

$$\begin{aligned} x_2[k+2] &= x_2[k+1] + \left(\frac{1.5(L_d - L_q)i_m^{\,2}}{2J}\right)\sin 2(x_1[k+1]) \\ &+ \left(\frac{1.5P\Phi_f}{J}\right)\left(\frac{-\Phi_f P}{L_q}\right)x_2[k] + \left(\frac{1.5P\Phi_f}{J}\right)\left(\frac{-R}{L_q}\right)\sin(x_1[k]) + \left(\frac{1.5P\Phi_f}{L_q\, J}\right)u_1[k] + \\ &\left(\frac{1.5P\Phi_f}{J}\right)\left(-p\frac{L_d}{L_q}\right)\cos(x_1[k])x_2[k] + \left(\frac{1.5P\Phi_f\, i_m}{J}\right)\sin(x_1[t]) \end{aligned} \tag{8}$$

Equation (8) is rewritten in terms of load angle by using the relation between first and second state variables:

$$\begin{aligned} x_1[k+3] - x_1[k+2] &= x_1[k+2] - x_1[k+1] + \\ &\left(\frac{1.5P\Phi_f}{J}\right)\left(\frac{-\Phi_f P}{L_q}\right)(x_1[k+1] - x_1[k]) + \left(\frac{1.5P\Phi_f}{J}\right)\left(\frac{-R}{L_q}\right) \\ &\sin(x_1[k]) + \left(\frac{1.5P\Phi_f}{L_q\, J}\right)u_1[k] + \left(\frac{1.5P\Phi_f}{J}\right)\left(-p\frac{L_d}{L_q}\right) \\ &\cos(x_1[k])(x_1[k+1] - x_1[k]) + \left(\frac{1.5P\Phi_f\, i_m}{J}\right)\sin(x_1[t]) + \left(\frac{1.5(L_d - L_q)i_m^2}{2J}\right)\sin 2(x_1[k+1]) \end{aligned} \tag{9}$$

The above equation is rewritten to the below form by defining new variables:

$$y_1[k] = A_1 y_{11} + A_2 y_{12} + A_3 y_{13} + A_4 y_{14} + A_5 y \tag{10}$$

$$A_1 = \left(\frac{1.5P\Phi_f}{J}\right)\left(\frac{-\Phi_f P}{L_q}\right) \qquad A_2 = \left(\frac{1.5P\Phi_f}{J}\right)\left(\frac{-R}{L_q}\right) + \left(\frac{1.5P\Phi_f\, i_m}{J}\right)$$

$$A_3 = \left(\frac{1.5P\Phi_f}{L_q\, J}\right) \qquad A_4 = \left(\frac{1.5P\Phi_f}{J}\right)\left(-p\frac{L_d}{L_q}\right)$$

$$A_5 = \left(\frac{1.5(L_d - L_q)i_m^2}{2J}\right)$$

$$y_{11} = (x_1[k+1] - x_1[k]) \qquad y_{12} = \sin(x_1[k])$$

$$y_{13} = u_1[k] \qquad y_{14} = \cos(x_1[k])(x_1[k+1] - x_1[k])$$

$$y_{15} = \sin 2(x_1[k+1]) \qquad y_1[k] = x_1[k+3] - 2x_1[k+2] + x_1[k+1]$$

Finally a non-linear model of PMSM is written to common linear regression form considering equation (10) without any linearization in which $A_1,\ldots,A_7$ are factors that are obtained from multiplying physical parameters of the system and $y_{11},\ldots,y_{15}$ are variables that are composed of non-linear functions, input and output.

Equation (10) can be written to the linear regression matrix:

In equation (10), ϕ_1 is estimator vector for first regression form and θ_1 parameters vector related to this form.

$$y_1[k] = \phi_1^{\,T}\theta_1 \tag{11}$$

$$\phi_1 = \begin{bmatrix} y_{11} & y_{12} & y_{13} & y_{14} & y_{15} \end{bmatrix}^T$$

$$\theta_1 = \begin{bmatrix} A_1 & A_2 & A_3 & A_4 & A_5 \end{bmatrix}$$

3-2- Second form

The second state variable of equation (6) can be rewritten by using equation (5) as below:

$$x_2[k+T_S] = x_2[k] + T_S\left(\frac{1.5P\Phi_f\, i_m}{J}\right)\sin(x_1[t]) + T_S\left(\frac{1.5(L_d - L_q)i_m}{J}\right)\sin(x_1[k])x_4[t] \tag{12}$$

By shifting forward in equation (12) and putting $x_3[k+1]$ in it from equation (3) and substituting $T_s = 1$:

$$x_2[k+2]=x_2[k+1]+\left(\frac{1.5P\Phi_f\, i_m}{J}\right)\sin\left(x_1[k+1]\right)+\left(\frac{1.5(L_d-L_q)\,i_m^2}{J}\right)\sin\left(x_1[k+1]\right)\cos\left(x_1[t]\right)$$
$$+\left(\frac{1.5(L_d-L_q)\,i_m}{L_d\, J}\right)u_2+\left(\frac{1.5(L_d-L_q)i_m^2}{J}\right)\left(\frac{-R}{L_d}\right)\sin\left(x_1[k+1]\right)\cos\left(x_1[t]\right)+$$
$$\left(\frac{1.5(L_d-L_q)\,i_m^2}{J}\right)\left(P\frac{L_q}{L_d}\right)\sin\left(x_1[k+1]\right)\sin(x_1[k])x_2[k] \qquad (13)$$

Equation (13) is rewritten in terms of load angle by using the relation between first and second state variables:

$$x_1[k+3]-x_1[k+2]=x_1[k+2]-x_1[k+1]+\left(\frac{1.5P\Phi_f\, i_m}{J}\right)\sin\left(x_1[k+1]\right)+\left(\frac{1.5(L_d-L_q)\,i_m^2}{J}\right)$$
$$\sin\left(x_1[k+1]\right)\cos(x_1[k])+\left(\frac{1.5(L_d-L_q)\,i_m}{L_d\, J}\right)\sin\left(x_1[k+1]\right)u_2+\left(\frac{1.5(L_d-L_q)i_m^2}{J}\right)\left(\frac{-R}{L_d}\right)$$
$$\sin\left(x_1[k+1]\right)\cos(x_1[k])+\left(\frac{1.5(L_d-L_q)\,i_m^2}{J}\right)\left(P\frac{L_q}{L_d}\right)\sin\left(x_1[k+1]\right)\sin(x_1[k])(x_1[k+1]-x_1[k]) \qquad (14)$$

The above equation is rewritten to the below form by defining new variables:

$$y_2[k]=B_1y_{21}+B_2y_{22}+B_3y_{23}+B_4y_{24} \qquad (15)$$

$$B_1=\left(\frac{1.5P\Phi_f\, i_m}{J}\right)$$

$$B_2=\left(\frac{1.5(L_d-L_q)i_m^2}{J}\right)\left(1+\left(\frac{-R}{L_d}\right)\right)$$

$$B_3=\left(\frac{1.5(L_d-L_q)\,i_m}{L_d\, J}\right)$$

$$B_4=\left(\frac{1.5(L_d-L_q)\,i_m^2}{J}\right)\left(P\frac{L_q}{L_d}\right)$$

$$y_2[k]=x_1[k+3]-2x_1[k+2]+x_1[k+1]$$
$$y_{21}=\sin\left(x_1[k+1]\right) \qquad y_{22}=\sin\left(x_1[k+1]\right)\cos\left(x_1[k]\right)$$
$$y_{23}=\sin\left(x_1[k+1]\right)u_2[k] \qquad y_{24}=\sin\left(x_1[k+1]\right)\sin\left(x_1[k]\right)\left(x_1[k+1]-\right.$$

Finally a non-linear model of PMSM is written to common linear regression form like form NO.1 considering equation (15) without any linearization in which $B_1,....,B_7$ are factors that are embedded in the physical parameters of the system and $y_{21},....y_{24}$ are variables that are composed of non-linear functions, input and output.

Equation (15) can be written to the linear regression matrix like form NO.1:

$$y_2[k]=\phi_2{}^T\theta_2 \qquad (16)$$

$$\phi_2=\left[y_{21}\quad y_{22}\quad y_{23}\quad y_{24}\right]^T$$
$$\theta_2=\left[B_1\quad B_2\quad B_3\quad B_4\right]$$

In equation (11), ϕ_2 is estimator vector and θ_2 parameters vector related to form NO.2

4. Simulation

To validate and investigate the strategy of active identification method, the proposed method is implemented on a state space model of PMSM which is rewritten to linear regression form in section 3 with specifications of Table 1.[24]

Table (1): Parameters of the under study system

R	L_q	L_d	λ_f	j	p
2.87 Ω	9 mH	7 mH	0.175mWb	8 gm^2	4

To show the superiority of the proposed method, it is compared to common recursive least square estimator in terms of speed of convergence, accuracy in parameters estimation and initial estimation in noise-free situation. System is in stable mode and power angle is considered as output. Active identification method is started in parallel with the initial estimation of physical parameters in an accidental way for both of the linear regression forms explained in section 3. At first, the inputs of the system are cut, outputs are sampled and if needed, the purposed input is applied to the system based on the algorithm.

Stop criterion for identification is considered as the second norm error of parameter estimation vector according to equation (17).

$$L_2=\left\|\theta-\hat{\theta}\right\|_2 \qquad (17)$$

Diagram (1) shows that the second norm error of parameter estimation is reached to zero in 6 samples that illustrates the high speed of convergence (high efficiency) for estimator. Now it is possible to obtain the physical parameters from factors by simple mathematical operations and deliver them to the controller for gaining best input for control system. In this context, the results of parameter estimation by common RLS estimator (Figure 2) shows the slow convergence speed comparing to active identification method with the same samples. Table (2) is a numerical comparison between actual and estimated parameters by the two mentioned methods which shows high accuracy of the proposed method.

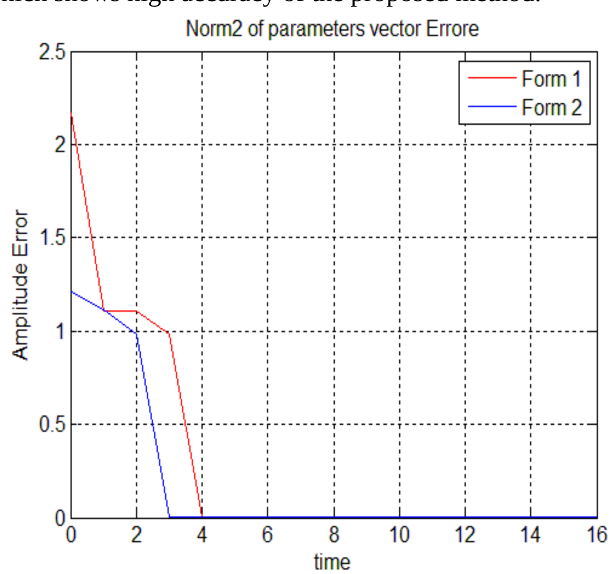

Figure 1. Second norm of parameters estimation error in Active Identification

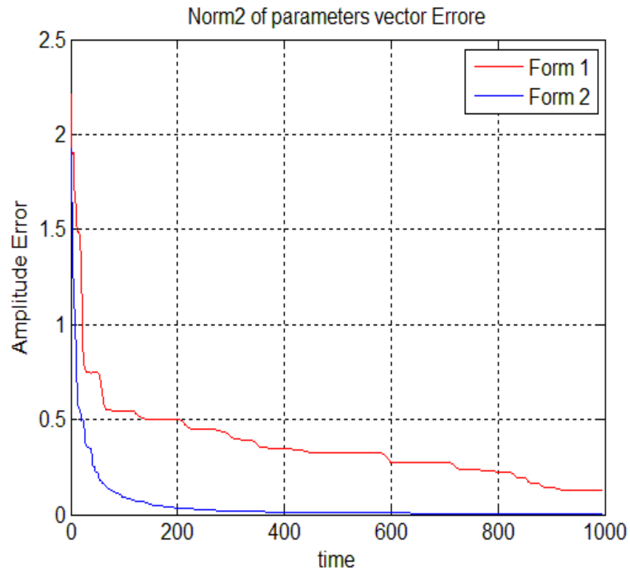

Figure 1. Second norm of parameters estimation error in RLS Estimation

Table 2. Comparison between the convergence of Active and RLS algorithms with the same condition

	R	L_q	L_d	λ_f	j	p	Sample time
Real	2.875	9	7	0.175	8	4	__
Active	2.875	9	7	0.175	8	4	6
RLS	1.9549	15.2866	0.9583	0.0098	-30.61	-67.45	1000

To evaluate the estimated parameters, PRBS signal is applied in parallel to the actual model field voltage and simulated model. Figure (3) that shows the error between these two models, illustrates the accordance of simulated and actual outputs.

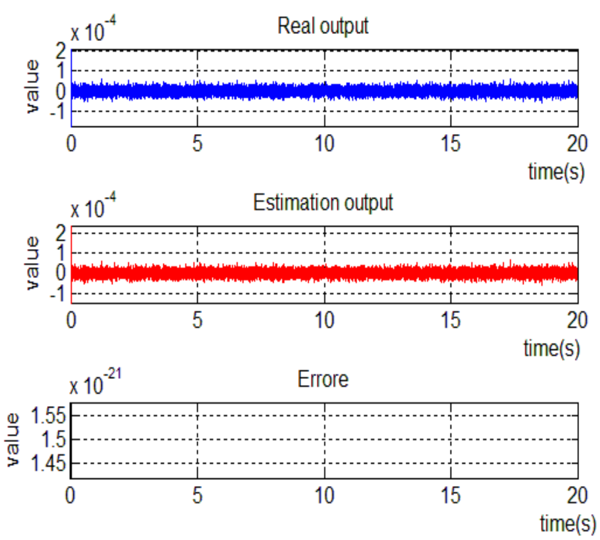

Fig. 3. shows output of real condition and estimated model and their difference. As shown, estimated and real output

One of the widely used criteria to show the error of identification is the normalized residue criterion according to equation (18) [28-29]. Here, this criterion is calculated and is given in Table 3. It is observed that the proposed method has higher superiority to the other methods.

$$J_{dB} = 10\log\left(\sum_{1}^{N}\left(y(t)-\hat{y}(t)\right)^2 \Big/ \sum_{1}^{N} y(t)^2\right) \qquad (18)$$

Table 3.Investigation of normalized residue in two methode.

	The normalized Residual
RLS Methode	-10.8923(dB)
Active Methode	-189.2896(dB)

5. CONCLUSION

In this paper, online active identification was proposed for parameter estimation of PMSM. To do this, non-linear model of PMSM was changed into linear regression form without any simplification or linearization, and then parameter estimation was performed in a certain time range. To show the superiority of the estimator, some indices are investigated such as speed of convergence, estimation accuracy and selecting the initial estimation of parameters by the explained criteria. It is understood by the simulation results that active identification method can be an appropriate online estimator for any system where state space model of the system is rewritten to linear regression form.

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