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RESEARCH ON SPEED-SENSORLESS INDUCTION MOTOR CONTROL SYSTEM BASED ON AMESIM-SIMULINK SIMULATION

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***Abstract*—This paper will establish the simulation model and the inverter model of induction motor based on the multi function simulation software AMESim. Considering the influence on the motor from the temperature and other complex factors, and Using Matlab / Simulink software to establish a simulation model of direct torque control system, then we go on combined simulation through the combination of the two aspects. The simulation result shows that the controller make the speed faster and the robustness stronger of the motor control system, but at the same time it exposes the shortcoming that torque pulsing will enlarge at the low speed. Pointing at the shortcoming, this article starts with the principle of extended kalman filtering algorithm, uses of measuring current, voltage on the pattern of stator, deduces from a new motor speed, flux state observer model without speed sensor, and estimates the rotor speed and stator flux. The simulation result shows that this method can solve the problem of flux and torque pulsing effectively.**

Keywords- Extended Kalman filter; direct torque control; the simulation software AMESim; torque ripple

I. INTRODUCTION (HEADING 1)

The full name of AMESim is LMS Imagine.Lab AMESim, that is complex system modeling and simulation platform of the interdisciplinary field. It provides a complete platform of system project design, this makes it possible that the user can build complex model of multidisciplinary field system on a platform. By using of various components provided by system, the user can using the physical model to build the simulation platform, and this improved the difficulties that general modeling software to do it by using of complicated mathematical model. AMESim model is more close to the reality.

Direct torque control is a new type of high performanced AC adjustable-speed transmission control technique. It abandonees the decoupling control theory in vector control. By using of the stator flux orientation and instantaneous space vector theory, and detecting the stator voltages and currents, this control method observes flux and torque of motor in the stator coordinate, then compares the observation value with the given one. By hysteresis controller regulating the error value gets corresponding control signal. To control motor, through synthesizing flux and torque signal to select the corresponding voltage space vector. The advantage of direct torque control is that the torque has faster dynamic response, and the rotor parameters change has certain robustness. The defect of this control method is that torque and flux pulsing is strong especially in the low speed.

The motor speed and flux observer given in this paper check the feasibility of the algorithm, by computer simulation and the comparison between the actual rotor speed and stator flux. The simulation results show that the design of new state observer can reduce the motor flux and torque pulsing effectively, and improve the motor torque performance. And it make high performance motor control possible.

II. THE INDUCTION MOTOR STATE ESTIMATION BASED ON THE EXTENDED KALMAN FILTER

The object of this paper is the AC induction motor, which is a typical nonlinear system. Under normal circumstances, the Kalman filter is used for state estimation of linear systems, if it is used in the state estimation of nonlinear systems, you must consider to use the extended Kalman filter (Extended Kalman

Filter, EKF). The largest difference between the general Kalman filter and EKF is attempting to make the nonlinear systems linearization [3-7]. After the Jacobian matrix linearization, there is little difference with the general Kalman filter in form.

A. The Extended Kalman Filter Design Based On AC Induction Motor

In two-phase stationary coordinate, in order to use EKF to predict the rotor speed, we need to add to a new state variable [8] [9]. The block diagram of the direct torque control system based on the extended Kalman filter is shown in figure 1. That is where we use voltage and current value which is easy to measure to estimate the value of the stator flux and achieve the speed identification based on the extended Kalman filter algorithm. So as to improve the performance of induction motor direct torque control system [10] [11].

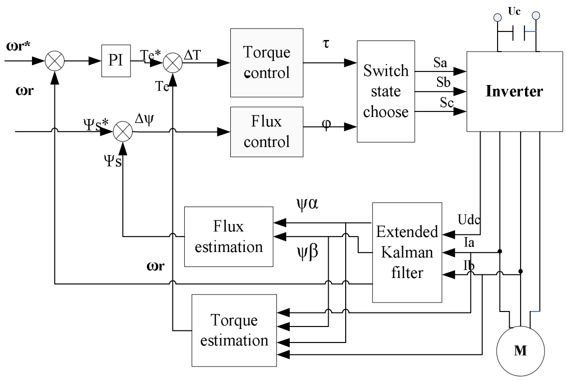


Figure 1 the system block diagram of EKF-DTC

Under the conditions that the sampling period is very short, we can think that the change is zero. Rewriting of the induction motor state-space model:

$$\begin{aligned} \dot{x} &= A \cdot x(t) + B \cdot u(t) \\ y(t) &= C \cdot x(t) \end{aligned} \tag{1}$$

Among the formula:

State variable $x = [i_{\alpha s}\ i_{\beta s}\ \psi_{\alpha r}\ \psi_{\beta r}\ \omega_r]^{\mathrm{T}}$, measurement variable $y = [i_{\alpha s}\ i_{\beta s}]^{\mathrm{T}}$, input variable $u = [u_{\alpha s}\ u_{\beta s}]^{\mathrm{T}}$,

$$A = \begin{bmatrix} -\dfrac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2} & 0 & \dfrac{L_m R_r}{\sigma L_s L_r^2} & \dfrac{n_p L_m \omega_r}{\sigma L_s L_r^2} & 0 \\ 0 & \dfrac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2} & -\dfrac{n_p L_m \omega_r}{\sigma L_s L_r^2} & \dfrac{L_m R_r}{\sigma L_s L_r^2} & 0 \\ \dfrac{R_r L_m}{L_r} & 0 & -\dfrac{R_r}{L_r} & -n_p \omega_r & 0 \\ 0 & \dfrac{R_r L_m}{L_r} & n_p \omega_r & -\dfrac{R_r}{L_r} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} \dfrac{1}{\sigma L_s} & 0 \\ 0 & \dfrac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \qquad C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Where R_s is the stator winding resistance, R_r is the rotor winding resistance, L_s is the stator cyclic inductance, L_r is the rotor cyclic inductances, L_m is mutual cyclic inductance, $\sigma = 1 - \dfrac{L_m^2}{L_s \tau_r \sigma}$, n_p is the number of pairs. ω_r is the rotor speed. It can be seen from the above state equation expression, in addition to the speed, the rest of the amount are all the stator side variables or motor constants, but also it shows the system is a nonlinear system. In other words we can use the extended Kalman filter algorithm. The actual system contains the system and measurement noise inevitably, so we add the noise matrix to the fifth-order model of the AC induction motor. It constitutes the following stochastic nonlinear control system:

$$\begin{aligned} \dot{x}(t) &= f(x(t)) + W(t) \\ y(t) &= h(x(t)) + V(t) \end{aligned} \tag{2}$$

Among the formula:

$f(x(t)) = A \cdot x(t) + B \cdot u(t)$, $h(x(t)) = C \cdot x(t)$, $W(t)$ is the system noise matrix, $V(t)$ is the process noise matrix. So the space state equation of an AC induction motor conforms the form of general nonlinear systems state equation in 2.1 section. So this paper may be using extended Kalman filter algorithm to research the AC induction motor. Firstly we should linear and discrete the state space model (1) and (2) of the AC induction motor. Specific process is as follows: we can expand the model using of the Taylor series mentioned in the previous section, and then ignore the higher order terms and retain only first order, get the approximation linear model. Assuming that the state equation of the discrete system is as follows:

$$\begin{aligned} \dot{x} &= A_k x(k) + B_k u(k) + W(k) \\ y &= C_k x(k) + V(k) \end{aligned} \tag{3}$$

The dispersion coefficient is :

$$A_k = e^{AT} \approx I + AT\ , B_k = \int_0^T e^{A\xi} B d\xi \approx BT\ , C_k = C\ .$$

We substitute A, B, C into the above equation to get:

$$A_k = \begin{bmatrix} -\frac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2} T_s & 0 & \frac{L_m R_r}{\sigma L_s L_r^2} T_s & \frac{n_p L_m \omega_r}{\sigma L_s L_r^2} T_s & 0 \\ 0 & \frac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2} T_s & -\frac{n_p L_m \omega_r}{\sigma L_s L_r^2} T_s & \frac{L_m R_r}{\sigma L_s L_r^2} T_s & 0 \\ \frac{R_r L_m}{L_r} T_s & 0 & -\frac{R_r}{L_r} T_s & -n_p \omega_r T_s & 0 \\ 0 & \frac{R_r L_m}{L_r} T_s & n_p \omega_r T_s & -\frac{R_r}{L_r} T_s & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$B_k = \begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \qquad C_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Known by the five formulas of the extended Kalman filter, we must also know the nonlinear state matrix f, output matrix h and vector partial differential matrix F 、 H. The F is called the Jacobian matrix, and the H is called the transfer matrix.

We can get $f = A_k \cdot x + B_k \cdot u$ from the formula $f(x(t)) = A \cdot x(t) + B \cdot u(t)$, and get $h(x(t)) = C \cdot x(t)$ from $h = C_k \cdot x$. So

$$F(\hat{x}(t)) = \frac{\partial f(x(t))}{\partial x(t)}\bigg|_{x(t)=\hat{x}(t)}$$

$$= \begin{bmatrix} -R_s/(\sigma L_s) - 1/(\sigma T_r) & -\omega_r & R_r/L_r & \omega_r/(\sigma L_s) & -i_{\beta s} + \psi_{\beta r}/(\sigma L_s) \\ \omega_r & -R_s/(\sigma L_s) - 1/(\sigma T_r) & -\omega_r/(\sigma L_s) & R_r/L_r & i_{\alpha s} - \psi_{\alpha r}/(\sigma L_s) \\ -R_s & 0 & 0 & 0 & 0 \\ 0 & -R_s & 0 & 0 & 0 \\ (-n_p^2/J)\psi_{\beta r} & (n_p^2/J)\psi_{\alpha r} & (n_p^2/J) i_{\beta s} & (-n_p^2/J) i_{\alpha s} & 0 \end{bmatrix}$$

$$H = \frac{\partial C}{\partial x(t)}\bigg|_{x(t)=\hat{x}(t)} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

After calculating the above functions and the corresponding matrix, we can apply the five steps of the Extended Kalman Filter. Substituting into the following recursive formula:

$$x(k+1/k) = x(k) + T * f(x(k), u(k)) \quad (4)$$

$$P_{k+1/k} = P_k + (F(x(k)) * P_k + P_k * F^T(x(k))) * T + Q \quad (5)$$

$$K(k+1) = P_{k+1/k} * H^T * [H P_{k+1/k} H^T + R]^{-1} \quad (6)$$

$$P_{k+1} = P_{k+1/k} - K(k+1) * H * P_{k+1/k} \quad (7)$$

$$x(k+1) = x(k+1/k) + K(k+1)(y(k+1) - H * x(k+1/k)) \quad (8)$$

Among the formulas, K is the Kalman gain, P is the state error covariance matrix, Q and R are noise covariance matrix whose initial value is artificially given. This article gets each parameter by trial and error method under the premise of ensuring the steady-state tracking and filtering divergence.

B. System Simulation Model Based On The EKF-DTC System

When the simulation model is set up, the extended Kalman filter is using of the S function. Figure 2 is the Simulink. Simulation diagram with the EKF-DTC.

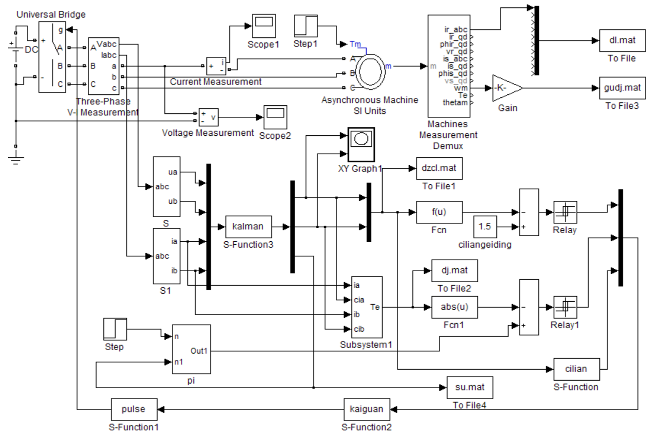


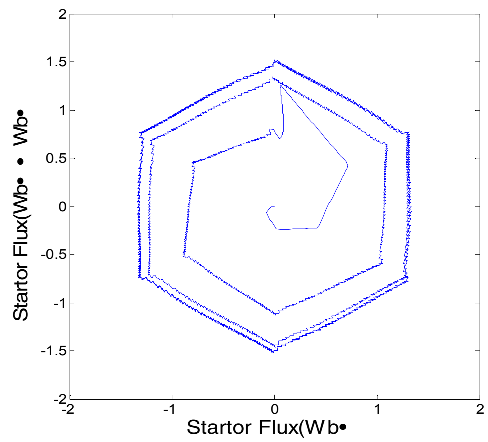
Figure 2. Simulink Simulation model based on EKF-DTC.

Induction motor simulation parameters:

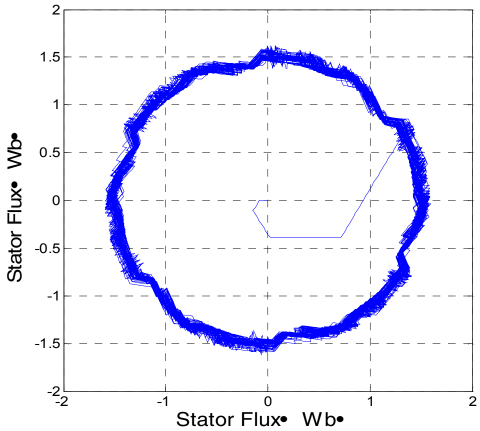
rated power P_N =1.1kw, stator winding resistances R_s =5.793Ω, rotor winding resistances R_r =3.421Ω, stator cyclic inductances L_s =0.368H, rotor cyclic inductances L_r =0.368H,mutual cyclic inductance L_m =0.363H,moment of inertia J =0.0267Kg.m2,the number of pairs P =2.

Based on the EKF-DTC method and the traditional DTC stator flux vector, electromagnetic torque and current simulation waveform, we compare the simulation results.

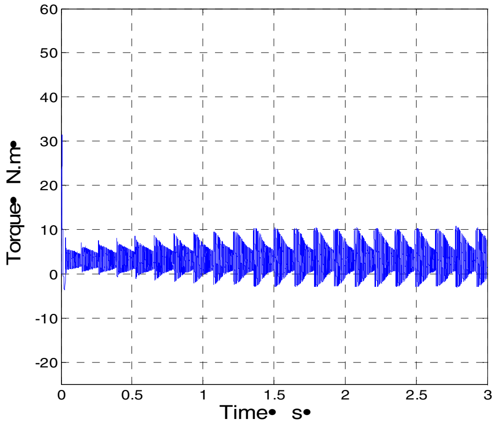
the given speed is 30 r / s (the rated speed is 150 r/s), and the load torque is 3 N. m.



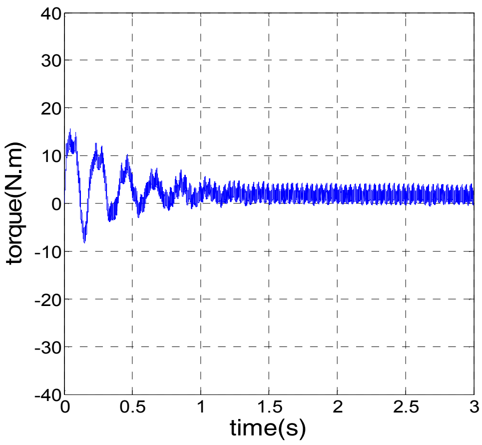
(a1) stator flux waveform of traditional DTC



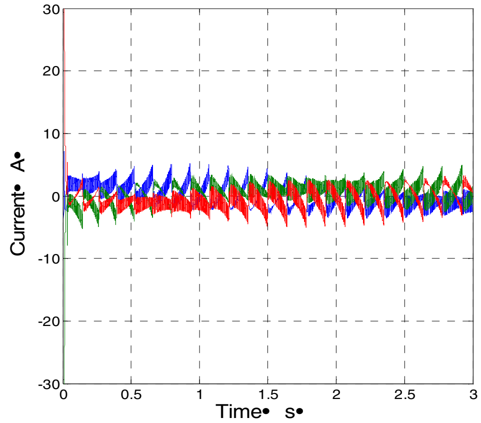
(a2) stator flux waveform of EKF-DTC



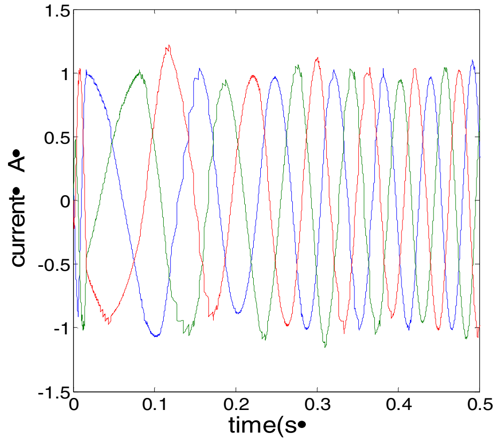
(b1) Electromagnetic torque waveform of traditional DTC



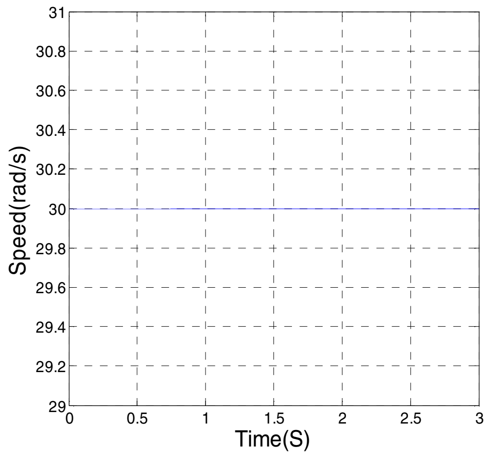
(b2) Electromagnetic torque waveform of EKF-DTC



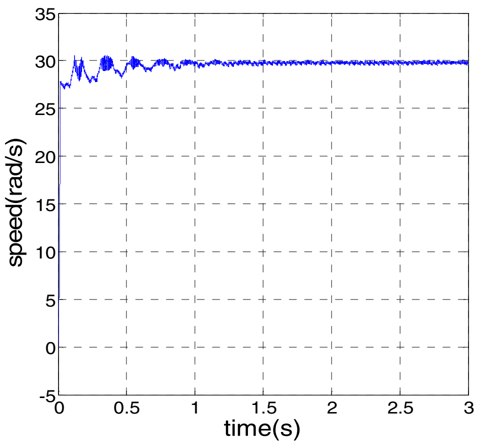
(c1) Current waveform of traditional DTC



(c2) Current waveform of EKF-DTC



(d1) Given speed waveform



(d2) speed waveform of EKF-DTC

Figure 3 Comparative experiment waveforms

III. SIMULINK AND AMESIM SIMULATION REALIZATION AND VALIDATION OF THE ALGORITH

A. The Structures Of The Joint Simulation Model

We use the motor model in AMESim to instead of the induction motor model of control system in front. At the same time its inverter drive section is also created in the software, to verify the effect of this control algorithm designed. In AMESim, the mathematical model of the induction motor takes the relationship between the temperature and the parameters into account, the system makes it closer to the actual motor system environment, and makes the powerful validation of the effectiveness of the proposed algorithm. In AMESim model, the relationship between the temperature and the motor parameters is as follows:

$$R_s = R_{s_0}(1 + alphaR_s(Temp - T_0))$$

$$tauR = T_{r_0}(1 + alphaT_r(Temp - T_0))$$

Co-simulation electronic control system and Simulink single software simulation model are different. In the co-simulation electronic control system, we introduce the voltage, current sensor signal and speed signal in AMESim into the Simulink model. We can calculate the inverse change switch signal by the computing in the Simulink model and then act on the inverter device of AMESim model. As shown in Figure 4, the S-function in the simulation model is corresponding to the AMESim co-simulation interface in figure 5, to complete the data reception and transmission.

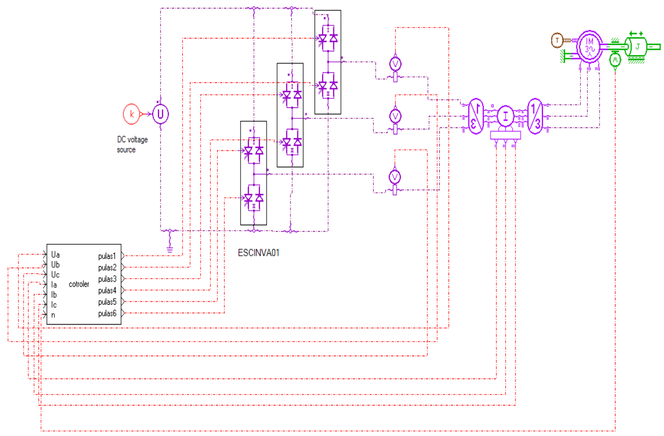


Figure 4 AMESim simulation model of Co-simulation

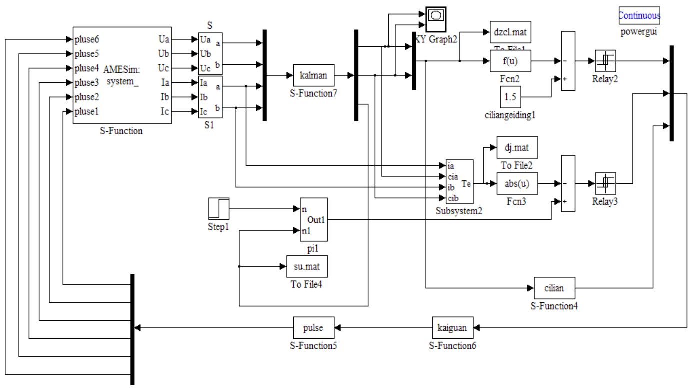


Figure 5 Simulink simulation model of Co-simulation

B. The Simulation Experiment Of Algorithm Verification

Simulation: the motor parameters still choose the same parameters as the previous ones.

The experimental setup: the reference temperature is 25 degrees Celsius. The given speed is 30rad / s. Observing the stator flux and speed simulation waveform.

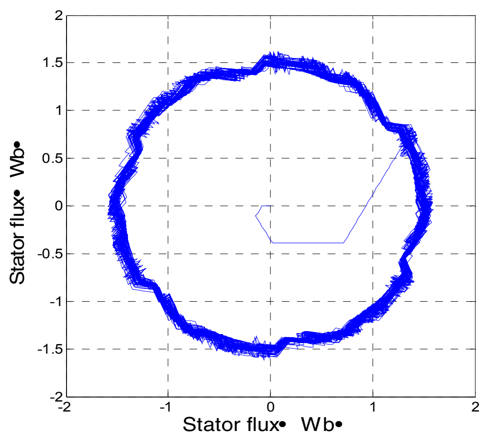


Figure 6. Stator flux waveform of Co-simulation

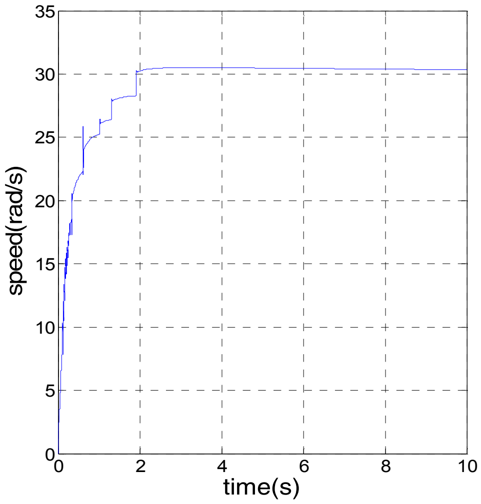


Figure 7. The waveform of the observables under Low-speed

IV. CONCLUSION

Analyzing figure 3:

1. It is visible from the comparison between Figure (a1) and Figure (a2). When the motor is running at low speed 30rad / s, the stator flux trajectory is a hexagon in the Traditional DTC method. The control effect is far from ideal. But the stator flux trajectory is approximately circular in EKF-DTC method, and the pulse also significantly reduces.

2. It is visible from the comparison between Figure (b1) and Figure (b2). The electromagnetic torque ripple reduces to a large extent based on the EKF-DTC method.

3. It is visible from the comparison between Figure (c1) and Figure (c2). The current waveform pulse is obvious in traditional DTC method. The current sine wave has been significantly improved based on EKF-DTC method.

4. It is visible from the comparison between Figure (d1) and Figure (d2). The value of a given speed is 30rad / s. The EKF identification value is also about 30rad / s. That is to say that we can achieve the speed recognition based on the EKF-DTC and the no speed sensor technology.

It can clearly be seen that the method reduce the stator flux, electromagnetic torque, the current waveform pulsation to a large extent and improve the steady-state performance of a direct torque control system based on EKF-DTC. Analyzing the reason is that the stator flux observer model is the UI model in the traditional DTC, the accuracy declines seriously at a low speed. However the EKF can remove the error caused by the cumulative integral. The introduction of EFK is equivalent to change the original open-loop stator flux model into a closed-loop control, and eliminate the error in the ring. At the same time EKF achieve speed identification and the speed sensor control, and also maintain the advantages of the DTC fast dynamic response.

Analyzing Figure 6 and Figure 7

The stator flux trajectory is almost circular, but the trajectory is coarse, and it shows that the pulse is large. However, the shape and thickness of the track can still determine that it is limited within an acceptable range. The given speed is 30rad / s. It can be seen from the experimental results that the actual speed can track a given speed. Above all we can conclude that the design algorithm of this paper is effective.

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