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MÔ PHỎNG BỘ ĐIỀU KHIỂN MỜ THÍCH NGHI VÀ KALMAN MỞ RỘNG TRONG ĐIỀU KHIỂN TỐC ĐỘ ĐỘNG CƠ PMSM KHÔNG SỬ DỤNG CẢM BIẾN

Modelsim/Simulink co-simulation of adaptive fuzzy and EKF-based flux angle and rotor speed estimation for PMSM

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Abstract. This article has presented an adaptive fuzzy controller for permanent magnet synchronous motor. The rotor speed estimation based on reduced-order extended kalman filter (reduced-order EKF). The sensor less algorithm controls have implemented by very high speed integrated circuit hardware description language (VHDL). The simulation work is performed by MATLAB/Simulink and ModelSim co-simulation mode. The simulation results shown that the motor's speed has good dynamic performance and isn't sensitive to the parameter variations.

Keywords: *Adaptive fuzzy; Motor controller; VHDL; Extended kalman filter*

Tóm tắt. Bài báo này trình bày thuật toán mờ thích nghi dùng để điều khiển tốc độ cho động cơ đồng bộ nam châm vĩnh cửu. Tốc độ của rotor được ước lượng dựa trên bộ lọc kalman mở rộng giảm bậc. Toàn bộ thuật toán điều khiển của động cơ được lập trình bằng ngôn ngữ mô tả phần cứng VHDL. Hệ thống mô phỏng được kết hợp giữa Matlab/Simulink và ModelSim. Kết quả mô phỏng thể hiện, tốc độ động cơ tốc độ động cơ đáp ứng tốt với tốc độ đặt và không ảnh hưởng khi thông số của hệ thống thay đổi.

Từ khóa: *Mờ thích nghi; Điều khiển động cơ; VHDL; Bộ lọc kalman mở rộng*

1. INTRODUCTION

The PMSM controller needs an optical encoder to calculate the rotor speed. However, sensor presents some disadvantages such as drive cost, machine size, reliability and noise immunity; therefore, a sensorless control without encoder for motor drive become a popular research topic in literature [1-3]. The reduced-order EKF is a good choice for estimation the rotor speed without encoder. The EKF requires heavy on-line matrix computing for a fix-pointed processor system. In realization, a fix-pointed processor using digital signal processor (DSP) or field programmable gate array (FPGA) both can provide a solution in this issue. Especially, FPGA is better for the implementation of the digital system than DSP [3].

In this article, a co-simulation is designed for sensorless speed control for PMSM drive (Fig.1). The reduced-order EKF is used to estimates the rotor flux angle (FA) and velocity. The vector control is applied for PMSM drive with Clark, Park, invert Clark and invert Park transformation. After using vector control, the PMSM will be decoupled and controlling a PMSM is like controlling a DC motor. The adaptive fuzzy controller (AFC) is applied for controlling the velocity of PMSM. The AFC herein uses singleton fuzzifier, triangular membership function, product-inference rule and central average defuzzifier method [4-6].

2. VELOCITY CONTROLLER DESIGN

The structure of AFC was shown in Fig.2. It includes Fuzzification (FI), inference mechanism, knowledge base, adjust mechanism, defuzzification (DFI), and PI controller.

The input linguist values of fuzzy controller:

$$e(k) = \omega^*_{RM}(k) - \hat{\omega}_r(k) \quad (1)$$

$$de(k) = e(k) - e(k-1) \quad (2)$$

Membership function was symmetrical triangle and controlling rules is:

If e was A_m and de was B_n then u_f was $C_{m,n}$ (3)

Crisp value in the output of fuzzy controller:

$$u_f(e,de) = \frac{\sum_{n=i}^{i+1}\sum_{m=j}^{j+1} c_{m,n}[\mu_{A_n}(e) * \mu_{B_n}(de)]}{\sum_{n=i}^{i+1}\sum_{m=j}^{j+1}[\mu_{A_n}(e) * \mu_{B_n}(de)]} \approx \sum_{n=i}^{i+1}\sum_{m=j}^{j+1} c_{m,n} d_{n,m} \quad (4)$$

In which $c_{m,n}$ $d_{n,m}$ is adjusting parameters for fuzzy controller.

In this article, the adaptive feature of system was added for changing the knowledge base of fuzzy controller. With this adjusting mechanism, the controller can control the motor with a balance speed in case load changed. The adjust mechanism was added to fuzzy controller, so the controller becomes AFC. The input of adjust mechanism were error between estimated rotor speed ($\hat{\omega}_r$) and designed speed (ω^*). Using the method of gradient descent determines the adaptive control law for the system:[5]

Definition of instantaneous value function:

$$J(k+1)=\frac{1}{2}[e(k+1)]^2=\frac{1}{2}[\omega^*_{RM}(k+1)-\hat{\omega}_r(k+1)]^2 \quad (5)$$

Parameters $c_{m,n}$ was determined by variation of the instantaneous value function

$$\Delta c_{m,n}(k+1)=-\alpha\frac{\partial J(k+1)}{\partial c_{m,n}(k)} \quad (6)$$

In which: α = 0÷1 shows the adaptive rate of the system.

Bilinear transform of electromagnetic torque with considering the mechanical load:

$$\frac{\hat{\omega}_r(k)}{i^*_q(k)}=\frac{K_t}{F}\frac{(1-e^{\frac{-FT_s}{J_m}})z^{-1}}{1-e^{\frac{-FT_s}{J_m}}z^{-1}} \quad (7)$$

In which T_s is sampling time, z-1 is a stage of delay time

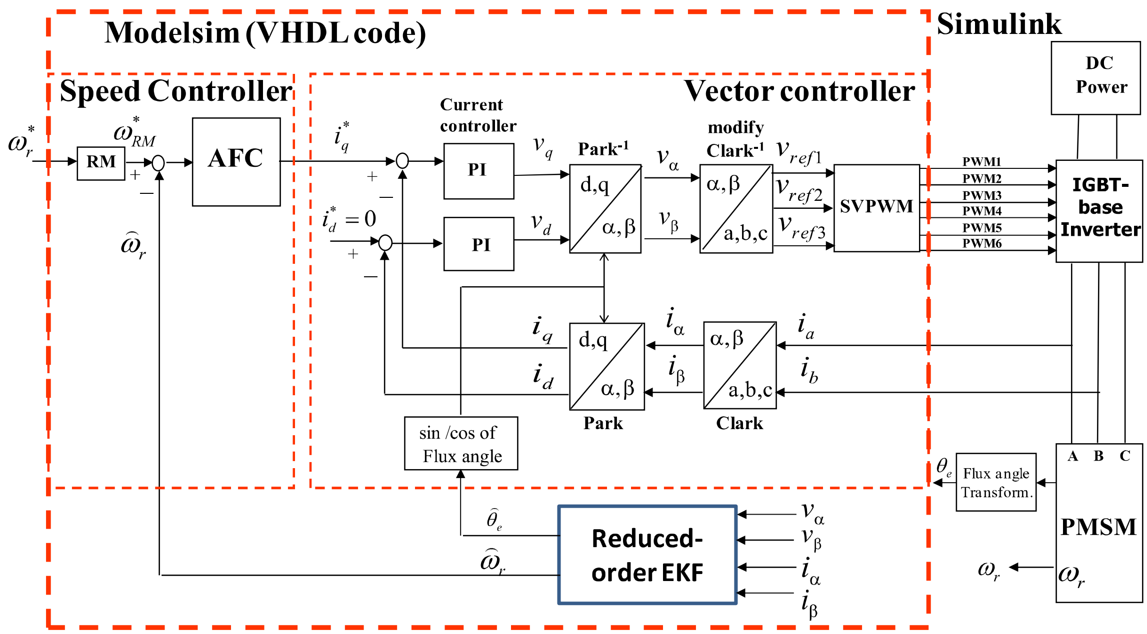


Figure 1. The controller with AFC, vector control and reduced-order EKF

Relationship between i^*_q current and output of velogcity controller was described by this equation (PI controller):

$$i^*_q(k)=u_i(k-1)+K_pu_f(k)+K_iu_f(k-1) \quad (8)$$

In which K_p, K_i are the gain of PI controller; u_f is output value of AFC.

From equation (7) and (8), we obtained the relationship between motor speed and output functions of the AFC:

$$\begin{aligned}\hat{\omega}_r(k)&=\Phi\hat{\omega}_r(k-1)+u_i(k-2)\gamma\\&+K_p\gamma u_f(k-1)+K_i\gamma u_f(k-2)\end{aligned} \quad (9)$$

In which: $\Phi=e^{\frac{-FT}{J_m}}, \gamma=\frac{K_t(1-\Phi)}{F}$

Variation of the instantaneous value function J(k+1) from equation (5) was:

$$\frac{\partial J(k+1)}{\partial C_{m,n}(k)}=-\frac{\alpha e(k-1)(\partial\hat{\omega}_r(k+1))}{\partial u_f(k)}\frac{\partial u_f(k)}{\partial C_{m,n}(k)} \quad (10)$$

Therefore, the parameters of the AFC could be adjusted through the function

$$\begin{aligned}\Delta C_{m,n}(k)&=\alpha(K_pe(k)+K_ie(k-1))\gamma d_{m,n}\\&\approx\alpha(K_pe(k)+K_ie(k-1))Sign(\gamma)d_{m,n}\end{aligned} \quad (11)$$

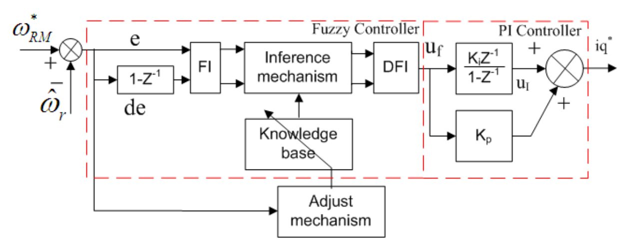


Figure 2. The structure of AFC

3. EKF-BASED FA AND ROTOR SPEED ESTIMATION FOR PMSM [7]

The equation of PMSM on the $\alpha-\beta$ axis:

$$\begin{bmatrix}v_\alpha\\v_\beta\end{bmatrix}=\begin{bmatrix}r_s+sL_s & 0\\0 & r_s+sL_s\end{bmatrix}\begin{bmatrix}i_\alpha\\i_\beta\end{bmatrix}+\omega_e\lambda_f\begin{bmatrix}-\sin\theta_e\\\cos\theta_e\end{bmatrix} \quad (12)$$

EMF is defined as

Where $L_s \triangleq L_d = L_q, [v_\alpha \; v_\beta]^T$ is voltage on fixed coordinate; $[i_\alpha \; i_\beta]^T$ is current on fixed coordinate; θ_e is angular position at magnet flux; s is differential operator.

$$e=\begin{bmatrix}e_\alpha\\e_\beta\end{bmatrix}\triangleq\omega_e\lambda_f\begin{bmatrix}-\sin\theta_e\\\cos\theta_e\end{bmatrix} \quad (13)$$

First, redefine the system

$$x(t)=\begin{bmatrix} z_\alpha \\ z_\beta \\ \omega_e \end{bmatrix}=\begin{bmatrix} \frac{T_c}{L_s}e_\alpha \\ \frac{T_c}{L_s}e_\beta \\ \omega_e \end{bmatrix} \quad and \quad y(t)=\begin{bmatrix} z_\alpha \\ z_\beta \end{bmatrix}=\begin{bmatrix} \frac{T_c}{L_s}e_\alpha \\ \frac{T_c}{L_s}e_\beta \end{bmatrix} \tag{14}$$

and assume that the rotor angular speed is constant at each sampling period. Then from (13)~(14), the state equation of PMSM stochastic model can be straightly obtained by

$$\begin{bmatrix} \dot z_\alpha \\ \dot z_\beta \\ \dot\omega_e \end{bmatrix}=\begin{bmatrix} -\omega_e z_\beta \\ \omega_e z_\alpha \\ 0 \end{bmatrix}+\sigma(t) \quad and \quad \begin{bmatrix} z_\alpha \\ z_\beta \end{bmatrix}=\begin{bmatrix} z_\alpha \\ z_\beta \end{bmatrix}+\mu(t) \tag{15}$$

The Jacobian matrices can be expressed as:

$$F(x(t))=\left.\frac{\partial f}{\partial x}\right|_{x=x(t)}=\begin{bmatrix} 0 & -\omega_e & -z_\beta \\ \omega_e & 0 & z_\alpha \\ 0 & 0 & 0 \end{bmatrix}$$
$$H(x(t))=\left.\frac{\partial h}{\partial x}\right|_{x=x(t)}=\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{16}$$

The simplified exponential matrix can be:

$$\Phi(t_n,t_{n-1},x(t_{n-1}))\cong I+FT_c$$
$$=\begin{bmatrix} 1 & -\omega_e T_c & -z_\beta T_c \\ \omega_e T_c & 1 & z_\alpha T_c \\ 0 & 0 & 1 \end{bmatrix}\triangleq\begin{bmatrix} 1 & \phi_{12} & \phi_{13} \\ \phi_{21} & 1 & \phi_{23} \\ 0 & 0 & 1 \end{bmatrix} \tag{17}$$

Where $\phi_{12}=-\omega_e T_c$, $\phi_{21}=\omega_e T_c$, $\phi_{13}=-z_\beta T_c$ *and* $\phi_{23}=z_\alpha T_c$. Further, due to the PMSM stochastic model in (14) has not input signals and the states of z_α and z_β (e_α and e_β) cannot be directly observed, the EKF algorithm cannot be applied. Considering (11)~(12), e_α and e_β can be indirectly calculated by the discrete model:

$$\begin{bmatrix} z_\alpha(n) \\ z_\beta(n) \end{bmatrix}=-\begin{bmatrix} i_\alpha(n+1) \\ i_\beta(n+1) \end{bmatrix}+\begin{bmatrix} 1-\frac{r_s}{L_s}T_c & 0 \\ 0 & 1-\frac{r_s}{L_s}T_c \end{bmatrix}\begin{bmatrix} i_\alpha(n) \\ i_\beta(n) \end{bmatrix}+\begin{bmatrix} \frac{T_c}{L_s} & 0 \\ 0 & \frac{T_c}{L_s} \end{bmatrix}\begin{bmatrix} v_\alpha(n) \\ v_\beta(n) \end{bmatrix} \tag{18}$$

However, it is not a causal system because $i_\alpha(n+1)$ and $i_\beta(n+1)$ cannot be measured at sampling instant time n. To solve this problem, we assume that the current is constant at each sampling period, and the (17) can be further simplified as

$$\begin{bmatrix} z_\alpha(n) \\ z_\beta(n) \end{bmatrix}=-\begin{bmatrix} \frac{r_s}{L_s}T_c & 0 \\ 0 & \frac{r_s}{L_s}T_c \end{bmatrix}\begin{bmatrix} i_\alpha(n) \\ i_\beta(n) \end{bmatrix}+\begin{bmatrix} \frac{T_c}{L_s} & 0 \\ 0 & \frac{T_c}{L_s} \end{bmatrix}\begin{bmatrix} v_\alpha(n) \\ v_\beta(n) \end{bmatrix} \tag{19}$$

The initial values of Q_d, R and P_0 need to be chosen. Through the recursive calculation, the state value of $\hat x(n)=[\hat z_\alpha(n),\hat z_\beta(n),\hat\omega_e(n)]^T$ is estimated at each sampling period, then the rotor angular speed and rotor position can be respectively derived by

$$\hat\omega_r(n)=\frac{\hat\omega_e(n)}{N_P} \quad and \quad \hat\theta_e(n)=\tan^{-1}\left(\frac{-\hat z_\alpha(n)}{\hat z_\beta(n)}\right) \tag{20}$$

Finally, a summary for estimating the rotor position and rotor speed based on reduced-order EKF is shown by the following design procedures:

Step A: Set the values for Q_d, R and P_0

Step B: Calculate the $z_\alpha(n)$, $z_\beta(n)$ from (19).

Step C: Estimate the temporary state variables

$$\begin{aligned}\hat z_\alpha(n|n-1)&=\hat z_\alpha(n-1)-\hat\omega_e(n-1)T_C\hat z_\beta(n-1)\\ \hat z_\beta(n|n-1)&=\hat z_\beta(n-1)+\hat\omega_e(n-1)T_C\hat z_\alpha(n-1)\\ \hat\omega_e(n|n-1)&=\hat\omega_e(n-1)\end{aligned} \tag{21}$$

Step D: Obtain the temporary covariance matrix

$$P_{n|n-1}=\Phi_{n-1}P_{n-1}\Phi_{n-1}^T+Q_d \tag{22}$$

Step E: Calculate the Kalman gain from

$$K_n=P_{n|n-1}H^T[HP_{n|n-1}H^T+R]^{-1} \tag{23}$$

Step F: Tune the present state variables

$$\begin{aligned}\hat z_\alpha(n)&=\hat z_\alpha(n|n-1)+k_{11}\tilde z_\alpha(n)+k_{12}\tilde z_\beta(n)\\ \hat z_\beta(n)&=\hat z_\beta(n|n-1)+k_{21}\tilde z_\alpha(n)+k_{22}\tilde z_\beta(n)\\ \hat\omega_e(n)&=\hat\omega_e(n|n-1)+k_{31}\tilde z_\alpha(n)+k_{32}\tilde z_\beta(n)\end{aligned} \tag{24}$$

With $\tilde z_\alpha(n)=z_\alpha(n)-\hat z_\alpha(n|n-1)$; $\tilde z_\beta(n)=z_b(n)-\hat z_b(n|n-1)$

Where k_{ij} is the element of Kalman gain k_n.

Step G: Update the present covariance matrix P_n.

$$P_n=P_{n|n-1}-K_nHP_{n|n-1} \tag{25}$$

Step H: Calculate the rotor angular speed and rotor flux position from (20); back to Step B.

4. SIMULATION STRUCTURE AND SIMULATION RESULTS

The Fig.3 shown the simulation structure of system, the work-1 to work-3 respectively performs the function of AFC, vector control and reduced-order EKF. All works in ModelSim are coded by VHDL and the FPGA resource usages shown in table 1. The PMSM and inverter are executed by SimPowerSystem blockset. The ModelSim executes the co-simulation using VHDL code. The PMSM parameters are shown in table 1.

The desired speed is set 500rpm, 1000rpm, 1500rpm, 2000rpm, 2500rpm, 2000rpm, 1500rpm, 2000rpm and 1500rpm for testing. The results of the actual rotor FA, the estimated rotor AF under different motor speed are shown in Fig.4. The error of the estimated rotor FA and the actual rotor FA are among 0.5% at high speed (Fig.4a) and 1% at low speed (Fig.4b).

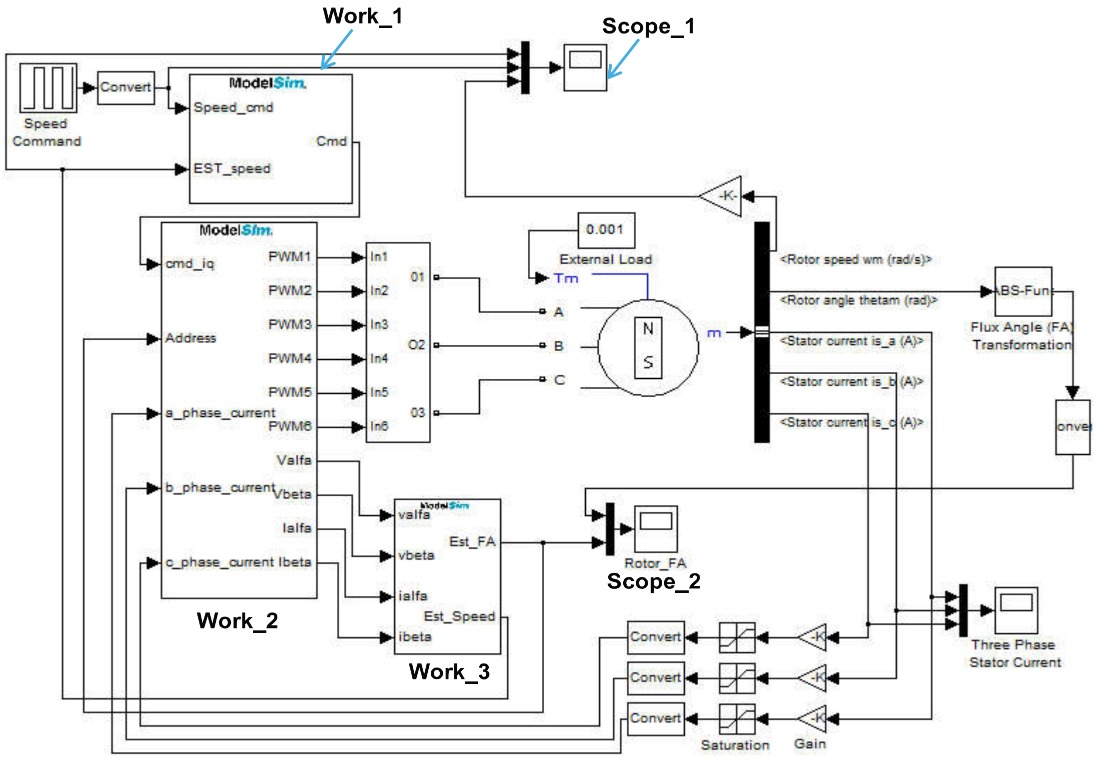


***Figure 3.** The co-simulation system of sensorless controller build in Matlab/Simulink and Modelsim*

The Fig.4 shows that the reduced-order EKF apparently gives accuracy, especially in high speed condition. In the next step, the estimated rotor FA is feed-backed to the current loop and the estimated rotor speed is feed-backed to the speed loop as Fig.1.

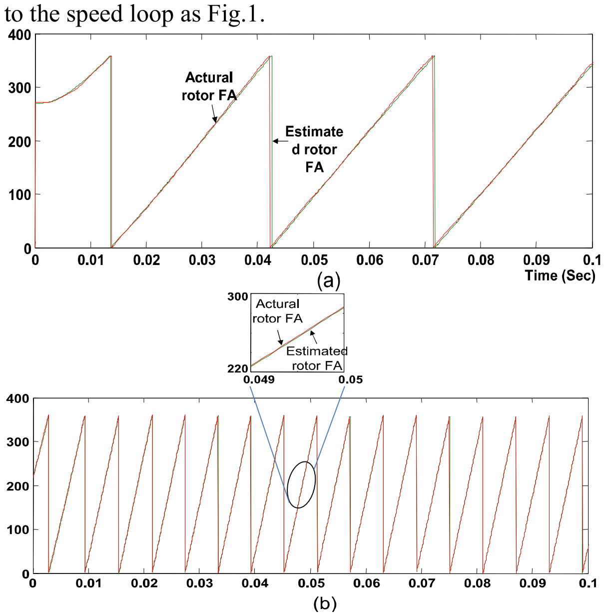
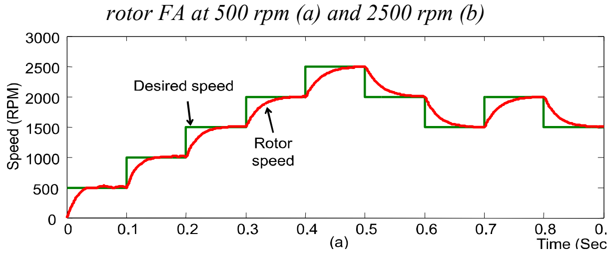


***Figure 4.** Comparision between actural rotor FA and estimated rotor FA at 500 rpm (a) and 2500 rpm (b)*



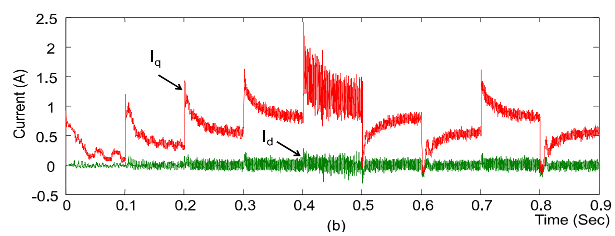


***Figure 5.** With AFC and reduced-order EKF, the rotor speed can track speed command very well (a), the i_d current approached to zero, the motor torque was controlled by i_q current (b).*

In Fig.5a and Fig.6, they showed that the rotor speed using AFC can track the designed speed very well. The rotor speed is running without overshoot and sluggishness. The i_d current in Fig.5b approached to zero, it shown that the vector control algorithm was correct. From Figs.4~5 demonstrates that the AFC sensorless control can give good speed tracking.

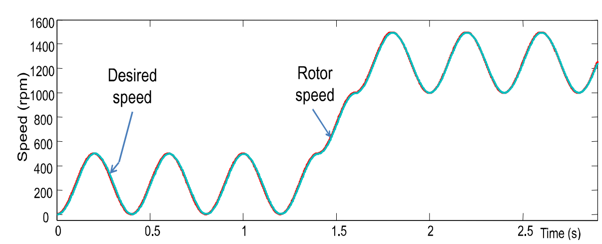


***Figure 6.** With AFC and reduced-order EKF, the desired speed is sine shape, the rotor speed still track desired speed very well.*

5. CONCLUSION

This article has been succefully presented an adaptive fuzzy sensorless speed control for PMSM drive based on reduced-order. It demonstrated through co-simulation by using Simulink and ModelSim. The system separate to three parts, the vector control is used to decouple the nonlinear characteristics of PMSM, the AFC is designed to cope with the dynamic uncertainty effect, the reduced-order EKF is applied to estimate the rotor FA without using sensor. The VHDL is used to describe the behavior of whole system.The paper has been demonstrated to be the best tracking rotor speed under different external load condition.

***Table 1**. FPGA resources and PMSM's parameter*

FPGA resources

Item	Les	RAM bits
Work-1	2,887	0
Work-2	1,828	98,304
Work-3	4,226	75,264

***Table 2**. PMSM's parameter*

PMSM's parameter

Item	Value
R	1.3Ω
L_d, L_q	6.3mH
P	4
J_m	0.000108 kg*m^2
F	0.0013 N*m*s

6. REFERENCES

[1] S. Bolognani, O. Roberto, and Z. Mauro, "Sensorless full-digital PMSM drive with EKF estimation of speed and rotor position", IEEE Transactions on Industrial Electronic, vol.46, no.1, pp.184-191, Feb 1999. Doi:10.1109/41.744410.

[2] M. C. Huang, A. J. Moses, & F. Anayi, "The comparison of sensorless estimation techniques for PMSM between extended Kalman filter and flux-linkage observer", in Twenty-First Annual IEEE Applied Power Electronics Conference and Exposition, 2006. APEC'06.

[3] L. Idkhajine, E. Monmasson and A. Maalouf, "Extended kalman filter for ac drive sensorless speed controller, FPGA-based solution or DSP-based solution", Proceedings of IEEE International on Industrial Electronics (ISIE), pp. 2759-2764, 2010. Doi: 10.1109/ISIE.2010.5636605.

[4] Ying-Shieh Kung, Nguyen Vu Quynh, Chung-Chun Huang and Liang-Chiao Huang, "Simulink/ModelSim co-simulation of sensorless PMSM speed controller", IEEE Symposium on Industrial Electronics and Applications, pp. 24-29, 2011. Doi: 10.1109/ISIEA.2011.6108709.

[5] Ying-Shieh Kung and Ming-Hung Tsai, "FPGA-Based speed control IC for PMSM drive with adaptive fuzzy control", IEEE transactions on power electronics, vol.22, no.6, pp.2476,2486, Nov. 2007. Doi: 10.1109/TPEL.2007.909185.

[6] Y. S. Kung, C. C. Huang, & M. H. Tsai, " FPGA realization of an adaptive fuzzy controller for PMLSM drive", Industrial Electronics, IEEE Transactions on, vol.56, no.8, 2923-2932, 2009.

[7] Ying-Shieh Kung, Nguyen Vu Quynh, Nguyen Trung Hieu, and Jin-Mu Lin, "FPGA realization of sensorless PMSM speed controller based on extended kalman filter", Mathematical Problems in Engineering, vol. 2013, article ID 919318, 13 pages, 2013. Doi:10.1155/2013/919318.

TIỂU SỬ TÁC GIẢ

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