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Implementation of disturbance observer for sensorless speed estimation in induction motor

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ABSTRACT

The use of speed sensors in induction motors is considered to be less effective because of the high price and diminishing reliability. Over time, a speed estimator was developed to increase the speed of the sensor. This paper describes the application of a disturbance observer algorithm as an estimator of the speed of an induction motor. In this case, the estimator is seen as an embedded system that only uses current information to measure speed of induction motor. To test the performance of the disturbance observer-based estimator, a comparison was made with the estimator based on the extended Kalman filter. From the experiment, it is found that the speed estimation using the disturbance observer has a smaller root mean square error in the low-speed operation than one of the extended Kalman filter, i.e. the root mean squared error (RMSE) value is below 4% in the range of 250 revolution per minute (RPM)–600 RPM.

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1. INTRODUCTION

An induction motor is a type of alternating current (AC) electric motor. These motors are also called asynchronous motors because these machines never run at synchronous speed. The induction motor has a working principle based on the induction of a magnetic field between the stator and the rotor. These motors are divided into single-phase and three-phase induction motors. Induction motors have been widely used in industry. This motor is one of the important components that function as a driver of various industrial equipment. The number of uses of induction motors is due to this motor having advantages over other electric motors. The advantages of induction motors are simple and sturdy structure, high efficiency, easy and inexpensive maintenance, and excellent reliability [1]. In many applications, induction motors need to operate at certain speeds with varying loads. In this system, speed information is needed from speed measurement instruments such as encoders, tachometers, hall sensors, and among others. These instruments are attached to the motor shaft. However, the use of speed sensors has several drawbacks such as the installation of sensors which are quite complicated, high costs, and the installation of sensors can reduce the strength and mechanical resistance of the system [2]. Therefore, currently a lot of research is being done on how to obtain speed information without using a hardware instrument or known as a speed sensorless system. The sensorless system has many advantages, mainly are decreasing maintenance, reducing number of connections, and the cost.

In speed sensorless, the role of the measuring instrument is replaced by an estimator as a soft sensor. There are two types of estimators here, namely based on the dynamical model and based on the ripple component. The ripple component based estimator has drawbacks in terms of problems that arise due to noise [3]. There are several algorithms regarding the induction motor speed estimator such as Luenberger observer (LO), sliding mode observer (SMO), artificial neural network (ANN) based observer, model reference adaptive system (MRAS), and extended Kalman filter (EKF) observer are described in the literatures [4]–[19]. To overcome the problem of nonlinearity, an EKF is proposed so that the estimation error can be minimized throughout the speed range. However, the extended Kalman filter in general will be still optimal if the measurement and the state transition model are both linear. Its estimated covariance matrix risks becoming inconsistent in the statistical sense without the addition of "stabilizing noise" [20]–[22].

Previously, research has been carried out on the estimation of the speed of an induction motor using the disturbance observer (DO) algorithm in the simulation which produces better estimation results than using an extended kalman filter when there is a change in torque [23]. This was done by comparing the root-mean-square error (RMSE) of the two algorithms when the induction motor was loaded. This paper reports the experimental results in realizing a real-time estimator for DO-based speed on an induction motor.

2. PROPOSED METHOD

The development of real-time estimators for speed based on DO is made with several steps that must be carried out. These steps include modeling induction motors, designing estimators based on disturbance observers, and implementing the real time estimator on an induction motor. The modeling step serves to obtain a state space model that will be used in building the disturbance observer. The observer's results are in the form of state variable estimates which will be used to estimate speed. The estimator design is tested in simulation before being implemented in real time.

2.1. Induction motor modeling

Induction motor modeling can be viewed as a stator reference frame or a rotor reference frame and the parameters used in the modeling are stator current or rotor current with rotor flux. The induction motor parameters used are listed in Table 1. The induction motor equation using the stator reference frame can be expressed as the following fifth-order nonlinear equation [24]:

$$\frac{di_{\alpha s}^{s}}{dt} = \frac{L_m R_r}{(L_s L_r - L_m^2)L_r}\lambda_{\alpha r}^{s} + \frac{PL_m}{2(L_s L_r - L_m^2)}\omega_0 \lambda_{\beta r}^{s} - \frac{L_m^2 R_r + L_r^2 R_s}{(L_s L_r - L_m^2)L_r} i_{\alpha s}^{s} + \frac{L_r}{(L_s L_r - L_m^2)} V_{\alpha s}^{s} \quad (1)$$

$$\frac{di_{\beta s}^{s}}{dt} = \frac{L_m R_r}{(L_s L_r - L_m^2)L_r}\lambda_{\beta r}^{s} - \frac{PL_m}{2(L_s L_r - L_m^2)}\omega_0 \lambda_{\alpha r}^{s} - \frac{L_m^2 R_r + L_r^2 R_s}{(L_s L_r - L_m^2)L_r} i_{\beta s}^{s} + \frac{L_r}{(L_s L_r - L_m^2)} V_{\beta s}^{s} \quad (2)$$

$$\frac{d\lambda_{\alpha s}^{s}}{dt} = -\frac{R_r}{L_r}\lambda_{\alpha r}^{s} + \frac{P}{2}\omega_0 \lambda_{\beta r}^{s} + \frac{R_r L_m}{Lr} i_{\alpha s}^{s} \quad (3)$$

$$\frac{d\lambda_{\beta s}^{s}}{dt} = -\frac{R_r}{L_r}\lambda_{\beta r}^{s} + \frac{P}{2}\omega_0 \lambda_{\alpha r}^{s} + \frac{R_r L_m}{Lr} i_{\beta s}^{s} \quad (4)$$

$$\frac{d\omega_0}{dt} = \frac{2}{3}\frac{PL_m}{2JL_r}\left(\lambda_{\alpha s}^{s} i_{\beta s}^{s} - \lambda_{\beta s}^{s} i_{\alpha s}^{s}\right) - \frac{T_L}{J} \quad (5)$$

where:

R_s, R_r = Stator and rotor resistance
$\lambda_{\alpha r}^{s}, \lambda_{\alpha s}^{s}$ = *α-axis* rotor and stator flux
$\lambda_{\beta r}^{s}, \lambda_{\beta s}^{s}$ = *β-axis* rotor and stator flux
$V_{\alpha s}^{s}, i_{\alpha s}^{s}$ = *α-axis* stator voltage and current
$V_{\beta s}^{s}, i_{\beta s}^{s}$ = *β-axis* stator voltage and current
$L_{r,} L_s, L_m$ = Rotor, stator, and mutual inductance
ω_0 = Rotor speed
T_L = Load torque
P = Number of pole
J = Rotor inertia

The induction motor is a nonlinear plant, with its state-space modeling is being as:

$$\dot{x} = A(x)x + Bu \quad (6)$$

$$y = Cx \quad (7)$$

where the state vector $x \in R^{5\times1}$and the input vector $u \in R^{2\times1}$ is being as.

$$x = \begin{bmatrix} i_{\alpha s} \\ i_{\beta s} \\ \lambda_{\alpha r} \\ \lambda_{\beta r} \\ \omega_r \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} u = \begin{bmatrix} v_{\alpha s} \\ v_{\beta s} \end{bmatrix} \quad (8)$$

Referring to (1)-(5), the matrix A $\in R^{5\times5}$ is not a constant but is function of the rotor speed and the rotor/stator fluxes, while $B \in R^{5\times2}$ is a constant. Both matrices are written as follows:

$$A = \begin{bmatrix} -A_1 & 0 & A_2 & A_3\omega_r & 0 \\ 0 & -A_1 & -A_3\omega_r & A_2 & 0 \\ A_4 & 0 & -A_5 & -P\frac{\omega_r}{2} & 0 \\ 0 & A_4 & -P\frac{\omega_r}{2} & -A_5 & 0 \\ -A_6\lambda_{\beta r} & A_6\lambda_{\alpha r} & 0 & 0 & 0 \end{bmatrix} \quad (9)$$

$$B = \begin{bmatrix} B_1 & 0 \\ 0 & B_1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (10)$$

$$\sigma = 1 - \frac{Lm^2}{Lr\ Ls} \qquad B_1 = \frac{1}{\sigma\ L_s}$$

$$A_1 = \frac{L_m{}^2 R_r + L_r{}^2 R_s}{\sigma\ L_r{}^2\ L_s} \quad A_4 = \frac{L_m\ R_r}{Lr} \quad (11)$$

$$A_2 = \frac{L_m\ R_r}{\sigma\ L_r{}^2\ L_s} \quad A_5 = \frac{R_r}{L_r}$$

$$A_3 = \frac{\mathrm{P}\ L_m}{2\ \sigma\ L_r\ L_s} \qquad A_3 = \frac{2\ \mathrm{P}L_m}{3\ 2\mathrm{J}\ L_r}$$

Because the measured states are only the stator currents, a matrix $C \in R^{2\times5}$ is defined as follows:

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \quad (12)$$

Table 1. Parameters of the induction motor used

Parameter	Symbol	Value
Mutual Inductance	Lm	0.258 H
Rotor Inductance	Lr	0.274 h
Stator Inductance	Ls	0.274 H
Rotor Resistance	Rr	3.805 Ohm
Stator Resistance	Rs	4.850 Ohm
Rotor Inertia	J	0.031Kgm^2
Number of Pole	P	4
Sampling Time	Ts	0.0006

2.2. Disturbance observer-based estimator

The DO is a modification of the Luenberger observer with the addition of a state vector *d* or what is called a disturbance. The state estimates generated by the disturbance observer are the current, flux, and the disturbance. Hence, the inputs for DO are the voltage input *v* and the measured current *i*. In designing the estimator for the disturbance observer, the estimated value of ω_r is influenced by the estimated flux state $\hat{\lambda}$ and the estimated disturbance state $\hat{\xi}$. In this paper, the DO algorithm that is supposed to be used is a modification of the algorithm in [25], and has a scheme as shown in the Figure 1. The disturbance observer design is carried out after the induction motor modeling is obtained. However, in (8), the matrix A is nonlinear because there is a value of the speed and the fluxes so that the form of the matrix A is modified to be linear by adding a new matrix to the induction motor equation is being as:

$$\begin{bmatrix} \dot{i}_{\alpha s} \\ \dot{i}_{\beta s} \\ \dot{\lambda}_{\alpha r} \\ \dot{\lambda}_{\beta r} \end{bmatrix} = \begin{bmatrix} -A_1 & 0 & A_2 & 0 \\ 0 & -A_1 & 0 & A_2 \\ A_4 & 0 & -A_5 & 0 \\ 0 & A_4 & 0 & -A_5 \end{bmatrix} \begin{bmatrix} i_{\alpha s} \\ i_{\beta s} \\ \lambda_{\alpha r} \\ \lambda_{\beta r} \end{bmatrix} + \begin{bmatrix} A_3 & 0 \\ 0 & -A_3 \\ -\frac{P}{2} & 0 \\ 0 & \frac{P}{2} \end{bmatrix} \begin{bmatrix} \xi_\alpha \\ \xi_\beta \end{bmatrix} + \begin{bmatrix} B_1 & 0 \\ 0 & B_1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{\alpha s} \\ v_{\beta s} \end{bmatrix} \quad (13)$$

where

$$x = \begin{bmatrix} i_{\alpha s} \\ i_{\beta s} \\ \lambda_{\alpha r} \\ \lambda_{\beta r} \end{bmatrix}, d = \begin{bmatrix} \xi_\alpha \\ \xi_\beta \end{bmatrix}, u = \begin{bmatrix} v_{\alpha s} \\ v_{\beta s} \end{bmatrix}, \quad (14)$$

$$A = \begin{bmatrix} -A_1 & 0 & A_2 & 0 \\ 0 & -A_1 & 0 & A_2 \\ A_4 & 0 & -A_5 & 0 \\ 0 & A_4 & 0 & -A_5 \end{bmatrix}, E = \begin{bmatrix} A_3 & 0 \\ 0 & -A_3 \\ -\frac{P}{2} & 0 \\ 0 & \frac{P}{2} \end{bmatrix}, B = \begin{bmatrix} B_1 & 0 \\ 0 & B_1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (15)$$

The disturbance observer equation is then written is being as:

$$\begin{bmatrix} \dot{\hat{x}} \\ \dot{\hat{d}} \end{bmatrix} = \begin{bmatrix} A & E \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} v + \begin{bmatrix} 0 \\ k_3 \widehat{\omega}_\lambda \widehat{d} \end{bmatrix} + \begin{bmatrix} k_1 & k_2 \\ k_4 & 0 \end{bmatrix} \begin{bmatrix} e_i \\ e_d \end{bmatrix} \quad (16)$$

where: $\widehat{\omega}_\lambda$ is the flux angular velocity which can be obtained by:

$$\frac{d\widehat{\omega}_\lambda}{dt} = k_5 [\, |i_s| - |\hat{\imath}_s| \,] \quad (17)$$

$$|i_s| = \sqrt{i_{\alpha s}^2 + i_{\beta s}^2} \quad (18)$$

$$|\widehat{\imath_s}| = \sqrt{\hat{\imath}_{\beta s}{}^2 + \hat{\imath}_{\beta s}{}^2} \quad (19)$$

$$e_i = i_s - \hat{\imath}_s \quad (20)$$

$$e_d = \widehat{\omega}_r \hat{\lambda} - \widehat{d} \quad (21)$$

with:
$\hat{\imath}_{\alpha s}, \hat{\imath}_{\beta s}$ = Estimated stator current on the reference axis αβ
$\hat{\lambda}_{\alpha r}, \hat{\lambda}_{\beta r}$ = Estimated rotor flux on the reference axis αβ
$\hat{d}$ = Estimated disturbance vector
$\hat{\xi}_\alpha, \hat{\xi}_\beta$ = Estimated disturbance
$\widehat{\omega}_\lambda$ = Angular flux speed

In this DO, there are five gains, namely k_1, k_2, k_3, k_4, and k_5 where the values are obtained through the linear quadratic regulator (LQR) method and the trial-error method. Gains k_1, k_2, and k_4 are gains obtained from the LQR method. While the gain k_3 and k_5 are obtained from the trial and error. In the LQR method, a matrix of $Q \in R^{6x6}$ and $R \in R^{4x4}$ are needed to find the gain value. The next step is to calculate ω_r. The equation for estimating the value ω_r is defined is being as:

$$\widehat{\omega}_r = \hat{S} \sqrt{\frac{\hat{\xi}^2{}_\alpha + \hat{\xi}^2{}_\beta}{\hat{\lambda}^2{}_{\alpha r} + \hat{\lambda}^2{}_{\beta r}}} \quad (22)$$

where $\hat{S}$ is a signum function which is defined is being as:

$$\hat{S} = sign(\hat{\xi}_\alpha \hat{\lambda}_{\alpha r} + \hat{\xi}_\beta \hat{\lambda}_{\beta r} \quad (23)$$

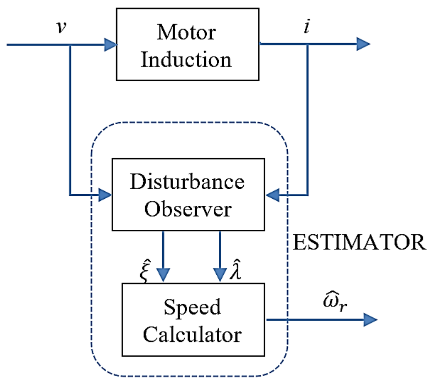

Figure 1. The basic concept of the proposed DO based-estimator

3. RESEARCH METHOD

The components used in this study are an induction motor as a plant, current sensor to measure the current coming out of the inverter, speed sensor to measure actual motor speed. A more detailed explanation as follows:

- The 3-phase induction motor used in this study is the A-Y3A series three-phase asynchronous motor from alliance motor. This motor has a squirrel cage type that has a fan cooling. This A-Y3A series motor features compact structure, low noise, high efficiency, large torque, and excellent starting performance.
- The inverter is used to generate a three-phase voltage which is the input for the induction motor. The frequency of this three-phase voltage affects the speed of the induction motor. Therefore, to make the induction motor work at the desired speed (setpoint), the inverter gets a direct current (DC) signal input whose value is equal to the frequency value which is proportional to the setpoint speed value.
- For current measurement used hall effect current sensor H3A-ACDC whose data is sent to Simulink via data acquisition (DAQ) board. This module is used to read AC current from the inverter to the induction motor. The current measurement module used has a measurement range of 0.91 A–1.36 A with an accuracy rate of 97%.
- The result of the current measurement becomes the input for the estimator build on Simulink-MATLAB. In addition, the estimator gets a simulated voltage signal that is generated with a frequency whose value is the same as the result of the frequency calculation based on the setpoint value used in the inverter.
- The speed measurement module uses an infrared (IR) speed sensor HW-201 which is connected to the Arduino, so that the actual speed value of the induction motor can be known. This measurement data is used to validate the estimation result of the proposed estimator. The speed measurement module used has a measurement range of 100–650 RPM with an accuracy rate of 98.3%. The block diagram of the entire system can be seen on Figure 2, while the setup experiment is shown in Figure 3.

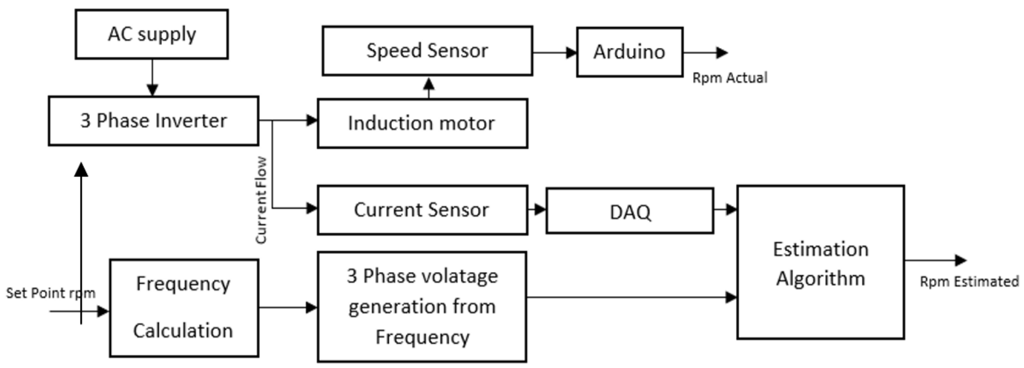

Figure 2. Block diagram of the real-time estimator

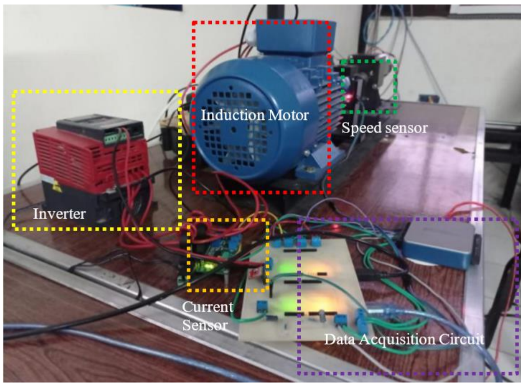

Figure 3. Induction motor plant hardware circuit

4. RESULTS AND DISCUSSION

The realtime estimator based on DO carried out at several RPM. The designed estimator was tested to determine the performance of the estimator. The test was carried out by comparing the average readings from the speed sensor and the estimator results at steady state conditions. The performance of DO-estimator is also compared with the estimator based on EKF at the same speed.

4.1. Realtime test results using the disturbance observer estimator

The results of realtime speed estimation using DO for one speed case (i.e. the setpoint value of 350 RPM) are shown in Figure 4. It can be seen that the speed estimator has obtained good results. The estimate values are almost the same as the measurement value so that the average error value is 0.029% of the measured speed. The calculation of the error value for another speed is as shown in Table 2. It can estimate the motor speed value where the error value for all speeds is below of 4%.

Note, that the measurement value is not the same as the setpoint value. This is because there is no controller that works on this plant so that the speed of the induction motor cannot be made the same as the setpoint. Thus, the value of the inverter voltage to the motor is not the same as the value of the frequency-based generation voltage (see Figure 2) which is one of the inputs for the estimator. So this contributes to the estimation error. However, because the deviations from the setpoints are only below 4%, the generated voltage signal can be assumed to be close to the actual inverter voltage value.

At steady state, the RMSE value from the estimation results tends to decrease with increasing motor speed. The smallest RMSE value is 0.979%. While the largest RMSE value is at the motor speed of 242.683 RPM, which is 4.296%. This indicates the lower limit of the motor speed at which the DO estimator is still able to estimate with the error of about under 4%.

The dynamic response of the DO estimator results in a slight overshoot as a result of the high observer gain. This high gain is the observer's way of overcoming the disturbance so that the estimation results are good. To reach the steady state condition, the estimator takes 0.20 seconds in average. There is a dead time of about 0.1 second.

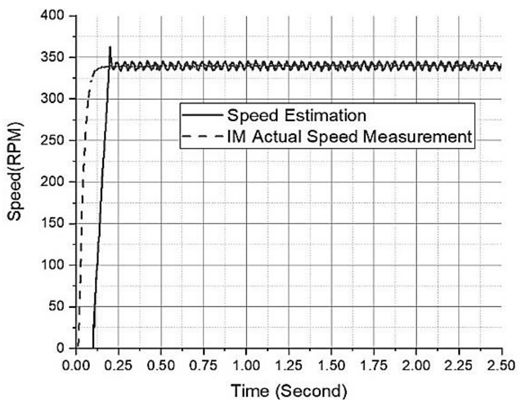

Figure 4. Speed estimate for the setpoint of 350 RPM using DO

Table 2. RMSE value estimation and measurement using DO

The Setpoint value	Average Speed Sensor measurement results	Average Speed Estimation Results	Average Error (%)	RMSE Steady state (%)
250	242.683	251.783	3.749	4.296
300	290.264	294.375	1.416	1.710
350	339.938	340.038	0.029	0.979
400	387.330	390.098	0.714	1.509
450	431.866	437.629	1.334	1.408

4.2. Comparison of disturbance observer estimator with extended Kalman filter estimator

The following is a comparison of the final results of real-time speed estimation using the DO and EKF where the estimation graph was obtained at several speed, one of them on the setpoint of 500 RPM as shown in Figure 5. From this comparison, it can be concluded that the speed estimator using the DO has a smaller RMSE than one using the EKF. In addition, the initial performance of the EKF estimator appears to be worse than that of the DO estimator, although the settling time is slightly faster. For another speed, the RMSE value of both estimators can be seen on Table 3.

At the setpoint speed of 500 RPM, the RMSE value of the DO-based estimator and the EKF-based estimator is almost the same, which is around 2.5%. From the DO estimator side, this error value is greater than the error value in the setpoint speed range of 350–450 rpm. So, it can be concluded that there is an upper limit of the motor speed value where the DO estimator still works with an error below 4%, namely at the setpoint of 600 RPM.

The speed estimation results from the EKF estimator show that the RMSE value increases as the motor speed decreases. The lower limit setpoint value where the EKF estimator still produces an estimate with an error below 4% is at 500 RPM, which is higher than the one of the DO estimators. Meanwhile, the upper limit of the setpoint speed at which the EKF estimator produces an estimate with an error below 4% cannot be determined because the speed sensor's measuring range is only up to 650 RPM. Thus, it can be concluded that the range of estimates of the DO estimator is between 250 RPM–600 RPM, while the estimated range of the EKF observer is above 500 RPM.

From the point of view of the working range, the DO-based estimator is able to overcome nonlinearity better than the EKF-based estimator. It is commonly known that the nonlinearity of the motor will be higher at low-speed operation. While the derivation of the EKF algorithm applies the linearization method. It is seen in the data of Table 3, the lower the motor speed, the greater the RMSE value of the EKF. In the DO, the linearization technique is not performed. The nonlinearity aspect is accommodated as a nuisance so that this makes the DO able to work in a larger range of nonlinearity.

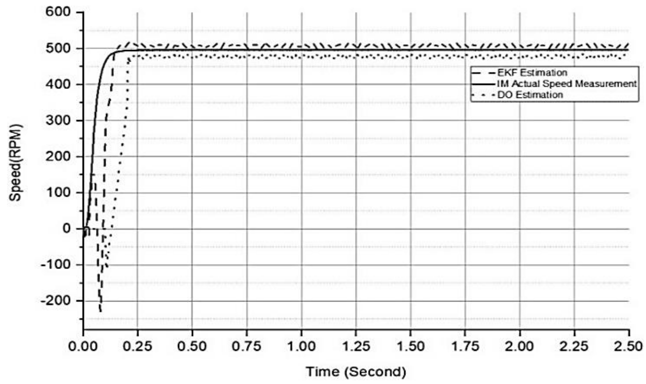

Figure 5. Comparison of realtime estimator for the setpoint of 500 RPM

Table 3. The RMSE steady value comparation of the DO and the EKF

The Setpoint Value	RMSE of the DO (%)	RMSE of the EKF (%)
350	0.979	12.134
400	1.509	7.489
450	1.408	4.984
500	2.449	2.574
550	2.643	1.844
600	4.029	1.084
650	4.458	0.637

5. CONCLUSION

The induction motor speed estimator based on DO has been successfully applied in real time for low speed induction motor operation, namely 250 RPM–600 RPM. The estimator can estimate the motor speed value in real time where the steady-state error value expressed in RMSE for all speeds is below 4%. The results of the comparison between the DO-based estimator and the EKF-based estimator show that the DO-based estimator excels in handling errors due to nonlinearity. Based on these results, a speed sensorless control for the induction motor can be designed using the DO-based estimator for further research. Furthermore, with the integration with the control system, it is expected that the estimation results are better than those reported now because the assumptions used in voltage generation are no longer used.

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REFERENCES

[1] H. Yu and J. Hu, “Speed and Load Torque Estimation of Induction Motors based on An Adaptive Extended Kalman Filter,” *Advanced Materials Research*, vol. 433, pp. 7004–7010, 2012, doi: 10.4028/www.scientific.net/AMR.433-440.7004.

[2] F. Gustafsson, "Rotational speed sensors: limitations, pre-processing and automotive applications," in *IEEE Instrumentation & Measurement Magazine*, vol. 13, no. 2, pp. 16–23, Apr. 2010, doi: 10.1109/MIM.2010.5438333.

[3] E. Kessler and W. Schulter, “Method for Establishing the Rotational Speed of Mechanically Commutated DC Motors,” *U.S. Patent 6144179 A*, Nov. 2000. [Online]. Available: https://patents.google.com/patent/US6144179A/en.

[4] Z. Wang, Y. Zheng, Z. Zou, and M. Cheng, "Position Sensorless Control of Interleaved CSI Fed PMSM Drive with Extended Kalman Filter," in *IEEE Transactions on Magnetics*, vol. 48, no. 11, pp. 3688–3691, Nov. 2012, doi: 10.1109/TMAG.2012.2197180.

[5] A. Pal, S. Das, and A. K. Chattopadhyay, "An Improved Rotor Flux Space Vector Based MRAS for Field-Oriented Control of Induction Motor Drives," in *IEEE Transactions on Power Electronics*, vol. 33, no. 6, pp. 5131-5141, Jun. 2018, doi: 10.1109/TPEL.2017.2657648.

[6] W. Yaonan, L. Jiantao, H. Shoudao, and Q. Sihai, "Speed sensorless vector control of induction motor based on the MRAS theory," *The 4th International Power Electronics and Motion Control Conference, 2004. IPEMC 2004.*, vol. 2, pp. 645–648, 2004. [Online]. Available: https://ieeexplore.ieee.org/document/1375643.

[7] Z. Yin, G. Li, Y. Zhang, J. Liu, X. Sun, and Y. Zhong, "A Speed and Flux Observer of Induction Motor Based on Extended Kalman Filter and Markov Chain," in *IEEE Transactions on Power Electronics*, vol. 32, no. 9, pp. 7096–7117, Sep. 2017, doi: 10.1109/TPEL.2016.2623806.

[8] F. Alonge, T. Cangemi, F. D'Ippolito, A. Fagiolini, and A. Sferlazza, "Convergence Analysis of Extended Kalman Filter for Sensorless Control of Induction Motor," in *IEEE Transactions on Industrial Electronics*, vol. 62, no. 4, pp. 2341–2352, Apr. 2015, doi: 10.1109/TIE.2014.2355133.

[9] M. Koteich, A. Maloum, G. Duc, and G. Sandou, "Discussion on “AC Drive Observability Analysis”," in *IEEE Transactions on Industrial Electronics*, vol. 62, no. 11, pp. 7224–7225, Nov. 2015, doi: 10.1109/TIE.2015.2438777.

[10] O. Aydogmus and M. F. Talu, "Comparison of Extended-Kalman-and Particle-Filter-Based Sensorless Speed Control," in *IEEE Transactions on Instrumentation and Measurement*, vol. 61, no. 2, pp. 402–410, Feb. 2012, doi: 10.1109/TIM.2011.2164851.

[11] N. K. Quang, N. T. Hieu, and Q. P. Ha, "FPGA-Based Sensorless PMSM Speed Control Using Reduced-Order Extended Kalman Filters," in *IEEE Transactions on Industrial Electronics*, vol. 61, no. 12, pp. 6574–6582, Dec. 2014, doi: 10.1109/TIE.2014.2320215.

[12] M. Barut, S. Bogosyan, and M. Gokasan, "Speed-Sensorless Estimation for Induction Motors Using Extended Kalman Filters," in *IEEE Transactions on Industrial Electronics*, vol. 54, no. 1, pp. 272–280, Feb. 2007, doi: 10.1109/TIE.2006.885123.

[13] E. Zerdali and M. Barut, "The Comparisons of Optimized Extended Kalman Filters for Speed-Sensorless Control of Induction Motors," in *IEEE Transactions on Industrial Electronics*, vol. 64, no. 6, pp. 4340–4351, Jun. 2017, doi: 10.1109/TIE.2017.2674579.

[14] I. M. Alsofyani and N. R. N. Idris, "Lookup-Table-Based DTC of Induction Machines with Improved Flux Regulation and Extended Kalman Filter State Estimator at Low-Speed Operation," in *IEEE Transactions on Industrial Informatics*, vol. 12, no. 4, pp. 1412–1425, Aug. 2016, doi: 10.1109/TII.2016.2571682.

[15] S. Jafarzadeh, C. Lascu, and M. S. Fadali, "State Estimation of Induction Motor Drives Using the Unscented Kalman Filter," in *IEEE Transactions on Industrial Electronics*, vol. 59, no. 11, pp. 4207–4216, Nov. 2012, doi: 10.1109/TIE.2011.2174533.

[16] K. L. Shi, Y. K. Wong, and S. L. Ho, “Speed estimation of an induction motor drive using an optimized extended Kalman filter,” *IEEE Transactions on Industrial Electronics*, vol. 49, pp. 124–133, Feb. 2002, doi: 10.1109/41.982256.

[17] O. Aydogmus and S. Sunter, “Implementation of EKF based sensorless drive system using controlled PMSM fed by a matrix converter,” *Electrical Power and Energy Systems*, vol. 43, no. 1, pp. 736–743, Dec. 2012, doi: 10.1016/j.ijepes.2012.06.062.

[18] S. Allaoui, K. Chafaa, Y. Laamari, and B. Athamena, "Induction motor state estimation using tuned Extended Kalman Filter," *2015 4th International Conference on Electrical Engineering (ICEE)*, 2015, pp. 1–5, doi: 10.1109/INTEE.2015.7416676.

[19] K. Indriawati, F. P. Wijaya, and C. Mufit, "Comparing Particle Filter, Adaptive Extended Kalman Filter and Disturbance Observer for Induction Motor Speed Estimation," *2020 12th International Conference on Information Technology and Electrical Engineering (ICITEE)*, 2020, pp. 57–62, doi: 10.1109/ICITEE49829.2020.9271744.

[20] G. P. Huang, A. I. Mourikis, and S. I. Roumeliotis, "Analysis and improvement of the consistency of extended Kalman filter based SLAM," *2008 IEEE International Conference on Robotics and Automation*, 2008, pp. 473–479, doi: 10.1109/ROBOT.2008.4543252.

[21] R. Schneider and C. Georgakis, “How to NOT Make the Extended Kalman Filter Fail,” *Industrial & Engineering Chemistry Research*, vol. 52, no. 9, pp. 3354–3362, Jan. 2013, doi: 10.1021/ie300415d.

[22] A. Ahmadian and A. M. Pezeshk, "A modified extended Kalman filter for bearings-only tracking," *2014 22nd Iranian Conference on Electrical Engineering (ICEE)*, 2014, pp. 1712–1716, doi: 10.1109/IranianCEE.2014.6999814.

[23] K. Indriawati, B. L. Widjiantoro, and N. R. Rachman, "Disturbance Observer-Based Speed Estimator for Controlling Speed Sensorless Induction Motor," *2020 3rd International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 2020, pp. 301–305, doi: 10.1109/ISRITI51436.2020.9315387.
[24] B. Peterson, "Induction Machine Speed Estimation-Observations on Observers," *Lund Institute of Technology (LTH)*, Sweden, 1996.
[25] M. Adamowicz, "Observer of induction motor speed based on simplified dynamical equations of disturbance model," *Doctoral school of energy and geotechnology*, pp. 63–67, Jan. 2006.

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