

Article

Adaptive Sliding Mode Observers for Speed Sensorless Induction Motor Control and Their Comparative Performance Tests

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Abstract

This paper presents adaptive sliding mode observers (A-SMOs) performing speed estimation for sensorless induction motor drives utilized in both industrial and electrical vehicle (EV) applications due to their computational simplicity. The fact that the constant switching gain (λ_0) is used in conventional SMOs (C-SMOs) leads to the chattering problem, especially in low-speed regions. To tackle this issue, this paper proposes two different λ_0 adaptation mechanisms based on fuzzy and curve fitting methods. To estimate stator stationary axis components of stator currents and rotor fluxes together with the rotor speed, the proposed A-SMOs only utilize the measured stator currents and voltages of the IM. Here, the difference only between the estimated and measured stator currents is determined as the sliding surface in the proposed A-SMOs. To demonstrate the effectiveness of the proposed fuzzy-based A-SMO (FA-SMO) and curve fitting-based A-SMO (CFA-SMO), they are compared with C-SMO in real-time experiments for different scenarios including wide speed range operations of IM with/without load torque changes. Moreover, the stator and rotor resistances as well as the magnetizing inductance variations are also examined in real-time experiments of the proposed methods and the conventional one. The estimation results demonstrate how positively the λ_0 adaptations in FA-SMO and CFA-SMO affect the performance of C-SMO. Finally, two A-SMOs with improved performance are introduced and verified through real-time experiments.

Keywords: induction motor; sliding mode observer; fuzzy logic adaptation; curve fitting adaptation



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1. Introduction

With the developing technology in recent years, speed sensorless induction motor (IM) control has become increasingly important because of IM's low cost, widespread use, and advanced drive technology [1]. Depending on the application, the speed sensorless IM drives require the estimation of rotor speed (ω_m) as well as the stator stationary axis components of stator ($\varphi_{s\alpha}$ and $\varphi_{s\beta}$) or rotor fluxes ($\varphi_{r\alpha}$ and $\varphi_{r\beta}$) [2]. To carry out these estimations, various state observers/estimators have been proposed in the literature such as model reference adaptive systems (MRAS) [3], Kalman filter-based observers [4,5], Luenberger observer [6,7], and sliding mode observer (SMO) [8,9].

Conventional MRAS estimators suffer from the use of pure integrators and performance degradation due to parameter changes. To overcome these problems, different adaptation methods are used in the adaptation mechanism of the MRAS estimators in the literature such as least mean square and least mean Kurtosis algorithms [10]. Furthermore, hybrid structures are used to make MRAS methods robust against parameter variations [11]. Additionally, Kalman filter-based solutions are employed because they can conduct real-time estimations of states and parameters, accounting for system/process errors and measurement noises directly [4]. However, the obvious drawbacks of Kalman filter-based methods are difficulties in implementing them in a digital signal processor (DSP) due to their high complexity [12] and the laborious selection process of noise covariance matrices [13]. On the other hand, considering the extended Luenberger method, the pole-placement process needs to be performed by determining an appropriate gain matrix selection, which can be classified as one of the difficulties of this method [7] together with its sensitivity to changes in IM parameters.

Compared to other estimators/observers detailed above, the advantages of the sliding mode observer (SMO) can be given as low computational load, ease in implementation to DSP, and higher performance against uncertainties [14,15]. As is known, correct determinations of the model parameter values play a key role in the performance of the estimators/observers. Even if the IM parameter values are well determined, the observer and thus control performance may not be satisfying because of the parameter variations caused by the temperature, frequency, and flux level changes [16]. Since SMO is classified as a robust method, various SMO-based studies have been conducted on state/parameter estimation of IMs [17–19]. Due to the fact that parameter variations—particularly the stator and rotor resistances (R_s and R_r) in the low-speed region and the magnetizing inductance (L_m) in the field-weakening region—cause performance deterioration, the rotor speed (ω_m)-estimation performance of SMO has been improved in the literature through the online estimation of these varying parameters. In Wang et al. [20], a second-order SMO is combined by MRAS to perform ω_m estimation along with R_s estimation. In Mezouar et al. [21], the ω_m estimation is performed together with the inverse of the rotor time constant. In Zaky et al. [22], the R_s estimation is carried out to improve ω_m using SMO-based parallel identification schemes. Moreover, the L_m estimation is also performed in the field-weakening region operation. Furthermore, to improve the ω_m estimation performance, there are also hybrid structures utilized in the literature, as in Shen et al. [23], which uses a fuzzy dual sliding mode MRAS structure. Together with the advantages of the SMO technique, it also has some weaknesses such as chattering and parameter dependency since it is still a model-based method, and required time to reach the sliding surface. To overcome these problems, many SMO algorithms have been proposed so far, called first [24], high-order [25], and reaching law-based SMOs [8,26].

Given the different SMO algorithms, super-twisting SMO (STSMO) is one of the most well-known high-order SMO methods [9,27,28]. High-order SMOs are generally proposed to solve the chattering phenomenon in the first-order SMOs [29]. However, as stated in Gonzalez et al. [30], STSMOs do not compensate time-varying disturbances/uncertainties if they are designed with constant switching gains. Moreover, to solve chattering problems caused by the nature of conventional SMOs (C-SMOs) as in [24], fuzzy-based algorithms have been developed instead of the signum function used in C-SMOs [31]. Moreover, the sliding mode control law equations of high-order SMOs, such as STSMO, involve a relatively high computational load and include pure integration, as seen in Nurettin and Inanc [9] and Ammar et al. [28]. Additionally, other studies aim to eliminate the chattering components observed at the system output by employing a low-pass filter during rotor flux estimation [24,32]. However, in this case, it causes a delay in speed estimation and an

error in amplitude [19]. To solve this problem, a continuous hyperbolic tangent function is used instead of a low-pass filter [33]. Nevertheless, this method only guarantees the convergence of the sliding motion to the sliding surface. Furthermore, the chattering issue still persists due to the high switching gain (λ_0) [19]. Since using a constant λ_0 leads to chattering and performance degradation—particularly in the low-speed region—the value of λ_0 needs to be adjusted based on the operating conditions of IM. In addition to the aforementioned SMO techniques, adaptive SMO (A-SMO) methods that adjust λ_0 dynamically have also been proposed in the literature. A-SMOs have many advantages for speed estimation such as adaptation of switching gain and reduction in chattering problem in low-speed operation [9,18–20,25,34–40]. There are different approaches in the literature related to A-SMOs, which have observer gain adaptations and λ_0 or switching coefficient adaptation. The observer gain is changed depending on the IM parameters and ω_m [34,35,37]. When it comes to [9,18,19,25,36,38–42], Keyhani et al. [36] and Tarchala and Orłowska-Kowalska [38] propose a speed-adaptive SMO with a sliding surface defined as a function of stator current ($i_{s\alpha}$ and $i_{s\beta}$) errors and rotor fluxes. Here, the ω_m estimation is performed by multiplying the determined sliding surface and an adaptive λ_0 ; the adaptive λ_0 is obtained using a first-order polynomial of ω_m in both studies. In Hu et al. [39], an A-SMO is designed with a sliding surface determined as the stator current errors and the adaptive λ_0 values for each axis (α and β) are calculated as a function of IM parameters, the estimated states ($i_{s\alpha}$, $i_{s\beta}$, $\varphi_{r\alpha}$, $\varphi_{r\beta}$, and ω_m), and determined additional gain term. Therefore, the adaptive λ_0 value depends on the IM parameters, which results in the parameter sensitivity. Moreover, the trial and error method-based determination process of the additional gain terms can also be evaluated as a second drawback of the proposed method. In Kousalya and Singh [18], an adaptive STSMO (A-STSMO) is proposed with a sliding surface determined as the stator current errors. The speed-adaptive switching coefficients in STSMO are separately determined as functions of rotor speed and rotor speed squared. In Nurettin and Inanc [9], an A-STSMO with the same sliding surface defined in Kousalya and Singh [18] and Prince and Yoon [27] is proposed. Contrary to Kousalya and Singh [18], four switching coefficients, two for each axis, are used. One of the switching coefficients for each axis (α and β) is determined as constant while the other is adaptively calculated. Similar to Hu et al. [39] and Zerzeri et al. [42], the IM parameters, estimated states ($i_{s\alpha}$, $i_{s\beta}$, $\varphi_{r\alpha}$, $\varphi_{r\beta}$, and ω_m), and additional gain term are utilized in the determination of adaptive switching coefficients. In Sun et al. [19], an adaptive nonsingular terminal SMO (A-NTSMO) is introduced with a second-order nonsingular terminal sliding mode surface. Here, a speed-adaptive coefficient is used in A-NTSMO which contains a couple of constant coefficients to be determined. Therefore, the determination process of these constant coefficients can be evaluated as the difficulty of the proposed method. Wang et al. [25] and Bu et al. [43] propose a discrete SMO-based MRAS method with speed adaptation to avoid the chattering problem. The proposed discrete SMO-based MRAS in [25] is compared to existing STSMO-based MRAS with speed adaptation. In Wang et al. [41], a speed-adaptive high-order SMO is proposed to achieve finite-time convergence, and the method is compared with first-order and super-twisting SMOs. Two coefficients of the defined high-order sliding surface are selected as constants. Moreover, λ_0 is obtained as a first-order polynomial, independent of the estimated synchronous speed derived from the high-order SMO-based MRAS. In Bai et al. [40], an adaptive SMO structure that uses a continuous switching function instead of the *sng* function to suppress the chattering effect is proposed. In the proposed method, the λ_0 value is determined as the sum of the rotor speed and a constant coefficient, aiming to improve the performance in estimating the rotor speed and position information of the permanent magnet synchronous motor (PMSM). However,

the method used in this study to reduce the required time to approach the sliding surface also introduces a pure integration problem.

The main contribution of this paper is to propose two novel A-SMOs to overcome the operation speed region-based performance-deterioration problem of C-SMO as in [24] by changing the λ_0 value. The proposed A-SMOs use only the current errors in the sliding surface, similar to past studies [9,39] but with different adaptive mechanisms that are mathematically simpler and parameter-independent. This reality can be discovered by inspecting the adaptive mechanisms (Equation (23) in Nurettin and Inanc [9] and Equation (20) in Hu et al. [39]) which additionally require the estimated and/or measured states (flux and/or stator currents) and varying parameters (rotor time constant, L_m etc.); thus, the proposed adaptive mechanisms in this paper are more convenient than those of past studies [9,39] for real-time high performance control of industrial systems and electrical vehicles (EVs) requiring for speed sensorless drives. For λ_0 adaptation based on the operating speed, fuzzy logic and curve fitting methods are employed in the design of the proposed adaptive mechanisms. The motivation behind selecting these methods is that they introduce only a slight increase in computational load compared to the conventional SMO (C-SMO) [24], while also being parameter-independent and computationally simpler than those used in previous studies [9,39]. Since A-SMO with proposed adaptive mechanisms does not lead to a significant computational load increase, they can easily be used in the high performance control of EV and industrial systems. Therefore, the low-computational load characteristic, one of the most favourable sides of C-SMO [24], is also used in this paper. Moreover, the proposed A-SMOs with the online estimations of $i_{s\alpha}$, $i_{s\beta}$, $\varphi_{r\alpha}$, $\varphi_{r\beta}$, and ω_m only utilize measured stator voltages ($u_{s\alpha}$ and $u_{s\beta}$) as well as $i_{s\alpha}$ and $i_{s\beta}$. To show the effectiveness of the proposed fuzzy adaptive SMO (FA-SMO) and curve-fitting adaptive SMO (CFA-SMO) methods, they are tested in real-time experiments including wide speed range operation of IM with/without load torque changes. Additionally, the estimation performances of the proposed methods are fairly compared with that of C-SMO through real-time experiments in which all observers operate in parallel at the open-loop condition. Furthermore, to examine the effect of the parameter variation over the proposed A-SMOs and C-SMO, variations in R_s and R_r are performed in the low-speed region while the L_m -change is realized in the high-speed operation. Finally, the obtained experimental results demonstrate the superiority of the proposed λ_0 adaptive methods in this paper over C-SMO. Moreover, the experimental results clearly indicate that the proposed A-SMOs are highly promising candidates for sensorless IM drives utilized in both industrial and EV applications. In summary, the proposed methods in this study (FA-SMO and CFA-SMO) are different from:

- Nurettin and Inanc [9] utilizing STSMO and its adaptation mechanism sensitive to the parameters and states of IM.
- Kousalya and Singh [18] exploiting STSMO with the separately determined speed-adaptive two switching coefficients as functions of rotor speed and rotor speed squared, which results in problematic operations at zero speed, making both switching coefficients zero.
- Hu et al. [39] using C-SMO and its adaptation mechanism sensitive to the parameters and states of IM.
- Wang et al. [41] employing the high-order SMO defined with a mathematically complex sliding surface and the speed estimation performed by the high-order SMO-based MRAS.

This paper consists of five sections. Section 1 presents the literature review and the contribution of this study. Section 2 presents the dynamic model of IM and C-SMO equations. Section 3 explains FA-SMO and CFA-SMO to perform ω_m estimation. Section 4

presents the experimental setup, and shows the real-time results for C-SMO and the proposed A-SMOs to demonstrate the effectiveness of the proposed methods. Finally, Section 5 provides the conclusion.

2. Dynamic Model of IM and Conventional SMO

2.1. Dynamic Model of IM

Three-phase IMs are commonly modeled using a fifth-order nonlinear mathematical representation, under the assumptions of magnetic linearity (i.e., no saturation), negligible core losses, and insignificant effects from temperature and parameter variations. This model is well-suited for state-estimation purposes, as it offers a practical trade-off between computational complexity and estimation accuracy. It can be formulated in either the stationary reference frame (α - β) or the rotating reference frame (d - q). Similar to [8,9,24,27] in this study, the electrical equations of the IM model are expressed in the $\alpha\beta$ frame, as presented in Equations (1)–(4).

$$\frac{di_{s\alpha}}{dt} = \frac{L_m R_r}{\sigma L_m L_r^2} \varphi_{r\alpha} + \frac{L_m}{\sigma L_s L_r} \omega_m \varphi_{r\beta} - \frac{R_s L_r^2 + R_r L_m^2}{\sigma L_s L_r^2} i_{s\alpha} + \frac{1}{\sigma L_s} u_{s\alpha} \quad (1)$$

$$\frac{di_{s\beta}}{dt} = -\frac{L_m}{\sigma L_s L_r} \omega_m \varphi_{r\alpha} + \frac{L_m R_r}{\sigma L_m L_r^2} \varphi_{r\beta} - \frac{R_s L_r^2 + R_r L_m^2}{\sigma L_s L_r^2} i_{s\beta} + \frac{1}{\sigma L_s} u_{s\beta} \quad (2)$$

$$\frac{d\varphi_{r\alpha}}{dt} = -\frac{R_r}{L_r} \varphi_{r\alpha} - \omega_m \varphi_{r\beta} + \frac{R_r L_m}{L_r} i_{s\alpha} \quad (3)$$

$$\frac{d\varphi_{r\beta}}{dt} = \omega_m \varphi_{r\alpha} - \frac{R_r}{L_r} \varphi_{r\beta} + \frac{R_r L_m}{L_r} i_{s\beta} \quad (4)$$

where L_s , L_r , and L_m are the stator, rotor, and mutual inductances, respectively. $u_{s\alpha}$ and $u_{s\beta}$ represent the stationary axis components of stator voltages. Furthermore, $\sigma = 1 - (L_m^2)/(L_s L_r)$ is the leakage coefficient. Equations (1)–(4) can be represented in the matrix form as below:

$$\begin{bmatrix} \frac{di_{s\alpha}}{dt} \\ \frac{di_{s\beta}}{dt} \end{bmatrix} = k_1 \left(\begin{bmatrix} \frac{1}{T_r} & \omega_m \\ -\omega_m & \frac{1}{T_r} \end{bmatrix} \begin{bmatrix} \varphi_{r\alpha} \\ \varphi_{r\beta} \end{bmatrix} - \frac{1}{T_r} L_m \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} \right) - k_2 \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} + k_3 \begin{bmatrix} u_{s\alpha} \\ u_{s\beta} \end{bmatrix} \quad (5)$$

$$\begin{bmatrix} \frac{d\varphi_{r\alpha}}{dt} \\ \frac{d\varphi_{r\beta}}{dt} \end{bmatrix} = - \left(\begin{bmatrix} \frac{1}{T_r} & \omega_m \\ -\omega_m & \frac{1}{T_r} \end{bmatrix} \begin{bmatrix} \varphi_{r\alpha} \\ \varphi_{r\beta} \end{bmatrix} - \frac{1}{T_r} L_m \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} \right) \quad (6)$$

where $k_1 = (k_3 L_m)/L_r$, $k_2 = R_s/(\sigma L_s)$, $k_3 = 1/(\sigma L_s)$, and $1/T_r = R_r/L_r$.

The model in (5) and (6) can be defined in the following state-space form.

$$\begin{cases} \dot{x} = f(x, \omega_r) + Bu \\ y = h(x) \end{cases} \quad (7)$$

Remark 1. The system is said to be locally observable around point x_0 if the observability rank condition is satisfied; that is, the Jacobian of the stacked Lie derivatives with respect to the state vector x has full rank (which is 4 in this case).

The observability matrix $\mathcal{O}$, obtained from the gradients of these Lie derivatives [5], is constructed for the utilized IM model in this paper as follows:

$$\mathcal{O}(\mathbf{x}) = \begin{bmatrix} \nabla L_f^0 y_1 \\ L_f^0 y_2 \\ L_f^1 y_1 \\ L_f^1 y_2 \\ L_f^2 y_1 || L_f^2 y_2 \end{bmatrix}. \quad (8)$$

where $L_f^0 y_1 = i_{s\alpha}$, $L_f^0 y_2 = i_{s\beta}$, $L_f^1 y_1 = di_{s\alpha}/dt$, $L_f^1 y_2 = di_{s\beta}/dt$, and $L_f^2 y_1 || L_f^2 y_2 =$ function of $i_{s\alpha}, i_{s\beta}, \varphi_{r\alpha}, \varphi_{r\beta}, \omega_r$.

If this matrix has rank 4, the model is locally observable at the corresponding operating point. According to the analysis, when $\omega_r \neq 0$, the Lie derivatives exhibit nontrivial dependence on $\varphi_{r\alpha}$ and $\varphi_{r\beta}$ due to the speed-induced coupling between stator and rotor dynamics. As a result, the Jacobian of the Lie derivatives spans the full state space, satisfying the observability rank condition. In contrast, when $\omega_r = 0$, the Lie derivatives of the output functions fail to capture the full state information, particularly the rotor flux components, thereby rendering the system unobservable at standstill.

2.2. Conventional SMO

Looking at (5) and (6), a common term for current and flux equations stands out. Thus, this common term can be defined as a new matrix (G) as follows;

$$G = \begin{bmatrix} G_\alpha \\ G_\beta \end{bmatrix} = \left(\begin{bmatrix} \frac{1}{T_r} & \omega_m \\ -\omega_m & \frac{1}{T_r} \end{bmatrix} \begin{bmatrix} \varphi_{r\alpha} \\ \varphi_{r\beta} \end{bmatrix} - \frac{1}{T_r} L_m \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} \right) \quad (9)$$

Since the coupling (common) terms in (5) and (6) between the α - and β -axis are identical, it is possible to define a sliding mode function instead of these coupling terms. Subsequently, the sliding mode function can be employed to perform the estimation of the common terms as given in (9) [8]:

$$\begin{bmatrix} f_\alpha \\ f_\beta \end{bmatrix} = \hat{G} = \left(\begin{bmatrix} \frac{1}{T_r} & \hat{\omega}_m \\ -\hat{\omega}_m & \frac{1}{T_r} \end{bmatrix} \begin{bmatrix} \hat{\varphi}_{r\alpha} \\ \hat{\varphi}_{r\beta} \end{bmatrix} - \frac{1}{T_r} L_m \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix} \right) \quad (10)$$

Using the sliding mode function, the current and flux estimations can be performed with the help of (11) and (12). Here “ $\hat{\cdot}$ ” refers to the estimated state or parameters.

$$\begin{bmatrix} \frac{di_{s\alpha}}{dt} \\ \frac{di_{s\beta}}{dt} \end{bmatrix} = k_1 \begin{bmatrix} f_\alpha \\ f_\beta \end{bmatrix} - k_2 \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix} + k_3 \begin{bmatrix} u_{s\alpha} \\ u_{s\beta} \end{bmatrix} \quad (11)$$

$$\begin{bmatrix} \frac{d\hat{\varphi}_{r\alpha}}{dt} \\ \frac{d\hat{\varphi}_{r\beta}}{dt} \end{bmatrix} = - \begin{bmatrix} f_\alpha \\ f_\beta \end{bmatrix} \quad (12)$$

where

$$\begin{bmatrix} f_\alpha \\ f_\beta \end{bmatrix} = \begin{bmatrix} -\lambda_0 \text{sgn}(S_\alpha) \\ -\lambda_0 \text{sgn}(S_\beta) \end{bmatrix} \quad (13)$$

$$\text{sgn} = \begin{cases} -1 & : S_\alpha < 0 \\ 0 & : S_\alpha = 0 \\ 1 & : S_\alpha > 0 \end{cases} \quad (14)$$

As is well known, in (13), λ_0 is the switching gain of C-SMO which must be chosen large enough to obtain fast convergence of estimations and the stability of the observer. On the other hand, if a too large λ_0 is used in C-SMO, the estimated states will suffer from the chattering phenomenon. In this paper, it is also observed that the λ_0 value of C-SMO must be appropriately adjusted depending on the operation condition of IM, particularly with respect to the speed region, to enhance the estimation performance [44]. This is the reason why the λ_0 value is modified according to ω_m in the proposed A-SMO methods. Finally, the sliding surface is defined as follows:

$$\begin{bmatrix} S_\alpha \\ S_\beta \end{bmatrix} = \begin{bmatrix} \hat{i}_{s\alpha} - i_{s\alpha} \\ \hat{i}_{s\beta} - i_{s\beta} \end{bmatrix} \quad (15)$$

As seen in (12), flux estimation requires integration of f_α and f_β values. Due to the signum (sgn) function, f_α and f_β values change between positive and negative λ_0 values, resulting in high-frequency oscillation. In C-SMO, the equivalent control concept is utilized to maintain motion on the sliding surface and reducing the oscillation. For this purpose, the equivalent control term can be obtained as in (16) [39].

$$f_{\alpha\beta}^{eq} = \frac{1}{\mu s + 1} f_{\alpha\beta} \quad (16)$$

Here, the time constant (μ) of the low-pass filter should be large enough to eliminate high-frequency components and small enough to allow low frequency components of the f_α and f_β values. After defining the equivalent control term, (10) can be transformed to (17). Putting (17) into (12), then

$$\begin{bmatrix} f_\alpha^{eq} \\ f_\beta^{eq} \end{bmatrix} = \hat{G} = \left(\begin{bmatrix} \frac{1}{T_r} & \hat{\omega}_m \\ -\hat{\omega}_m & \frac{1}{T_r} \end{bmatrix} \begin{bmatrix} \hat{\phi}_{r\alpha} \\ \hat{\phi}_{r\beta} \end{bmatrix} - \frac{1}{T_r} L_m \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix} \right) \quad (17)$$

Rotor flux estimation can be performed as in (18).

$$\begin{bmatrix} \frac{d\hat{\phi}_{r\alpha}}{dt} \\ \frac{d\hat{\phi}_{r\beta}}{dt} \end{bmatrix} = - \begin{bmatrix} f_\alpha^{eq} \\ f_\beta^{eq} \end{bmatrix} \quad (18)$$

Realizing flux estimation by using (18) has some drawbacks such as DC offset due to a pure integration process. To overcome the DC offset problem and to obtain high estimation performance, a small amount of feedback maintaining the stability of the integral can be used as in [45]. After performing the flux estimation, ω_m can be estimated in the C-SMO method. To realize the ω_m estimation, row 1 and row 2 of (17) are multiplied by $\phi_{r\beta}$ and $\phi_{r\alpha}$, respectively, resulting in (19), and $\hat{\phi}_{r\alpha} f_\beta^{eq}$ is subtracted from $\hat{\phi}_{r\beta} f_\alpha^{eq}$. Thus, the resulting equation of ω_m can be obtained as in (20).

$$\begin{bmatrix} \hat{\phi}_{r\beta} f_\alpha^{eq} \\ \hat{\phi}_{r\alpha} f_\beta^{eq} \end{bmatrix} = \hat{G} = \left(\begin{bmatrix} \hat{\phi}_{r\beta} \frac{1}{T_r} & \hat{\phi}_{r\beta} \hat{\omega}_m \\ -\hat{\phi}_{r\alpha} \hat{\omega}_m & \hat{\phi}_{r\alpha} \frac{1}{T_r} \end{bmatrix} \begin{bmatrix} \hat{\phi}_{r\alpha} \\ \hat{\phi}_{r\beta} \end{bmatrix} - \frac{1}{T_r} L_m \begin{bmatrix} \hat{\phi}_{r\beta} \hat{i}_{s\alpha} \\ \hat{\phi}_{r\alpha} \hat{i}_{s\beta} \end{bmatrix} \right) \quad (19)$$

$$\hat{\omega}_m = \frac{\hat{\phi}_{r\beta} f_\alpha^{eq} - \hat{\phi}_{r\alpha} f_\beta^{eq} - \frac{1}{T_r} L_m (\hat{\phi}_{r\alpha} \hat{i}_{s\beta} - \hat{\phi}_{r\beta} \hat{i}_{s\alpha})}{\hat{\phi}_{r\alpha}^2 + \hat{\phi}_{r\beta}^2} \quad (20)$$

The expression in (20) can be used to estimate ω_m by using $\hat{i}_{s\alpha\beta}$ and $\hat{\phi}_{r\alpha\beta}$ values estimated by C-SMO. However, considering the C-SMO structure with (15), the measured and estimated $i_{s\alpha}$ and $i_{s\beta}$ are available, and utilized as in [46]. Thus, differently from past studies as in [8,24], the measured $i_{s\alpha}$ and $i_{s\beta}$ are used instead of estimated ones in (20) to reduce chattering effects on $\hat{\omega}_m$ in this paper. Thus, this paper also presents a comparison of

estimation performance, for which both measured and estimated currents are employed in the speed estimation. Examining the stability of the C-SMO method, the stability analysis of the current observer must be performed [24]. To perform the stability analysis, a positive definite Lyapunov function in (21) is chosen:

$$\dot{V} = \frac{1}{2} s_n^T s_n \quad (21)$$

where $s_n = [S_\alpha S_\beta]^T$. S_α and S_β are the values in (15). Due to the fact that a positive definite Lyapunov function is determined, the first Lyapunov stability condition is satisfied. To satisfy the second condition, the derivative of sliding mode functions must be negative definite as in (22).

$$\dot{V} = \frac{1}{2} \dot{s}_n^T s_n < 0 \quad (22)$$

Here, $\dot{s}_n$ refers to the derivative of s_n with respect to time.

$$\dot{s}_n = \begin{bmatrix} \dot{S}_\alpha \\ \dot{S}_\beta \end{bmatrix} \quad (23)$$

To obtain $\dot{s}_n$, (5) and (11) can be used. The resulting $\dot{s}_n$ is given in (24) and thus the derivative of the positive definite Lyapunov function can be calculated as in (25).

$$\dot{s}_n = k_1 \left(\begin{bmatrix} f_\alpha \\ f_\beta \end{bmatrix} \begin{bmatrix} \frac{1}{T_r} & \hat{\omega}_m \\ -\hat{\omega}_m & \frac{1}{T_r} \end{bmatrix} \begin{bmatrix} \hat{\phi}_{r\alpha} \\ \hat{\phi}_{r\beta} \end{bmatrix} - \frac{1}{T_r} L_m \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix} \right) - k_2 \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix} \quad (24)$$

$$\begin{aligned} \dot{V} = & k_1 \begin{bmatrix} S_\alpha \\ S_\beta \end{bmatrix}^T \left(\begin{bmatrix} f_\alpha \\ f_\beta \end{bmatrix} \begin{bmatrix} -\lambda_0 \text{sgn}(S_\alpha) \\ -\lambda_0 \text{sgn}(S_\beta) \end{bmatrix} - \begin{bmatrix} \frac{1}{T_r} & \hat{\omega}_m \\ -\hat{\omega}_m & \frac{1}{T_r} \end{bmatrix} \begin{bmatrix} \hat{\phi}_{r\alpha} \\ \hat{\phi}_{r\beta} \end{bmatrix} \right. \\ & \left. - \frac{1}{T_r} L_m \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix} \right) - k_2 \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix}^T \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix} \quad (25) \end{aligned}$$

To satisfy the second condition ($\dot{V} < 0$), the λ_0 value must be selected according to (26). In (26), the A and B values are as in (27) and (28), respectively.

$$\lambda_0 > \frac{|\hat{i}_{s\alpha} A + \hat{i}_{s\beta} B| - \frac{k_2}{k_1} (\hat{i}_{s\alpha}^2 + \hat{i}_{s\beta}^2)}{|\hat{i}_{s\alpha}| + |\hat{i}_{s\beta}|} \quad (26)$$

$$A = \frac{1}{T_r} \phi_{r\alpha} + \omega_m \phi_{r\beta} + \frac{1}{T_r} L_m \hat{i}_{s\alpha} \quad (27)$$

$$B = \frac{1}{T_r} \phi_{r\beta} + \omega_m \phi_{r\alpha} + \frac{1}{T_r} L_m \hat{i}_{s\beta} \quad (28)$$

As can be seen from (26), although a selected λ_0 number can guarantee the convergence of the current observer, an excessively large λ_0 can cause a chattering problem in the estimations. In this paper, it is also observed that the λ_0 value of C-SMO must be appropriately adjusted depending on the operation condition of IM, particularly with respect to the speed region to enhance estimation performance. This is why the λ_0 value is modified according to ω_m in the proposed A-SMO methods. This paper proposes two A-SMO methods to improve the estimation performance by changing λ_0 , and the proposed A-SMOs will satisfy the condition given in (26).

3. Proposed Adaptive SMO Methods

The accuracy of the estimated ω_m value depends on the accurate estimation of $\hat{i}_{s\alpha}$, $\hat{i}_{s\beta}$, $\phi_{r\alpha}$, and $\phi_{r\beta}$, as well as the used λ_0 value, as seen in (20). This paper first examines the effect

of λ_0 on the estimation performance at speeds from standstill to the rated speed and then determines a proper value of λ_0 for the specific operating speed. By using the empirically determined λ_0 values independent of the model disturbance bounds, two different A-SMO methods based on fuzzy logic and curve-fitting are designed and validated by experiments. In this paper, instead of model uncertainties, the upper bound of the λ_0 value is specifically determined by considering the speed estimation error and chattering. The details of the proposed adaptive structures are presented in the following subsections.

3.1. Fuzzy Adaptive SMO

In this subsection, the proposed FA-SMO method, using fuzzy logic to perform the λ_0 changes between the predetermined limits according to the operation speed of IM, is introduced. To realize the proposed FA-SMO method, the $\hat{n}_m$ (estimated rotor mechanical speed) feedback is needed to obtain the proper λ_0 value. The block diagram for the proposed FA-SMO is shown in Figure 1. Furthermore, the fuzzy logic-based adaptation mechanism used in the proposed FA-SMO is shown in Figure 2. In Figures 1 and 2, “ $\hat{\cdot}$ ” refers to the estimated state or parameter.

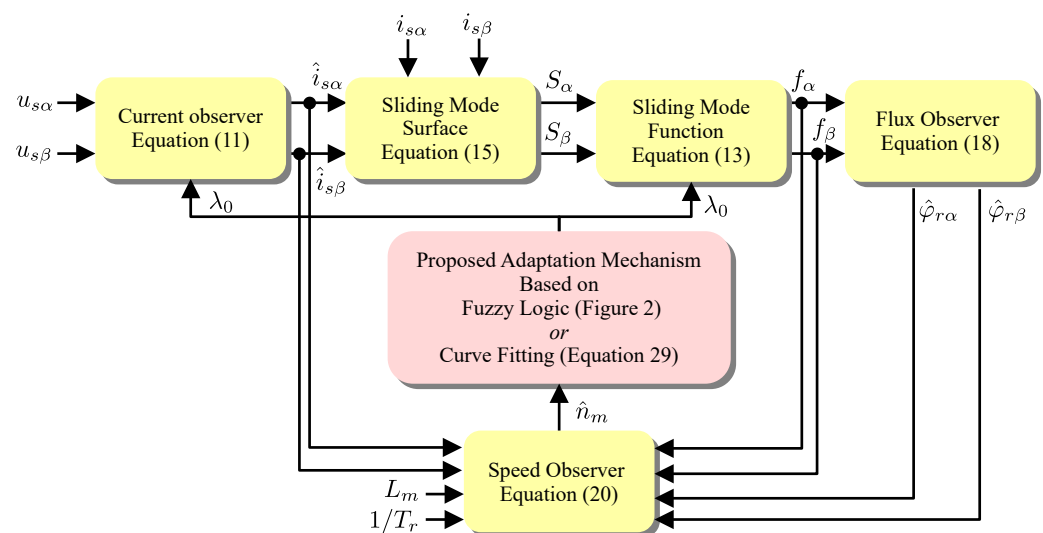


Figure 1. The block diagram of the proposed FA-SMO and CFA-SMO methods.

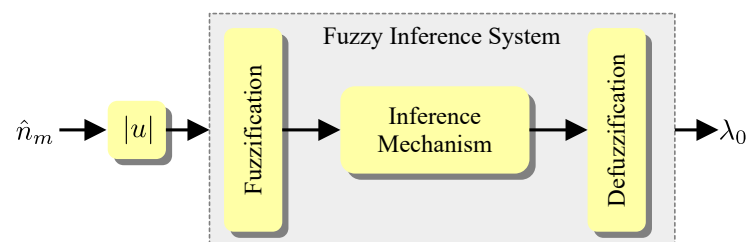


Figure 2. The fuzzy logic-based adaptation mechanism in the proposed FA-SMO.

Since the adaptive neuro-fuzzy inference system (ANFIS) tool of Matlab is utilized in the design process of FA-SMO, the defuzzification phase is carried out by using the wta-ver method based on the Sugeno inference method in Figure 2. In addition, during the training phase of the ANFIS block, the selected λ_0 values obtained through experimental experience are used as training data. The hybrid training method in the MATLAB 2024 ANFIS block is employed, which automatically determines the membership functions, as shown in Figures 3 and 4. Figure 5 presents the ANFIS model structure, while Figure 6 illustrates the fuzzy surface view between λ_0 and n_m . As a result of the training, a training error of 3.27

occurred. Here, the n_m value selected as input of the fuzzy system which has the following membership functions of very low (VL), low (L), medium (M), high (H), and very high (VH). By defining five membership functions, λ_0 changes are performed where λ_0 should be significantly changed according to the speed variation. To not significantly increase the computational load of FA-SMO, five membership functions resulting in low training error are chosen. In addition, Gaussian-shaped membership functions were preferred for the lowest training error. Five rules used in the proposed FA-SMO are given in Table 1.

Table 1. Rules used in the proposed FA-SMO.

Input Membership Functions	VL	L	M	H	VH
Output Membership Functions	VL	L	M	H	VH

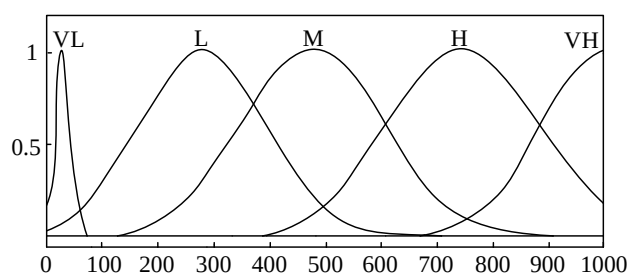


Figure 3. Fuzzy logic block input membership functions of FA-SMO.

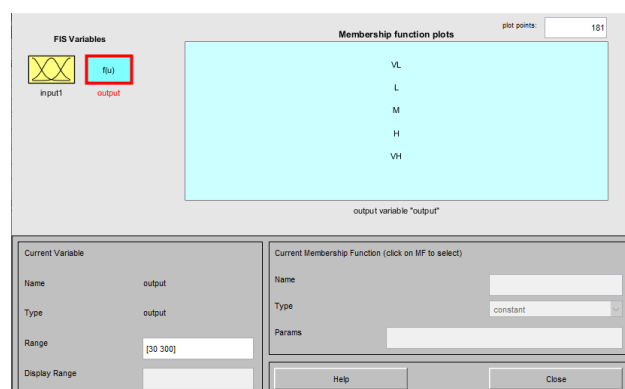


Figure 4. Fuzzy logic block output membership functions of FA-SMO.

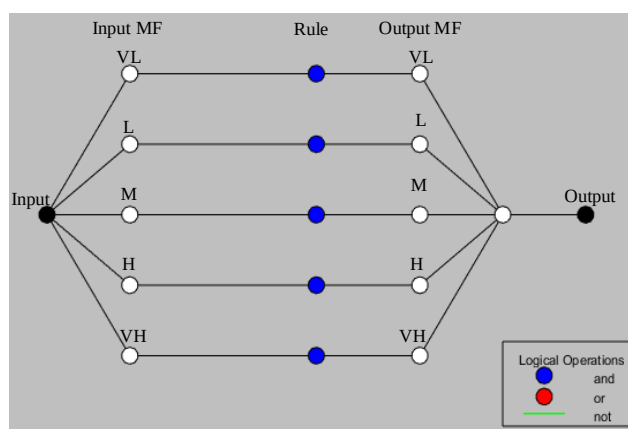


Figure 5. ANFIS model structure of FA-SMO.

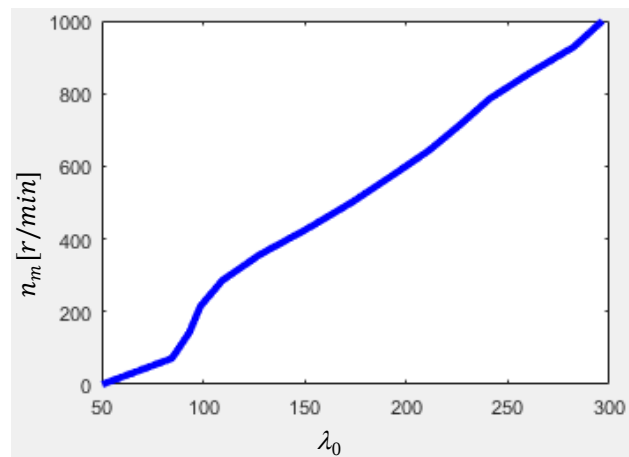


Figure 6. Fuzzy surface view (n_m - λ_0).

3.2. Curve Fitting Adaptive SMO

In this subsection, the curve fitting method is used to change λ_0 in the proposed CFA-SMO method given in Figure 1 to increase the estimation performance of C-SMO. Since the proper λ_0 values are determined in real-time experiments, it is noticed that it is possible to perform the λ_0 changes based on rotor speed by using a first-order function of n_m . Thus, using a simple function as in [36,38,41], λ_0 adaptation is achieved while preserving the computational efficiency of C-SMO, as in the FA-SMO method. The first-order function to be used for this purpose is determined using the Matlab Curve Fitting Toolbox as follows.

$$\lambda_0 = 0.2678|n_m| + 33.66 \quad (29)$$

As can be seen from (28), similar to the FA-SMO method, n_m feedback is required to calculate the proper λ_0 values in the CFA-SMO method. Thus, by using (28) in the λ_0 adaptation of CFA-SMO, it is possible to obtain a proper λ_0 value according to the operation speed of IM. Since both FA-SMO and CFA-SMO methods utilize experimentally determined λ_0 values, they present similar λ_0 values for the same operation speed of IM. Thus, the similar λ_0 values lead to similar performance for the proposed A-SMO methods in this paper.

4. Experimental Results

To test the proposed A-SMOs and demonstrate their superiority over C-SMO, they are tested in real-time experiments including a wide range of speeds with and without load variations. The experimental setup used in these tests is given in Figure 7, and its block diagram representation is illustrated in Figure 8. Here, a 30 N·m Foucault brake is used to load the three-phase squirrel-cage IM parameters which are presented in Table 2. To perform $i_{s\alpha\beta}$ and $u_{s\alpha\beta}$ measurements, LA55-P/SP1 and LV 100–400 transducers are used, respectively. Moreover, ω_m and t_L are measured by using an encoder with 5000 lines/rev and a 50 N·m torque transducer, respectively. As seen in Figure 8, the ω_m and t_L measurements are not utilized in the proposed A-SMOs and the C-SMO methods. The ω_m is measured only to validate the ω_m estimated by the proposed and conventional observers. Additionally, the t_L measurement is carried out to monitor the load condition under which IM operates. Furthermore, a three-phase array resistor is employed to externally add resistances in series R_s with the stator windings of the IM in order to investigate the effect of variations on the proposed A-SMOs and C-SMO. As shown in Figure 8, to ensure a fair comparison between the proposed A-SMOs and C-SMO, all observers are operated and tested under open-loop conditions, and an AC drive is utilized to drive the IM with pulse-width modulated voltages

and currents as in [5]. The proposed A-SMOs and the C-SMO methods were designed in the Matlab S-function block, using C/C++ language, and implemented on the DS1104 controller board. For online visualization of the data in real-time experiments, the dSPACE ControlDesk interface software is used. Utilizing the data-saving feature of ControlDesk, all data presented in this paper are saved and then plotted by using Matlab to provide high-quality figure presentations. Here, the sampling time (T) is 100 μ s for all tests. Also, as in [13], proposed A-SMOs are operated simultaneously and separately from the AC drive with utilization of $i_{s\alpha\beta}$ and $u_{s\alpha\beta}$ applied to IM, and the AC drive also runs in open-loop.

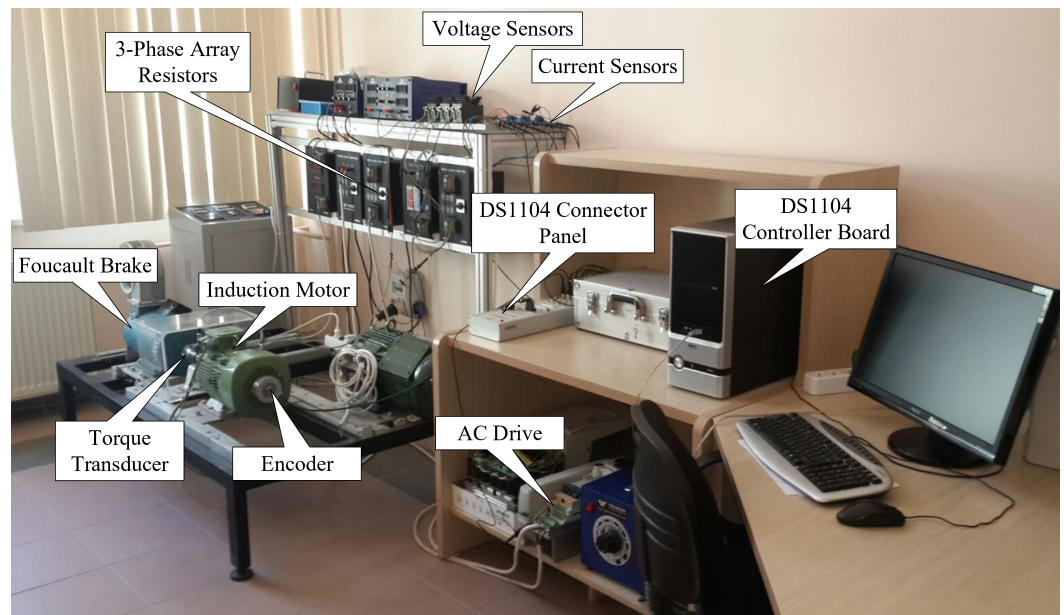


Figure 7. The experimental setup used in this paper.

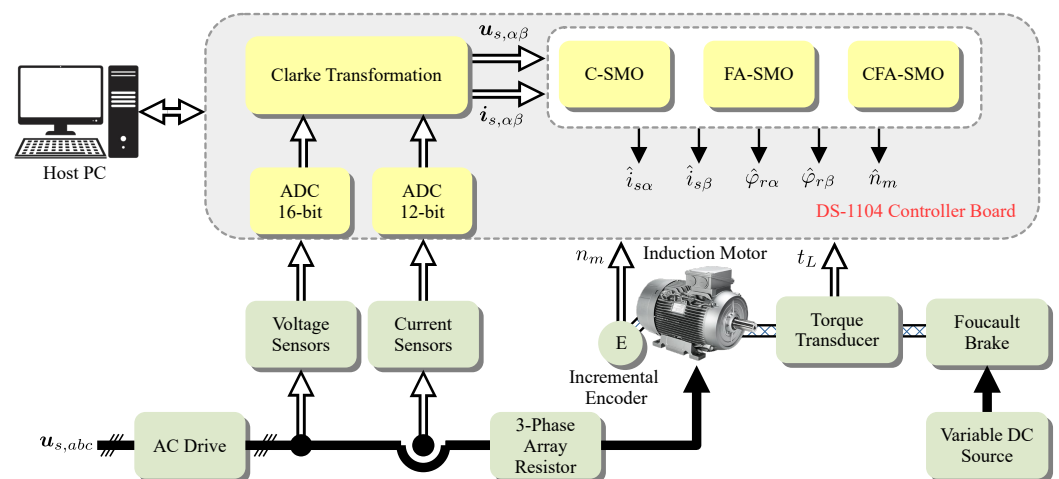


Figure 8. Block diagram of the experimental setup in Figure 7.

Table 2. The rated values and parameters of the three-phase IM used in experiments.

Parameter	Value	Parameter	Value
P	2.2 kW	R_s	3.03 Ω
V	380 V	R_r	2.54 Ω
I	5.5 A	L_s	0.1466 H
f	50 Hz	L_r	0.1524 H
N_m	950 r/min	L_m	0.135 H
τ_l	22 Nm	J_t	0.055 kg·m ²
p_p	3	B_t	0.001 Nm/(rad/s)

By utilizing the experimental setup in Figures 7 and 8, the proposed A-SMOs are tested under challenging scenarios including usage of measured and estimated current, zero speed operation, load variations, and parameter changes (R_s changes). In the real-time implementation of the proposed FA-SMO, the fuzzy logic controller is converted into a 1D look-up table to reduce the computational load and also the additional computational load caused by the proposed adaptive structures is obtained by measuring the execution time of each algorithm. Furthermore, the proposed A-SMOs are compared to C-SMO in all test scenarios. The details of the test scenarios are presented in the following subsections.

4.1. Scenario I: Usage of Measured Currents and Estimated Currents (Figure 9)

Scenario I tests the estimation performance of the measured stator currents of IM and the estimated currents of SMO in the case of sudden t_L variations for the high-speed region. Thus, the aim is to validate the correctness of the measured currents, used in (20) instead of the estimated currents which present chattering free against unknown t_L inputs. The obtained results are presented in Figure 9.

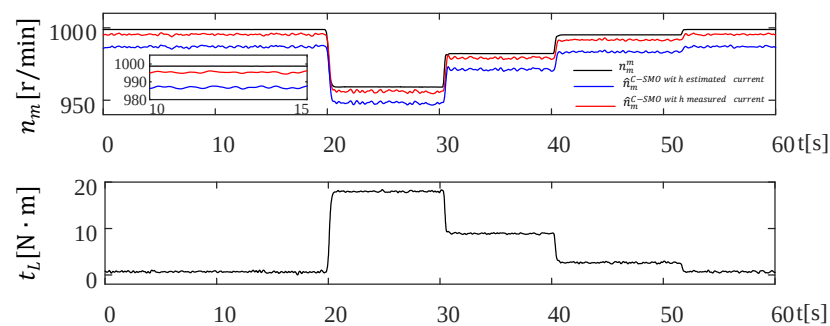


Figure 9. Test results against usage of the measured and estimated currents in the ω_m estimation.

4.2. Scenario II: Load Torque Variation Test (Figures 10–12)

Scenario II tests the estimation performance of the proposed A-SMOs and C-SMO in the case of sudden t_L variations for three different speed regions, namely high, medium, and low speeds. Thus, the aim is to validate the robustness of the proposed A-SMOs against unknown t_L inputs. The estimation results and corresponding estimation errors are presented in Figures 10–12 for high, medium, and low speeds, respectively. In all tests shown in Figures 10–12, it is also possible to see the changes of λ_0 in A-SMOs and their favorable effects on ω_m estimation by particularly inspecting e_{n_m} .

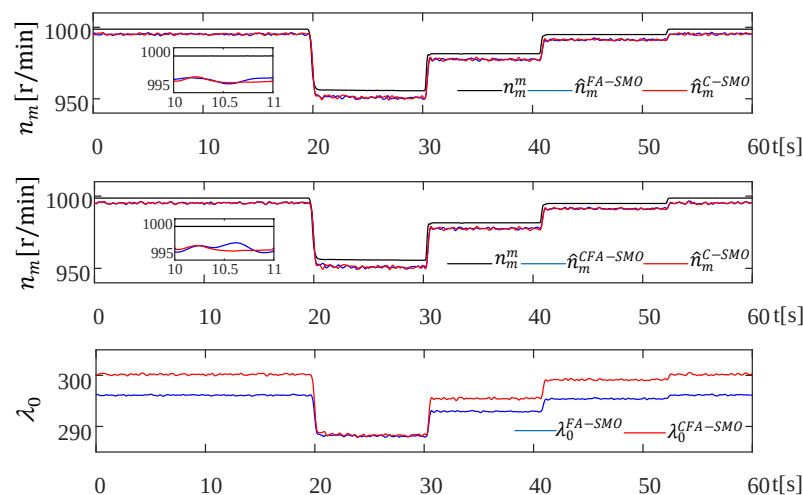


Figure 10. Cont.

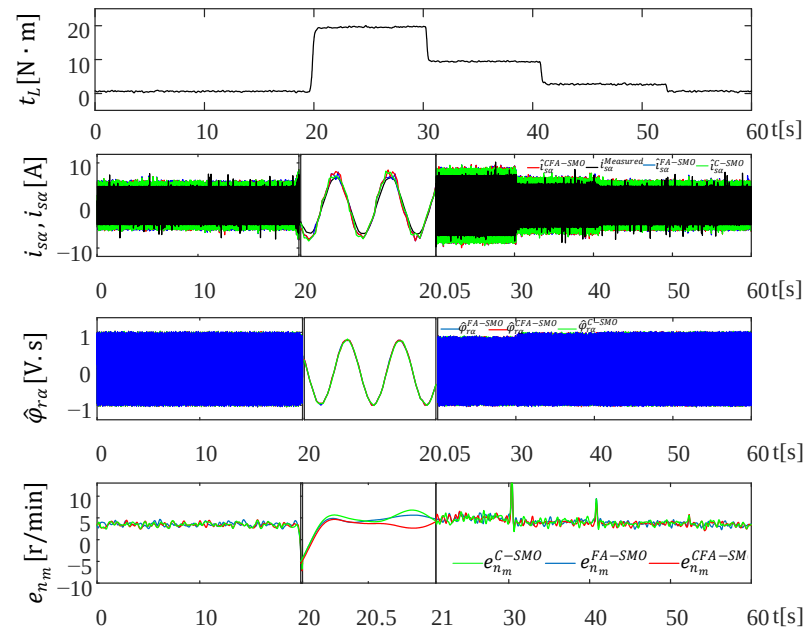


Figure 10. Real-time estimation results for steps like t_L changes in the high-speed region.

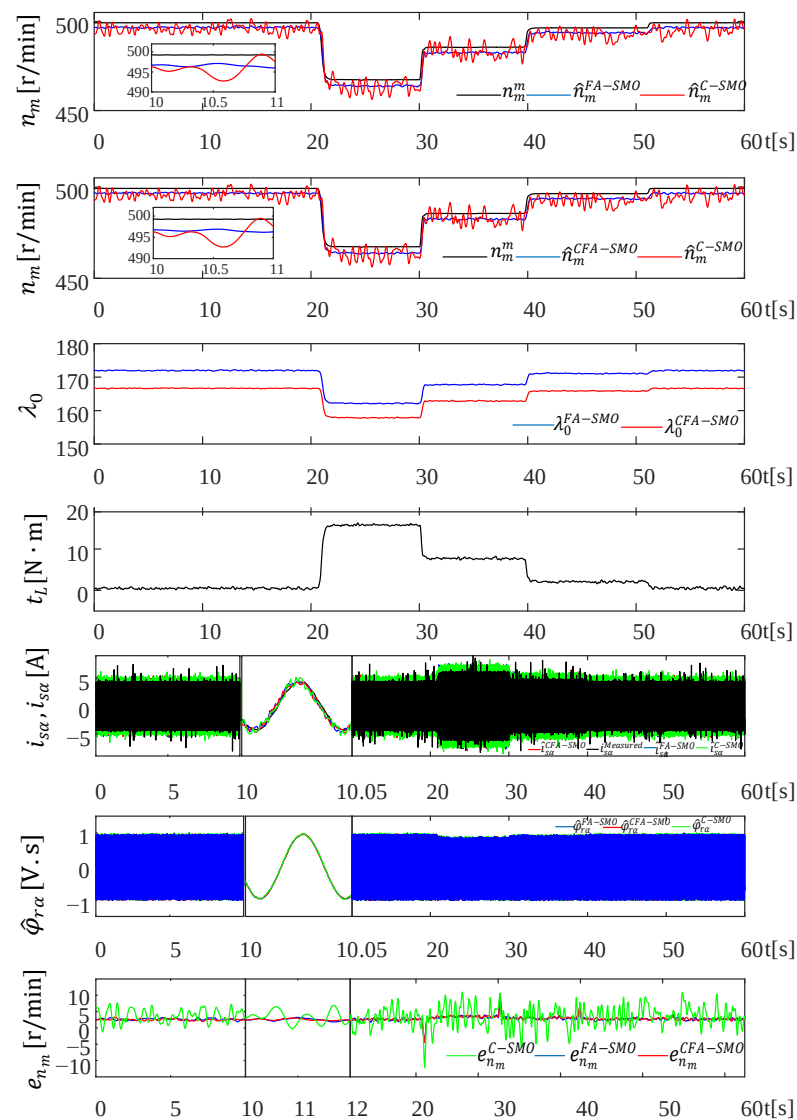


Figure 11. Real-time estimation results for steps like t_L changes in the medium-speed region.

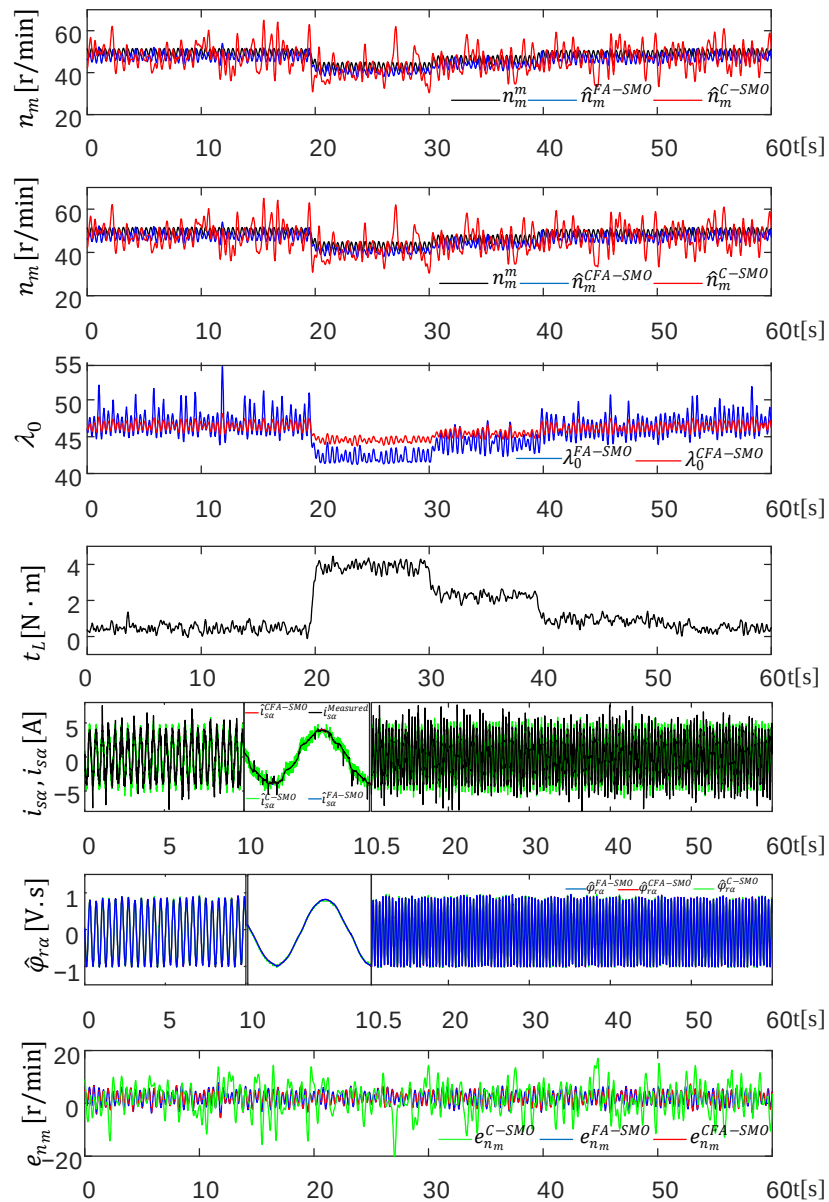


Figure 12. Real-time estimation results for steps like t_L changes in the low-speed region.

4.3. Scenario III: Speed-Reversal Test (Figure 13)

IM runs at its rated speed at no-load. After a sudden increase in load torque from no-load to rated load at approximately $t = 40$ s, the speed reversal is repeated at around $t = 50$ s. In this scenario demonstrated in Figure 13, the performance of the proposed A-SMO observers is intended to be tested in a wide range of speed ranges, including the nominal speed for each rotation direction. Additionally, λ_0 values calculated by A-SMOs and the Lyapunov stability criterion are compared in this scenario.

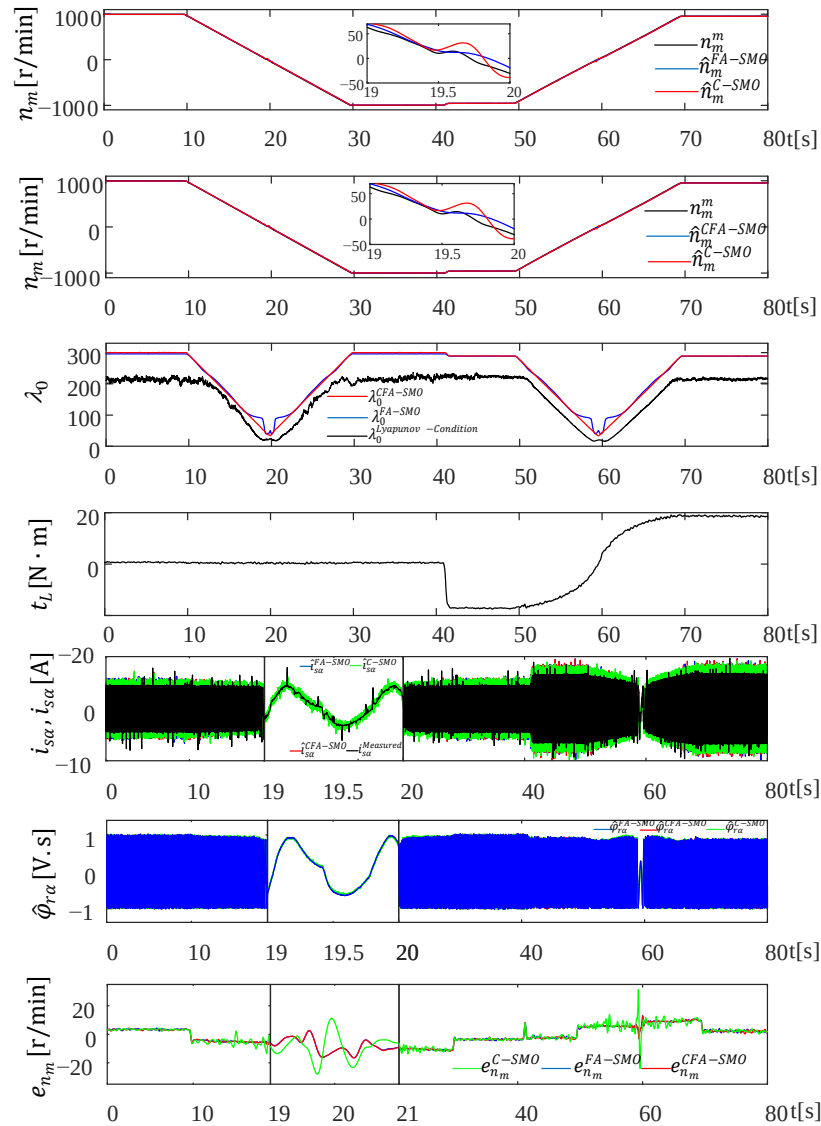


Figure 13. Estimation results for speed reversal with and without load conditions in the high-speed region.

4.4. Scenario IV: Sensitivity Tests on Parameters (Figures 14–16)

To examine the effects of parameter variations on the proposed A-SMOs, first of all an R_s -change test is performed in the low-speed region, where the R_s variation is more effective due to the relatively high voltage drop ratio on R_s . Later, the R_r -change is also examined in the low-speed operation, similar to R_s -change while L_m -change is performed in the high-speed operation. For this purpose, the R_s changes are performed as in Figure 14 through the group resistors connected in series to the stator terminals of IM. Since a squirrel cage IM is used in the experimental setup, it is not possible to change R_r by externally adding a group of series resistors. Therefore, to perform R_r variations in Figure 15, the applied R_r is defined as $R_r = \gamma \cdot R_{rn}$ in the A-SMOs and C-SMO algorithms, and the variations in R_r are generated by changing γ from 0 to 2. Similarly, the applied L_m is defined as $L_m = \eta \cdot L_{mn}$ in the A-SMOs and C-SMO algorithms, and thus variations in L_m at high-speed operation as in Figure 16 are developed by varying η from 0.5 to 2. Here, R_{rn} and L_{mn} are the rated values of R_r and L_m , respectively. γ and η represent uncertainties related to R_r and L_m , respectively. Thus, it is possible to compare the performance of the proposed A-SMOs with C-SMO under parameter variations.

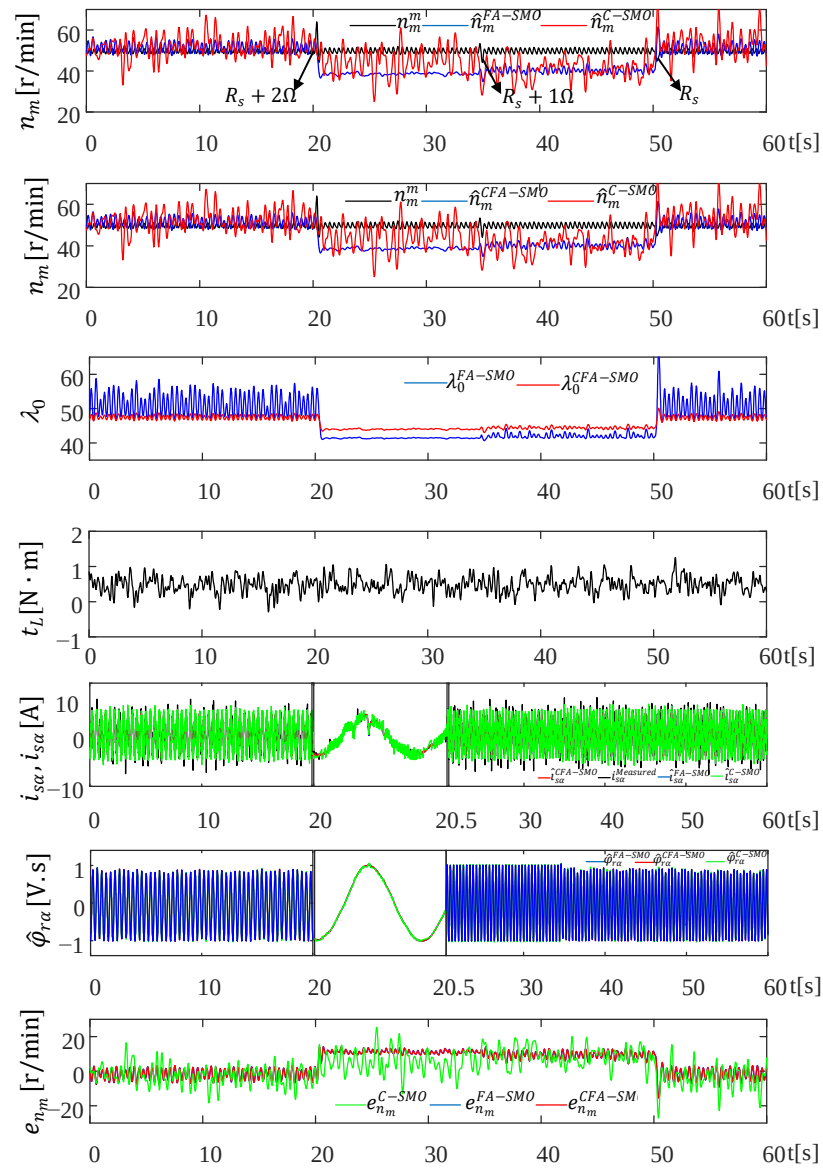


Figure 14. Estimation results for R_s changes in the low-speed operation region.

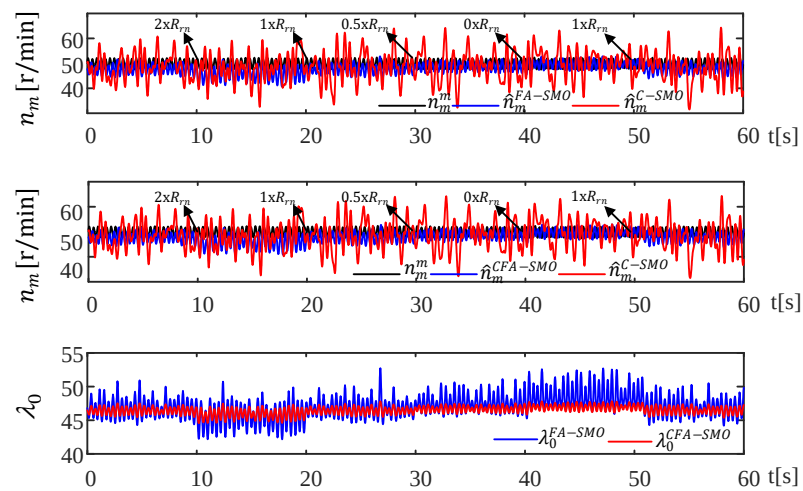


Figure 15. Cont.

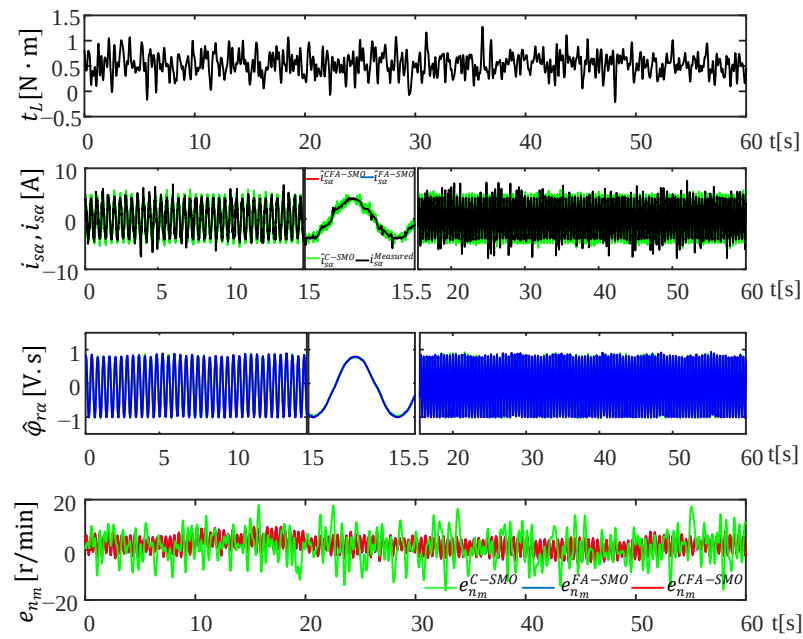


Figure 15. Estimation results for R_r changes in the low-speed operation region.

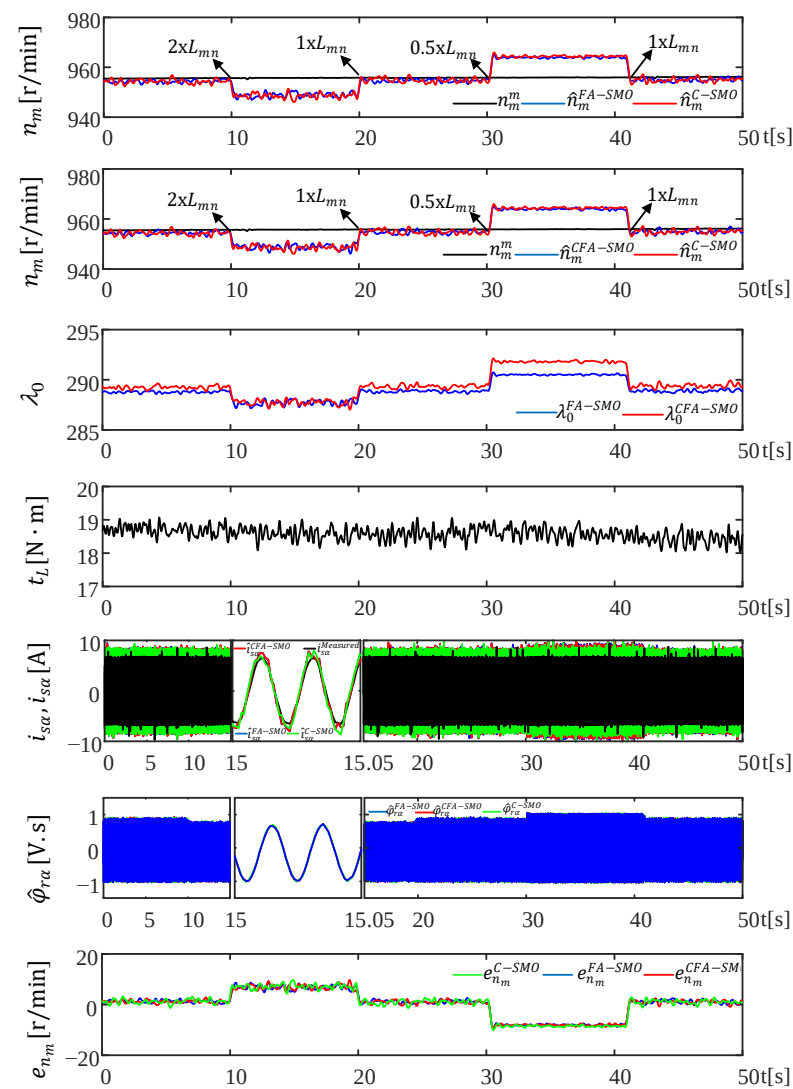


Figure 16. Estimation results for L_m changes in the high-speed operation region.

4.5. Scenario V: Continuous Zero Speed Test (Figure 17)

To test the estimation performance of the proposed A-SMOs in the case of continuous zero speed operation, the IM speed is decreased to zero while it is operating in the low-speed region without load as shown in Figure 17. The results confirm that the estimation performance of the proposed observers is still satisfactory and the estimations do not diverge despite the fact that IM is continuously operating at zero speed.

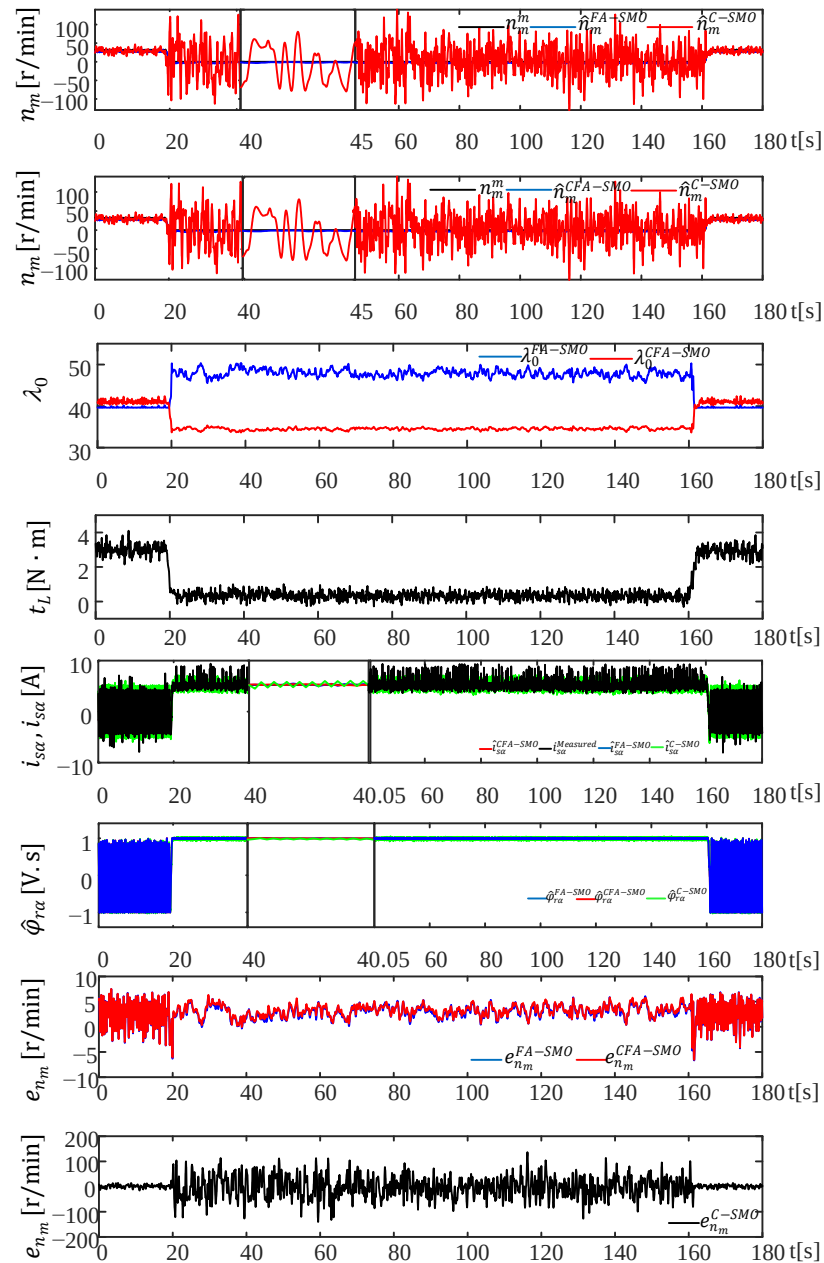


Figure 17. Estimation results with and without load conditions in the zero speed region.

Finally, the resulting mean square error (MSE), root mean square error (RMSE), and integral absolute error (IAE) values for estimations associated with each scenario are presented in Tables 3–5, respectively. The total harmonic distortion (THD) of the estimated α -axis current for the proposed A-SMOs and C-SMO is given in Table 6. The execution times for each observer obtained by calculating the average value for each iteration are given in Table 7. When the real-time test results given in Figures 9–17 are examined, the following observations can be made:

- To show the effect of the measured currents usage in the ω_m estimation in (20), the ω_m -estimation results are also presented in Figure 9 for both using measured and estimated currents cases. It is clear that the ω_m estimation can be improved by using measured currents, which is the main reason why the measured currents are used in (20) in this paper.
- The best value of λ_0 is determined for high-speed operation of IM in C-SMO and is kept constant in C-SMO for all scenarios. That is why the performance of C-SMO and the proposed A-SMOs are close to each other in Figure 10. As can be seen from Figures 11 and 12, while the IM speed is decreasing from the high-speed region to the medium- or low-speed region, the constant λ_0 in C-SMO leads to chattering in the estimations. On the other hand, the proposed A-SMO methods can overcome this challenge by adjusting λ_0 to its predetermined proper value. The obtained MSE, RMSE, and IAE results demonstrate that the proposed A-SMO methods outperform C-SMO for all presented results. Furthermore, the THD values calculated for 1000 (r/min), 500 (r/min), and 50 (r/min) with/without load condition in Table 6 also highlight the superior performance of FA-SMO and CFA-SMO over C-SMO.
- In the speed-reversal scenario, it can be seen in Figure 13 that the proposed A-SMOs are superior to C-SMOs, especially in the low-speed region. Moreover, it has been proven that the proposed A-SMOs satisfy the Lyapunov stability condition for each speed region.
- From the results of the R_s and R_r variation tests at low speeds in Figures 14 and 15, it is observed that the proposed A-SMOs in this paper demonstrate superiority (i.e., reduced chattering) over C-SMO due to their λ_0 adaptation. This can also be seen from the resulting MSE, RMSE, and IAE values in Tables 3–5, which verify the effectiveness of the proposed A-SMOs under R_s and R_r uncertainties. Moreover, in the L_m variation test at high-speed operation (Figure 16), both the proposed A-SMOs and C-SMO exhibit similar estimation performance, since they have approximately the same λ_0 values. Furthermore, these challenging L_m changes do not have a significant impact on their estimation performance, demonstrating the robustness of SMO methods against L_m variations for both the proposed A-SMOs and C-SMO.
- In continuous zero speed operation tests, it is obvious that the estimation performances of the proposed methods are satisfactory and the proposed methods easily overcome this challenge while C-SMO has high values chattering in the estimated ω_m .
- The proposed A-SMO methods (FA-SMO and CFA-SMO) are designed to preserve the low-computational-load superiority of C-SMO. As can be seen in Table 7, compared to C-SMO, the proposed FA-SMO and CFA-SMO methods resulted in a slight increase in computational load of only 0.55 μ s and 0.5 μ s, respectively.
- The proposed A-SMOs are built upon the C-SMO structure; therefore, the slight increase in their computational load mainly results from the λ_0 adaptation mechanisms. In addition, to further evaluate and compare the computational efficiency of the proposed A-SMOs, the computational complexities of the sliding mode function of (13) utilized in both C-SMO and A-SMOs and the one used in STSMO (Equation (16) in Nurettin and Inanc [9]) are presented in Table 8, as calculated by Bonaldo et al. [47]. The results indicate that both C-SMO and the proposed A-SMOs exhibit lower computational complexity in their sliding mode functions compared to STSMO in Nurettin and Inanc [9]. Moreover, when the proposed adaptive mechanisms in (29) are considered alongside the adaptive mechanism (Equation (23) in Nurettin and Inanc [9]), a similar analysis as in Table 8 can be realized. Since the adaptive mechanism in Nurettin and Inanc [9] involves multiple addition, division, multiplication, and absolute value operations, its estimated computational cost is higher than those of the simpler

adaptive structures proposed in this paper. These results are also coherent with the past results presented in Ullah et al. [48], which compares the conventional and super twisting sliding mode controllers.

Table 3. Resulting MSE values.

Method	Using Measured Currents			Using Estimated Currents		
	e_{n_m}			e_{n_m}		
Figure 9	12.016			135.307		
Method	C-SMO		FA-SMO		CFA-SMO	
	$e_{i_{sa}}$	e_{n_m}	$e_{i_{sa}}$	e_{n_m}	$e_{i_{sa}}$	e_{n_m}
Figure 10	1.072	16.277	1.103	16.576	1.074	15.771
Figure 11	0.605	19.948	0.396	8.627	0.393	8.575
Figure 12	0.424	32.715	0.061	10.523	0.061	10.512
Figure 13	0.843	42.222	0.762	36.299	0.747	36.261
Figure 14	0.428	65.298	0.062	61.130	0.061	60.939
Figure 15	0.424	36.168	0.059	13.102	0.059	13.079
Figure 16	1.005	26.884	1.091	24.129	1.077	24.393
Figure 17	0.418	1370.1	0.066	11.260	0.063	12.135

Table 4. Resulting RMSE values.

Method	Using Measured Currents			Using Estimated Currents		
	e_{n_m}			e_{n_m}		
Figure 9	3.466			11.632		
Method	C-SMO		FA-SMO		CFA-SMO	
	$e_{i_{sa}}$	e_{n_m}	$e_{i_{sa}}$	e_{n_m}	$e_{i_{sa}}$	e_{n_m}
Figure 10	1.035	4.034	1.050	14.071	1.036	3.971
Figure 11	0.778	4.466	0.629	2.937	0.627	2.928
Figure 12	0.651	5.719	0.248	3.243	0.248	3.242
Figure 13	0.918	6.497	0.873	6.024	0.864	6.021
Figure 14	0.654	8.080	0.249	7.818	0.247	7.806
Figure 15	0.651	6.013	0.244	3.616	0.243	3.616
Figure 16	1.002	5.185	1.044	4.912	1.038	4.938
Figure 17	0.646	37.014	0.256	3.355	0.250	3.483

Table 5. Resulting IAE values.

Method	Using Measured Currents			Using Estimated Currents		
	e_{n_m}			e_{n_m}		
Figure 9	2.407×10^5			8.272×10^5		
Method	C-SMO		FA-SMO		CFA-SMO	
	$e_{i_{sa}}$	e_{n_m}	$e_{i_{sa}}$	e_{n_m}	$e_{i_{sa}}$	e_{n_m}
Figure 10	6.056×10^4	2.788×10^5	6.161×10^4	2.821×10^5	6.0738×10^4	2.747×10^5
Figure 11	4.516×10^4	2.711×10^5	3.556×10^4	2.053×10^5	3.549×10^4	2.048×10^5
Figure 12	3.899×10^4	3.246×10^5	9.279×10^3	1.910×10^5	9.320×10^3	1.909×10^5
Figure 13	5.142×10^4	3.746×10^5	4.630×10^4	3.618×10^5	4.584×10^4	3.610×10^5
Figure 14	3.912×10^4	4.601×10^5	9.595×10^3	4.694×10^5	9.478×10^3	4.691×10^5
Figure 15	3.127×10^4	2.743×10^5	7.443×10^3	1.720×10^5	7.397×10^3	1.717×10^5
Figure 16	3.887×10^4	1.880×10^5	4.023×10^4	1.786×10^5	4.007×10^4	1.789×10^5
Figure 17	3.750×10^4	1.874×10^6	8.922×10^3	2.108×10^5	8.065×10^3	2.210×10^5

Table 6. Resulting THD values.

Method	C-SMO		FA-SMO		CFA-SMO	
Load Condition	No-Load	Loaded	No-Load	Loaded	No-Load	Loaded
Figure 10	19.60	13.07	18.48	12.51	19.35	12.31
Figure 11	20.29	14.41	12.89	8.53	12.97	8.50
Figure 12	23.91	22.03	9.94	8.09	9.90	8.15

Table 7. Execution times for each observer.

C-SMO	FA-SMO	CFA-SMO
1.65 μ s	2.20 μ s	2.15 μ s

Table 8. Computational cost estimation for sliding mode function used in C-SMO, FA-SMO/CFA-SMO, and STSMO strategies, the considering DS-1104 microprocessor.

Operation	C-SMO		FA-SMO/CFA-SMO		STSMO	
	Quantity	Cycles	Quantity	Cycles	Quantity	Cycles
Addition/subtraction	-	-	-	-	2	2
Multiplication with constant	2	2	1	1	4	4
Multiplication with variable	-	-	1	3	1	3
Comparisons (sgn)	1	1	1	1	2	2
Absolute value	-	-	-	-	1	1
Square root	-	-	-	-	1	20
Estimated total	-	3	-	5	-	32

5. Conclusions

In this paper, two novel A-SMOs using only the stator current errors in sliding surface are proposed for the speed sensorless IM drives utilized in both EV and industrial applications. By adjusting the λ_0 value in A-SMO methods, the aim is to overcome the operation region-based performance deteriorations of C-SMO. The adaptation of λ_0 through fuzzy logic and curve-fitting methods enhances estimation performance without significantly increasing the computational load.

The proposed A-SMOs estimate $i_{s\alpha}$, $i_{s\beta}$, $\varphi_{r\alpha}$, $\varphi_{r\beta}$, and ω_m in real time, utilizing measured currents and voltages. Experimental results demonstrate that A-SMOs outperform C-SMO in terms of estimation accuracy, robustness against variations in R_s , R_r , and L_m , and reduced chattering, particularly at low speeds. At higher speeds, proposed methods achieve similar estimation performance to C-SMO under L_m variations, although they still require accurate values of R_s and R_r for optimal performance.

Despite these improvements, limitations remain. The proposed methods rely on precise rotor and stator parameters for high-speed operation, and their performance may degrade under extreme operating conditions or parameter uncertainties. Future work will focus on addressing these limitations, including adaptive techniques to handle parameter variations and further reduction of computational complexity.

Finally, the proposed A-SMOs, featuring lower computational load and adaptive mechanisms independent of IM model parameters, outperform previous studies such as [9,39], making them more feasible for real-time sensorless control of IMs in both EV and industrial applications.

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