An improved permanent-magnet synchronous machine sensorless drive based on the fuzzy-PI phase-locked loop and the adjustable boundary-layer FOSMO

Shuaichen Ye  |  Xiaoxian Yao

School of Aerospace Engineering, Beijing Institute of Technology, Beijing, China

Correspondence
Shuaichen Ye, School of Aerospace Engineering, Beijing Institute of Technology, Beijing 100081, China.
Email: yesc_bit@163.com

Abstract
This study proposes a variable boundary-layer full-order sliding-mode observer (FOSMO) with a fuzzy proportional plus integral (PI) phase-locked loop (PLL) for the sensorless control of a permanent-magnet synchronous machine (PMSM). The sigmoid switching function-based FOSMO, which includes feedback speed information, is presented and considered as the conventional method. To address the contradiction between the convergence performance and the chatter-reduction ability of the sliding-mode control, a fuzzy logic controller (FLC) is introduced to adjust the boundary-layer thickness according to the estimation error. Furthermore, a real-time parameter tuning module is integrated into the PI regulator of the conventional PLL to adjust its noise bandwidth. Hence, adverse effects of disturbance and external noise, especially under transient operations, can be eliminated. An overall PMSM sensorless field-oriented control scheme incorporating the proposed method is designed, and the corresponding experimental platform is constructed. Several groups of comparative experiments reveal that system chatters are largely reduced using the proposed method under both of the high- and low-speed running conditions and the dynamic anti-interference performance can also be significantly improved under load and speed disturbances. Therefore, the feasibility and effectiveness of the proposed variable boundary-layer FOSMO + fuzzy-PI PLL method are validated.

1 INTRODUCTION

In recent decades, permanent-magnet synchronous machines (PMSMs) have been applied to various adjustable-speed instruments in industrial and domestic fields, such as electric ground vehicles [1] and industrial robots [2]. One of the most efficient high-accuracy control methods for PMSMs is the field-oriented control (FOC) method proposed by Blaschke [3]. The FOC method requires rotor angular position and speed information, which are conventionally detected by high-precision mechanical encoders or Hall sensors mounted on shafts. However, the installation of additional sensors increases the inertia of the motor and reduces the system reliability under vibrations and high-humidity operating environments [4]. Therefore, many sensorless detection methods have been developed to estimate the position and speed of the rotor and replace mechanical sensors.

Two main categories of sensorless detection techniques are mechanical anisotropy- and mathematical model-based methods. Mechanical anisotropy-based methods are designed for zero- and low-speed running conditions. In this method, the rotor kinematics information is obtained by demodulating the feedbacks of high-frequency (HF) injections [5, 6]. However, the drawbacks of mechanical anisotropy-based methods include extra harmonics and large torque ripples due to the extrinsic HF injections. Mechanical model-based methods that are suitable for medium- and high-speed running conditions mainly include the following: The model reference adaptive system method [7, 8], the Kalman filter observer method [9] and the sliding-mode observer (SMO) method [10–14].
Among these sensorless methods, the SMO method attracts the attention of many researchers due to its advantages in terms of a simple structure and superior anti-disturbance performance [15]. The SMO method utilises the estimated back-electromotive force (back-EMF) to calculate the kinematics information of the rotor; in earlier SMOs, a discontinuous signum function-based switching strategy is employed to construct the ideal sliding mode. However, according to [16], an essential condition for realising SMO based on the signum function is the infinity switching frequency of the system, which can only be guaranteed theoretically; for practical purposes, dynamic non-idealities of the system may destroy the switching performance of the signum-based SMO. Therefore, many quasi-SMO methods have been proposed by replacing the signum function with some continuous switching functions, such as the saturation function [17, 18], the sigmoid function [19] and the hyperbolic function most recently [20]. Relevant experimental results have verified the effectiveness of the quasi-SMOs. The difference among numerous quasi-SMOs lies in the approaching law and the convergence time, but their principle remains the same.

That is when the estimation error falls outside the region limited by the boundary layer, the system is under variable structure control, whereas when the estimation error falls in this region, the system is under continuous control. Thus, the continuous and the discontinuous controls are separated, and a ‘buffering’ region is formed to the high-frequency state-variable switching.

Nowadays, the sigmoid function-based quasi-SMO is regarded as the most efficient and popular scheme in the model-based method domain. However, it is not designed properly, and two major drawbacks still emerge: (1) According to Saadaoui et al. [21], the state equations of the original quasi-SMOs do not contain the information of the real-time feedback rotor angular signals, which reduces their estimation accuracy, and (2) according to Lin and Zhang [22], the constant boundary-layer value in the switching functions of the original quasi-SMO induces a contradiction between the convergence speed and the chatter-reduction performance. For example, when the estimation error is large, a small boundary-layer value is usually chosen to guarantee the fast convergence of the estimates; however, as the estimates approach their actual values, chattering occurs because of the narrow continuous control region limited by the small boundary-layer value, and a relatively large boundary-layer value should be chosen instead to smooth the switching process and reduce chatter.

To eliminate the first drawback of the conventional quasi-SMO, we construct an FOSMO based on the extended state equations proposed by Qiao et al. [23]. The novel FOSMO includes the feedback rotor speed information and can provide a more accurate estimation than that of the conventional quasi-SMO. Although the FOSMO contains the speed information, the second drawback of the conventional quasi-SMO (i.e. the chatter caused by the constant boundary-layer value) remains. To address the second flaw, some second- [24] and third-order [25] observers have been developed with more rigorous stability criteria to reduce the chatter. However, high-order observers require powerful calculating and processing capabilities of the hardware, which makes it complex to realise. Moreover, some iterative SMOs [26] have also been proposed, which utilise one observer for several times during one sampling period. However, this method can only adjust the SMO gain value gradually according to a fixed gradient and performances are unsatisfactory under the rapid transition process. Thus, a real-time adjustment method is urgently needed. In this research, we construct a fuzzy logic controller (FLC) to regulate the boundary-layer online according to the estimation error, and the chatter is reduced on the basis of guaranteeing a rapid convergence.

After the FOSMO process, the rotor position and speed can be calculated by the arc tangent method using the back-EMF. Section 3 introduces the variable boundary-layer observer for several times during one sampling period. However, this method can only adjust the SMO gain value gradually according to a fixed gradient and performances are unsatisfactory under the rapid transition process. Thus, a real-time adjustment method is urgently needed. In this research, we construct a fuzzy logic controller (FLC) to regulate the boundary-layer online according to the estimation error, and the chatter is reduced on the basis of guaranteeing a rapid convergence.

After the FOSMO process, the rotor position and speed can be calculated by the arc tangent method using the back-EMF. Section 3 introduces the variable boundary-layer observer for several times during one sampling period. However, this method can only adjust the SMO gain value gradually according to a fixed gradient and performances are unsatisfactory under the rapid transition process. Thus, a real-time adjustment method is urgently needed. In this research, we construct a fuzzy logic controller (FLC) to regulate the boundary-layer online according to the estimation error, and the chatter is reduced on the basis of guaranteeing a rapid convergence.

Thus, main contributions of this research compared with the state-of-the-art sigmoid function-based quasi-SMO can be summarised as follows: (1) An FOSMO including real-time feedback speed information is constructed to improve the system estimation accuracy, (2) an FLC-based variable boundary-layer method is proposed for the FOSMO to balance the system convergence speed and the chatter reduction characteristic, and (3) another FLC is designed to adjust the parameters of the PI module in the basic PLL to improve the anti-interference performance of the PMSM sensorless FOC scheme. Further, a platform for the proposed PMSM sensorless control scheme is built, and several groups of comparative experiments are performed to validate the superior performance and practicability of the proposed method.

The rest of this study is arranged as follows. Section 2 briefly discusses the dynamic model of the PMSM and presents the FOSMO using the sigmoid switching function with a constant boundary layer. Section 3 introduces the variable boundary-layer...
method and the corresponding FLC regulator. Section 4 proposes the conventional PLL and the fuzzy-PI PLL. Section 5 constructs the sensorless control strategy using the proposed FOSMO + fuzzy-PI PLL and describes the experimental platform. Section 6 compares the conventional method and the proposed method via experimental results. Section 7 concludes and suggests future research directions.

2 | FOSMO BASED ON THE SIGMOID SWITCHING FUNCTION

The PMSM current state equations are established under the two-phase stationary $\alpha - \beta$ coordinate system [13, 34], and it is assumed that the changing rate of the motor angular speed is negligible compared with the changing rate of the stator current, that is, the derivative of the rotor speed is approximately $\dot{\omega} \approx 0$ [23].

Then, the full-order PMSM state equations can be directly written as

\[
\begin{align*}
\frac{d\alpha}{dt} &= -\frac{R}{L_s}i_x + \frac{1}{L_s}u_x - \frac{1}{L_s}e_x \\
\frac{d\beta}{dt} &= -\frac{R}{L_s}i_\beta + \frac{1}{L_s}u_\beta - \frac{1}{L_s}e_\beta \\
\frac{d\omega_r}{dt} &= 0
\end{align*}
\]

(1)

and the FOSMO is constructed as

\[
\begin{align*}
\frac{d\hat{\alpha}}{dt} &= -\frac{R}{L_s}\hat{i}_x + \frac{1}{L_s}u_x - \frac{1}{L_s}k_1\text{sig}(\hat{\alpha}) \\
\frac{d\hat{\beta}}{dt} &= -\frac{R}{L_s}\hat{i}_\beta + \frac{1}{L_s}u_\beta - \frac{1}{L_s}k_1\text{sig}(\hat{\beta}) \\
\frac{d\hat{\omega}_r}{dt} &= \hat{\omega}_\alpha \hat{i}_\beta - \hat{\omega}_\beta \hat{i}_\alpha - k_2\text{sig}(\hat{\alpha}) - k_2\text{sig}(\hat{\beta})
\end{align*}
\]

(2)

where “$\hat{}$” and “$\check{}$” indicate estimations and their error values, respectively; $k_1$ and $k_2$ are two observer gains, and the sliding-mode surface is defined as

\[
s = [i_x \quad i_\beta]^T = [\hat{i}_x \quad \hat{i}_\beta]^T - [\hat{i}_x - i_x \quad \hat{i}_\beta - i_\beta]^T
\]

To verify the stable condition of the FOSMO and obtain two observer gain values, Lyapunov’s second method is utilised, and the following Lyapunov function is chosen:

\[
V = \frac{1}{2}(\hat{\alpha}^2 + \hat{\beta}^2 + \hat{\omega}_r^2) \tag{3}
\]

The derivative of Equation (3) with respect to time is written as

\[
\dot{V} = \hat{\omega}_r \hat{i}_\beta - \hat{\omega}_\alpha \hat{i}_\alpha + \hat{\alpha} \hat{\omega}_r
\]

(4)

By subtracting Equations (1) from (2), the estimation errors can be obtained as follows:

\[
\begin{align*}
\frac{d\alpha}{dt} &= -\frac{R}{L_s}i_x + \frac{1}{L_s}u_x - \frac{1}{L_s}k_1\text{sig}(\hat{\alpha}) \\
\frac{d\beta}{dt} &= -\frac{R}{L_s}i_\beta + \frac{1}{L_s}u_\beta - \frac{1}{L_s}k_1\text{sig}(\hat{\beta}) \\
\frac{d\omega_r}{dt} &= \hat{\omega}_\alpha \hat{i}_\beta - \hat{\omega}_\beta \hat{i}_\alpha - k_2\text{sig}(\hat{\alpha}) - k_2\text{sig}(\hat{\beta})
\end{align*}
\]

(5)

Substituting Equations (5) into (4), $\dot{V}$ becomes

\[
\dot{V} = -\frac{R}{L_s}i_x + \frac{1}{L_s}u_x - \frac{1}{L_s}k_1\text{sig}(\hat{\alpha})
\]

(6)

Equation (6) should be negative to gradually stabilise the FOSMO. Expressions of back-EMFs $e_x = -\omega \lambda_x \sin \theta_r$ and $e_\beta = \omega \lambda_x \cos \theta_r$ are substituted into Equation (6), and it is decomposed into the following four parts:

\[
\begin{align*}
\frac{R}{L_s}i_x + \frac{1}{L_s}u_x - \frac{1}{L_s}k_1\text{sig}(\hat{\alpha}) < 0 \\
\frac{R}{L_s}i_\beta + \frac{1}{L_s}u_\beta - \frac{1}{L_s}k_1\text{sig}(\hat{\beta}) < 0 \\
\hat{\omega}_x \omega_x \lambda_x \sin \theta_r - k_2\text{sig}(\hat{\alpha}) < 0 \\
\hat{\omega}_\beta \omega_x \lambda_x \cos \theta_r - k_2\text{sig}(\hat{\beta}) < 0
\end{align*}
\]

(7)

Hence, the stable conditions of the FOSMO can be derived as

\[
\begin{align*}
k_1 &> \max[|\alpha|, |\beta|] \\
k_2 &> \omega \lambda_x \max[|\alpha|, |\beta|]
\end{align*}
\]

(8)

3 | IMPROVED FOSMO WITH THE VARIABLE BOUNDARY LAYER

The sigmoid switching function used in the FOSMO is presented as [35]

\[
\text{sig}(i) = \frac{2}{1 + e^{-\sigma(i - \tilde{i})}} - 1 = \frac{2}{1 + e^{-\sigma}} - 1 \tag{9}
\]

where $\tilde{i} = [\hat{i}_x \quad \hat{i}_\beta]^T$, $i = [i_x \quad i_\beta]^T$ and $\sigma$ is a positive adjustable parameter. The graph of the sigmoid function is sketched in Figure 1.
Figure 1 shows that $\sigma$ in the expression of the sigmoid function represents the slope of the function, and a boundary layer $\psi$ of the independent variable occurs before the sigmoid grows to either $-1$ or $1$. Part of the values of the sigmoid function in the first quadrant is listed in Table 1.

Table 1 shows that when the value of $\sigma$ increases up to 6, the error between the dependent variable and 1 decays to less than 0.005. This 0.5% threshold is negligible for practical purposes [22]. Thus, the switching principle can be actually written as follows:

$$
\text{sig}(s) = \begin{cases} 
1 & s > \psi \\
\frac{2}{1+e^{-\sigma s}} - 1 & -\psi \leq s \leq \psi \\
-1 & s < -\psi 
\end{cases}
$$

(10)

Therefore, strictly speaking, the stable condition for the FOSMO (i.e. Equation 8) does not guarantee that the sliding-mode motion will asymptotically stabilise to the sliding-mode surface in finite time in this case. This condition can guarantee only the attractiveness of the boundary layer; in other words, the motion is limited in the region determined by the boundary layer, which is presented in Figure 2. It shows that the convergence time of the sliding-mode motion is mainly decided by the period in which the state point moves in the region limited by the boundary layer.

The reaching law in the boundary layer can be defined as follows [36]:

$$
\dot{s} = -\frac{k_1}{\psi} s
$$

(11)

An arbitrary point within the boundary layer is defined as

$$
s(t) = \psi e^{\frac{k_1}{\psi} t}
$$

(12)

Thus, the movement time from the boundary layer to one arbitrary point within the boundary layer is

$$
t = \frac{\psi}{k_1} \ln \left| \frac{s(t)}{\psi} \right|
$$

(13)

An infinite amount of time is needed for an arbitrary point to converge to the sliding-mode surface. However, for engineering purposes, a slight error is allowed. Another point that is close enough to the sliding-mode surface is denoted as

$$
s_{\text{close}} = \gamma \psi
$$

(14)

where $\gamma \ll 1$ is the convergence coefficient.

When the sliding-mode motion reaches the $|s(t)| < \gamma \psi$ area, there is sufficient reason to consider the state point close enough to the sliding-mode surface at an engineering level.

Therefore, the time of an arbitrary point within the boundary layer approaching $s_{\text{close}}$ is defined as $t_{\text{app}}$ and calculated as

$$
t_{\text{app}} = \frac{\psi \ln \gamma}{k_1}
$$

(15)

Equation (15) shows that there is a direct proportional relationship between the convergence speed and the value of the boundary-layer width $\psi$, which means that, for a small $\psi$ value, rapid convergence of the sliding mode can be achieved. However, for a small $\psi$ value, due to the dynamic non-idealities and mechanical delay of a practical system, obvious overshoots to the sliding-mode hypersurface occur because of the small continuous switching region, which induces the chatter in the system. Thus, the traditional constant $\psi$ cannot guarantee both rapid convergence and superior chatter-reduction performance. To solve this problem, an FLC module is designed in this section and integrated into the FOSMO to adjust the
TABLE 2 Fuzzy control rules for $\psi$

| $\dot{s}$ | NL | NS | ZO | PS | PL |
|----------|----|----|----|----|----|
| $s$ NL   | PL | PL | PM | PS | ZO |
| NS       | PL | PM | PS | ZO | NS |
| ZO       | PM | PS | ZO | NS | NM |
| PS       | PS | ZO | NS | NM | NL |
| PL       | ZO | NS | NM | NL | NL |

Notes: NL, negative large; NM, negative medium; NS, negative small; ZO, zero; PS, positive small; PM, positive medium; PL, positive large.

4 PROPOSED FUZZY-PI PLL

4.1 Conventional PLL structure

In the FOSMO method, rotor position and speed information can be directly obtained by the arctan function using the estimated back-EMF values (assuming that $\hat{e}_x$ and $\hat{e}_y$ are non-zero values to avoid the non-observable circumstance at zero speed). However, the estimation errors induced by the extrinsic noise and harmonic components are amplified by the division operation in the arctan calculation. Therefore, a PLL is always used to obtain accurate position and speed information.

Figure 4 shows the block diagram of the conventional PLL, where $K_p$ and $K_i$ represent the proportional and integral gains of the PI module, respectively. The symbol $\delta$ denotes the error input of the PI regulator, which can be expressed as follows:

$$\delta(t) = \omega \lambda_f \sin \dot{\theta}_e - \omega \lambda_f \cos \dot{\theta}_e \sin \theta_e$$

$$= \omega \lambda_f \sin(\dot{\theta}_e - \dot{\theta})$$

(16)

The major working principle of the PLL is to adjust the error $\delta$ using the PI regulator and converge it to zero. When $\delta$ approaches zero, the estimated rotor position $\hat{\theta}$ approaches the actual value $\theta_e$; therefore, accurate position and speed information can be subsequently obtained.

4.2 Fuzzy logic controller

The transfer function from $\delta(t)$ to $\theta_e(t)$ of the conventional PLL in Figure 4 is constructed as [28]

$$H(s) = \frac{- (K_p s + K_i)}{s^2 + K_p s + K_i}$$

(17)

from which the damping coefficient and the operation frequency can be calculated as $\zeta = K_p / 2 \sqrt{K_i}$ and $\omega_n = \sqrt{K_i}$, respectively. Further, according to [37], the transfer function in Equation (17) can also be expressed as

$$H(s) = \frac{- (2 \mu s + \mu^2)}{s^2 + 2 \mu s + \mu^2}$$

(18)

wherein $\mu$ is a constant value. As Equations (17) and (18) are equivalent, PI parameters can be simplified and re-written as $K_p = 2 \mu$ and $K_i = \mu^2$. According to the following calculation formula:

$$BW = \int_{-\infty}^{\infty} \frac{-(2 \mu j \omega + \mu^2)}{j \omega^2 + 2 \mu j \omega + \mu^2} df$$

(19)
the bandwidth of the conventional PLL can be determined as
\[ BW = 2.5 \mu. \] It is observed that the bandwidth of the PLL is
totally dependent on constant \( \mu \) and indirectly influenced by the
PI parameters \( K_P \) and \( K_I \).

Generally, a large bandwidth speeds up the convergence pro-
cess of the PLL but may affect its noise suppression perfor-
mance. In the conventional PLL, the parameters \( K_I \) and \( K_P \) are constant. Although these parameters were previously tuned
based on the system structural parameters, they cannot be
regulated online according to the PMSM running conditions.
Thus, in the dynamic state, especially under external disturb-
ance conditions, a contradiction between the fast-locking and
a noise elimination emerges, and the performance of conven-
tional PLL-based system is seriously affected.

To resolve this problem, in this study, an FLC is constructed
and combined with the conventional PLL to modulate the PI
parameters online. The two inputs of the FLC are the error
input \( \delta \) and its derivative \( \dot{\delta} \), and the one output is the varia-
tion of \( \mu \). Then, the following discrete iterative equation is per-
fomed to calculate the values of the PI parameters:

\[
\begin{align*}
K_P' &= K_P^0 + \frac{2\Delta \mu}{\Delta K_P} \\
K_I' &= K_I^0 + \frac{2\Delta \mu + \Delta \mu^2}{\Delta K_I}
\end{align*}
\] (20)

where \( K_P^0 \) and \( K_I^0 \) are the nominal parameters, and \( K_P' \) and \( K_I' \)
are the adjusted parameters.

The tuning rules of the FLC can be summarised as follows:
(1) During the initial period of the extrinsic noise input, abso-
lute values of the error \( \delta \) and its derivative \( \dot{\delta} \) are large. A wider
bandwidth is required to enhance the locking speed of the PLL;
(2) after phase stabilisation, a narrow bandwidth is preferred to
suppress the noise.

### 4.2.1 Domains and fuzzy sets

In the proposed FLC, the fuzzy domains of two inputs are both
selected as \([-3, 3]\), and their fuzzy sets are both adopted as NL, NM, NS, ZO, PS, PM, PL, with centre values of \([-3, -2, -1, 0,
1, 2, 3]\). The fuzzy domains of the output \( \Delta \mu \) are selected as
\([-50, 50]\), and it adopts the fuzzy set series as NEL, NL, NM, NS, NES, ZO, PES, PS, PM, PL, with centre values of \([-50, -40,
-30, -20, -10, 0, 10, 20, 30, 40, 50]\). NEL, NES, PES and PEL denote negative extreme large, negative extreme small, positive extreme small and positive extreme large, respectively.

### 4.2.2 Membership functions

The triangular membership function is adopted for both the
inputs and the outputs of the FLC to improve the execution
speed. The membership functions of the input and output vari-
ables are shown in Figure 5.

### 4.2.3 Control rules

The appropriate selection of control rules is indispensable for
FLC design. On this basis, fuzzy rule bases for \( \Delta \mu \) with 49 rules
are shown in Table 3.

### 4.3 Fuzzy-PI PLL

After the design, by incorporating the FLC into the PLL, the
integrated fuzzy-PI PLL can be generated as illustrated in Figure 6.
In this section, a PMSM sensorless FOC scheme utilising the variable boundary-layer FOSMO + fuzzy-PI PLL structure is constructed, and a corresponding experimental platform is built. Figure 7 shows the integrated block diagram of the scheme.

The experimental setup includes the following equipment: a Texas Instruments TMS320F28335 DSP-based PMSM controller; an SM060 PMSM with specifications listed in Table 4; a 24-V DC switching mode power supply (SMPS) and a 5-V DC SMPS to power the PMSM and the driver board, respectively; an air switch for the emergency braking of the setup; and an XDS100v2 USB emulator. A picture of the experimental equipment is shown in Figure 8.

In this section, several groups of comparative experiments are performed using the aforementioned platform to demonstrate the superior performance of the variable boundary layer-based FOSMO + fuzzy-PI PLL structure. Some of the parameter settings for the experiments are listed in Table 5. In this study, both steady-state experiments and dynamic experiments are performed. The purpose of the steady-state experiments is to validate the chatter reduction of the proposed FOSMO with a variable boundary layer, while the dynamic experiments aim to reveal the anti-disturbance performance of the novel fuzzy-PI PLL.

### 6 | EXPERIMENTAL RESULTS

In this section, several groups of comparative experiments are performed using the aforementioned platform to demonstrate the superior performance of the variable boundary layer-based FOSMO + fuzzy-PI PLL structure. Some of the parameter settings for the experiments are listed in Table 5. In this study, both steady-state experiments and dynamic experiments are performed. The purpose of the steady-state experiments is to validate the chatter reduction of the proposed FOSMO with a variable boundary layer, while the dynamic experiments aim to reveal the anti-disturbance performance of the novel fuzzy-PI PLL.

#### 6.1 | Steady-state experiments

Experiments in the steady state were conducted to compare the FOSMO with a variable boundary layer and the FOSMO with a constant boundary layer.
Figure 9 shows the three-dimensional graph of the relationship between the inputs and the output of the boundary-layer adjustment fuzzy logic controller, and it indicates that the width of the boundary layer can be adjusted in a self-adaptive manner according to the estimation error.

Figures 10(a) and (b) present the back-EMF signal estimates using the constant boundary layer-based FOSMO and the variable boundary-based FOSMO, respectively, under a high speed of 50 r/s. Figures 11(a) and (c) show the position and speed estimates, respectively, corresponding to the scenario of Figure 10(a). Figures 11(b) and (d) show the position and speed estimates, respectively, corresponding to the scenario of Figure 10(b). All the experimental results presented in Figures 10 and 11 were obtained under the no-load condition. These results show that obvious ripples emerge in the estimations of the conventional FOSMO with a constant boundary layer due to the chatter caused by the narrow continuous switching region. Such ripples affect the system performance and reduce the stability of the control system. After adjusting the boundary-layer value adaptively using an FLC, the improved FOSMO exhibits satisfactory performance for estimations, and the ripples are substantially reduced. It can also be observed from Figure 11 that steady-state error reduction from 8.5 to 2.6 degrees is attained for the position estimations, and a 70.7% performance enhancement is achieved in the speed estimation domain (dividing the conventional error 3.93 r/s with the difference between 3.93 and 1.15 r/s).

Figures 12(a) and (b) present the back-EMF signal estimates using the constant boundary layer-based FOSMO and the variable boundary-based FOSMO, respectively, under a relatively low speed of 5 r/s. Figures 13(a) and (c) show the position and speed estimates, respectively, corresponding to the scenario of Figure 12(a). Figures 13(b) and (d) show the position and speed estimates, respectively, corresponding to the scenario of Figure 12(b). The steady-state low-speed experiments were also performed with no load. Similar to Figures 10 and 11, the results in Figures 12 and 13 reveal that the ripples in the estimation profiles caused by chatter are much degraded by introducing the adjustable boundary-layer method. For the position and speed estimations, steady-state error reductions from 9.6° to 2.9° and from 0.95 to 0.18 r/s can be achieved, respectively. Moreover, it is worthwhile to notice that the position estimation errors under low-speed operation are even higher than those under the high-speed operation; this phenomenon attributes to the fact that the performance of the model-based observer gets worse with a lower back-EMF level under the low-speed condition. Therefore, from Figures 10–13, the chatter-reducing performance of the proposed adjustable boundary layer is validated for both high-speed and relatively low-speed operations.

Figures 14 and 15 depict the loaded experimental results under a steady speed of 20 r/s, in which a constant 0.3 Nm load was provided by a magnetic powder brake connected to the
YE AND YAO

FIGURE 14  Estimated back-EMFs \( \hat{e}_\alpha \) (red lines) and \( \hat{e}_\beta \) (blue lines) using (a) the conventional FOSMO with a constant boundary layer, and (b) the variable boundary-layer-based FOSMO at 20 r/s with a 0.3 Nm constant load.

FIGURE 15  (a) Estimated position, and (c) estimated speed using the conventional FOSMO with a constant boundary layer at 20 r/s under a 0.3 Nm constant load; (b) estimated position, and (d) estimated speed using the variable boundary-layer-based FOSMO at 20 r/s under a 0.3 Nm constant load.

motor shaft. Figures 14(a) and (b) present the back-EMF signal estimates using the constant boundary-layer-based FOSMO and the variable boundary-based FOSMO, respectively. Figures 15(a) and (c) show the position and speed estimates, respectively, corresponding to the scenario of Figure 14(a). Figures 15(b) and (d) show the position and speed estimates, respectively, corresponding to the scenario of Figure 14(b).

In the loaded experiments, the result profiles obtained by the FOSMO method with the constant boundary layer have large ripples, and there is a 2.74 r/s maximum error in the speed estimations. However, after utilising the adjustable boundary-layer method, the ripples caused by the system chatter are considerably eliminated, and the error for the speed estimation degrades to 0.89 r/s, which results a 67.5% system performance upgrade.

Similarly, a 5.7 degrees position estimation accuracy enhancement (reducing from 7.9° in Figure 15(a) to 2.2° in Figure 15(b)) is attained. Therefore, the chatter-reducing performance of the adjustable boundary layer is also verified under the loaded condition.

6.2 Dynamic experiments

Experiments in the dynamic state were performed to compare the proposed FOSMO with the fuzzy-PI PLL and the proposed FOSMO with a conventional PLL.

Figure 16 shows the three-dimensional graph of the relationship between the inputs and the outputs of the PI parameter adjustment FLC for PLL. Combined with Equation (20), PI parameters can be adjusted effectively online according to the input error \( \delta \).

FIGURE 16  Regulation graph of the parameter for the PI module in the PLL.

FIGURE 17  Estimated back-EMFs \( \hat{e}_\alpha \) (red lines) and \( \hat{e}_\beta \) (blue lines) using (a) FOSMO + basic PLL, and (b) the FOSMO + fuzzy-PI PLL with the speed ramping down from 50 to 20 r/s at 0.16 s without a load.

The experiments were performed under the no-load condition, and the reference speed ramped down from 50 to 20 r/s at 0.16 s. It can be observed that, for the FOSMO + basic PLL method, obvious estimation errors emerge in the back-EMF estimates, the position and speed estimates because of the speed variation; in particular, a maximum speed error of 1.78 r/s occurred after the speed decreased from 50 to 20 r/s. However, by utilising the proposed FOSMO + fuzzy-PI PLL, the estimation errors caused by the constant PI parameters are considerably reduced after the speed variation, and the maximum steady-state error does not exceed 0.85 r/s in the 20 r/s speed region. Similarly, after ramping down the speed, position errors reduce from 8.3 degrees in Figure 18(a) to 2.65 degrees in Figure 18(b). Therefore, by replacing the basic PLL with the fuzzy-PI PLL in the FOSMO, the system dynamic performance under a ramp speed variation disturbance can be much improved.
Corresponding to Figures 17 and 18, Figures 19 and 20 exhibit the back-EMF, the rotor position and the speed variation profiles under the speed step response. The command speed steps up at 0.2 s from 20 to 50 r/s under the no-load condition. It is observed that when using the proposed FOSMO with a basic PLL, large errors exist in the back-EMF and the position estimations after the speed-varying disturbance, while by introducing the fuzzy-PI PLL module, these errors are largely eliminated. Specially, for the speed estimates, a maximum estimation error of 4.12 r/s emerges in Figure 20(c) after the speed variation; however, this value reduces to only 1.36 r/s in Figure 20(d). Therefore, combing Figures 17 and 18, the anti-disturbance of the proposed fuzzy-PI PLL structure is validated under both the ramp and the step speed disturbances.

Figures 21(a) and (b) show the speed estimation profiles under a load disturbance using the FOSMO + basic PLL method and the FOSMO + fuzzy-PI PLL method, respectively. In this experiment, the motor steady-state speed was set to 20 r/s, and a load of 0.3 Nm was loaded at 4 s and unloaded at 8 s. With the FOSMO + basic PLL method, the speed cannot effectively converge to its steady value during load variations, and a non-negligible adjustment time of 2.5 s is observed after the load is added. However, by introducing the fuzzy-PI PLL method, the system can more rapidly adjust to the load disturbance, and the maximum convergence time decreases to only 0.9 s, which results in a 64% reduced time comparing with the basic PLL method. Therefore, the robustness of the proposed fuzzy-PI PLL against load disturbances can be verified.

### 6.3 Open-loop start-up procedure and ultra-low speed operation performance of the proposed method

In this research, to omit the detection of the rotor initial position, a robust \( I_f \) open-loop start-up strategy for the PMSM is utilised [22, 38] because under the zero-speed, the back-EMF information of the stator cannot be estimated, and the FOSMO-based close-loop control method loses its efficiency. The entire start-up process is described as following three steps:

1. **Open-loop \( I_f \) control:** During this procedure, the nominal stator frequency \( f \) is given as a ramping-up signal and starts from zero. The upper frequency boundary is set as \( f_{\text{min}} \), which means before \( f \) approaches \( f_{\text{min}} \), \( \hat{\theta} \) in Figure 7 is not obtained via the FOSMO, a reference position calculated by the integration of the frequency (\( \theta_{\text{ref}} = \int 2\pi f dt \)) is used as a replacement. Meanwhile, the \( i_{q\text{ref}} \) in Figure 7 is reproduced by the current PI controller from the given frequency.

2. **Smooth transformation from open-loop control to back-EMF based close-loop control:** When the frequency \( f \) surpasses the upper boundary \( f_{\text{min}} \) of the first step, a transformation to the close-loop sensorless control starts. The upper boundary frequency \( f_{\text{max}} \) is set for this procedure. During the frequency varies between \( f_{\text{min}} \) and \( f_{\text{max}} \), a first-order delay compensator is introduced to ensure a smooth transformation from \( \theta_{\text{ref}} \) to \( \hat{\theta} \):

\[
\theta_{\text{del}}(s) = \frac{\theta_{\text{ref}} - \hat{\theta}}{1 + 0.05s}
\]  

wherein \( \theta_{\text{del}} \) denotes the first-order angular delay and it is disabled when the frequency reaches \( f_{\text{max}} \) (\( \theta_{\text{del}} = 0 \)). Hence, a flat transition from the open-loop angular information to the close-loop angular information is realised and same for corresponding control strategies.

3. **Close-loop PMSM sensorless control:** After the frequency exceeding \( f_{\text{max}} \), the transition in step (2) finishes and the entire system turns to the sensorless control scheme proposed in this study, and in this stage, the speed and
FIGURE 22 Three-step start-up performance of the permanent-magnet synchronous machine

When choosing upper boundaries $f_{\text{min}}$ of step (1) and $f_{\text{max}}$ of step (2) as 2 and 4 Hz, respectively, the start-up performance of the proposed FOSMO + fuzzy-PI PLL method can be illustrated in Figure 22.

It is revealed from Figure 22 that, in the entire start-up procedure, speed estimates fluctuate at the initial period of steps (1) and (2) due to the control mode switching. After the smooth transformation from the open-loop control to the close-loop control in 0.4 s, the maximum speed estimation error is not more than 0.2 r/s. Thus, the start-up performance of the proposed method is verified.

However, having an unsatisfactory low-speed performance is a universally recognised drawback for the mechanical model-based methods, including the proposed FOSMO + fuzzy-PI PLL scheme. By adjusting the frequency boundary in the start-up process, the low-speed operation of the PMSM sensorless drive can be realised with the proposed method. Figure 23 shows the rotor acceleration performance from a low-speed of 100 to 300 rpm. It is observed that, the estimated speed under 100 rpm cannot reflect the actual speed accurately and large errors exist, and this is because under the low-speed condition, small back-EMF values are impressionable to external noise. This phenomenon is much eliminated with the increasing of the commanded speed. Therefore, this flaw of the proposed method needs more attention in the future.

7 | CONCLUSIONS

This study has proposed a variable boundary-layer-based FOSMO + fuzzy-PI PLL method to accurately track the position and speed of the PMSM. A prototype-based experimental setup is built according to the proposed motor-sensorless drive scheme. Major contributions of this research can be summarised as the following three aspects:

1. The real-time feedback speed information has been included in the sigmoid-switching function-based FOSMO, which prompts a more accurate estimation.
2. The boundary-layer thickness is adjusted adaptively according to the current error and its derivative to reduce the chatter as well as improve the convergence speed of the state variables. Steady experimental results verify the chatter-suppression ability of the variable boundary layer and it shows that steady speed estimation errors reduced at least 60% irrespective of being under the high or relatively low-speed operations.
3. A fuzzy-PI PLL structure is constructed to regulate the noise bandwidth of the conventional PLL which is used for obtaining the speed and position information. Dynamic experimental results macroscopically reveal a 64% adjustment time reduction of the enhanced PLL under load disturbance, which validates its satisfactory anti-interference performance.

Therefore, the practicability and effectiveness of the proposed method are both verified. In the future, some mechanical anisotropy-based sensorless control methods, such as the HF injection method, will be integrated into the proposed method to realise the full-speed region PMSM control, especially under ultra-low speeds.

Nomenclature

| Symbol | Description |
|--------|-------------|
| $i_{\alpha/\beta}$ | stator current under $\alpha/\beta$-axis |
| $u_{\alpha/\beta}$ | stator voltage under $\alpha/\beta$-axis |
| $e_{\alpha/\beta}$ | back-EMF under $\alpha/\beta$-axis |
| $\omega_r$ | rotor electrical angular speed |
| $\lambda_f$ | flux linkage of PMs |
| $\theta_e$ | rotor electrical angular position |
| $L_s$ | stator inductance |
| $R$ | stator resistance |
| $V^+$ | non-negative Lyapunov function |

ACKNOWLEDGMENTS

The authors thank the editor and anonymous referees for their useful suggestions and careful reviews, which helped to improve the quality of the paper.
REFERENCES

1. Wang, Y., et al.: Fault-tolerant control for in-wheel-motor-driven electric ground vehicles in discrete time. Mech. Syst. Signal Process. 121, 441–454 (2019).
2. Yuan, T., et al.: High-precision servo control of industrial robot driven by PMSM-DTC utilizing composite active vectors. IEEE Access 7, 7577–7587 (2019).
3. Blaschke, F.: The principle of field orientation as applied to the new transistor closed-loop system for rotating-field machines. Siemens Rev. 34(3), 217–220 (1972).
4. Wang, G., et al.: Position sensorless permanent magnet synchronous machine drives—A review. IEEE Trans. Ind. Electron. 67(7), 5830–5842 (2020).
5. Zhang, X., et al.: Improved initial rotor position estimation for PMSM drives based on HF pulsating voltage signal injection. IEEE Trans. Ind. Electron. 65(6), 4702–4713 (2018).
6. Seilmeier, M., Piepenbreier, B.: Sensorless control of PMSM for the whole speed range using two-degree-of-freedom current control and HF test current injection for low-speed range. IEEE Trans. Power Electron. 30(8), 4394–4403 (2015).
7. Zangari, Y.A., et al.: MRAS state estimator for speed sensorless ISFOC induction motor drives with Luenberger load torque estimation. ISA Trans. 61, 308–317 (2016).
8. Ammar, A., et al.: Feedback linearization based sensorless direct torque control using stator flux MRAS-sliding mode observer for induction motor drive. ISA Trans. 98, 382–392 (2020).
9. Xu, D., Zhang, S., Liu, J.: Very-low speed control of PMSM based on EKF estimation with closed loop optimized parameters. ISA Trans. 52(6), 835–843 (2013).
10. Ye, S.: Design and performance analysis of an iterative flux sliding-mode observer for the sensorless control of PMSM drives. ISA Trans. 94, 255–264 (2019).
11. Almeida, J.M., et al.: Robust sensorless observer-based adaptive sliding modes control of synchronous motors. J. Franklin Inst. 355(7), 3221–3248 (2018).
12. Kandoussi, Z., et al.: Real time implementation of a new fuzzy-sliding-mode-observer for sensorless IM drive. COMPEL 36(4), 938–958 (2017).
13. Ye, S.: Fuzzy sliding mode observer with dual SOGI-FLL in sensorless control of PMSM drives. ISA Trans. 85, 161–176 (2019).
14. Hosseyni, A., et al.: Sensorless sliding mode observer for a five-phase permanent magnet synchronous motor drive. ISA Trans. 58, 462–473 (2015).
15. Ren, J-J., et al.: Sensorless control of ship propulsion interior permanent magnet synchronous motor based on a new sliding mode observer. ISA Trans. 54, 15–26 (2015).
16. Utkin, V.I.: Sliding Modes and Their Application in Variable Structure Systems. MIR Publishers, Moscow (1978).
17. Shen, H., et al.: A robust dynamic decoupling control scheme for PMSM current loops based on improved sliding mode observer. J. Power Electron. 18(6), 1708–1719 (2018).
18. Zhao, Y., et al.: An adaptive quasi-sliding-mode rotor position observer-based sensorless control for interior permanent magnet synchronous machines. IEEE Trans. Power Electron. 28(12), 5618–5629 (2013).
19. Liang, D., et al.: Adaptive second-order sliding-mode observer for PMSM sensorless control considering VSI nonlinearity. IEEE Trans. Power Electron. 33(10), 8994–9004 (2018).
20. Gong, C., et al.: An improved delay-suppressed sliding-mode observer for sensorless vector-controlled PMSM. IEEE Trans Ind Electron 67(7), 5913–5923 (2020).
21. Saadouq, O., et al.: A new full-order sliding mode observer based rotor speed and stator resistance estimation for sensorless vector controlled pmsm drives. Asian J. Control 21(3), 1318–1327 (2019).
22. Lin, S., Zhang, W.: An adaptive sliding-mode observer with a tangent function-based PLL structure for position sensorless PMSM drives. Int. J. Electr. Power Energy Syst. 88, 63–74 (2017).
23. Qiao, Z., et al.: New sliding-mode observer for position sensorless control of permanent-magnet synchronous motor. IEEE Trans. Ind. Electron. 60(2), 710–719 (2013).
24. Liang, D., et al.: Sensorless control of permanent magnet synchronous machine based on second-order sliding-mode observer with online resistance estimation. IEEE Trans. Ind. Appl. 53(4), 3672–3682 (2017).
25. Zhang, T., et al.: A third-order super-twisting extended state observer for dynamic performance enhancement of sensorless IPMSM drives. IEEE Trans. Ind. Electron. 67(7), 5948–5958 (2020).
26. Lee, H., Lee, J.: Design of iterative sliding mode observer for sensorless PMSM control. IEEE Trans. Control Syst. Technol. 21(4), 1394–1399 (2013).
27. Zhang, G., et al.: ADALINE-network-based PLL for position sensorless interior permanent magnet synchronous motor drives. IEEE Trans. Power Electron. 31(2), 1450–1460 (2016).
28. Song, X., et al.: Adaptive compensation method for high-speed surface PMSM sensorless drives of emf-based position estimation error. IEEE Trans. Power Electron. 31(2), 1438–1449 (2016).
29. Lee, J., Kim, B.: A low-noise fast-lock phase-locked loop with adaptive bandwidth control. IEEE J. Solid-State Circuits 35(8), 1137–1145 (2000).
30. Moradi, M., Ehsanian, M.: Design of an FPGA based DPLL with fuzzy logic controllable loop filters with application customization capability. Int. J. Electron. Commun. 97, 54–62 (2018).
31. Nguyen, H.X., et al.: An adaptive linear-neuron-based third-order PLL to improve the accuracy of absolute magnetic encoders. IEEE Trans. Electron. 66(6), 4639–4649 (2019).
32. Golestan, S., et al.: An analysis of the PLLs with secondary control path. IEEE Trans. Ind. Electron. 61(9), 4824–4828 (2014).
33. Aravind, C.K., et al.: Performance evaluation of type-3 PLLs under wide variation in input voltage and frequency. IEEE J. Emerg. Sel. Top. Power Electron. 5(3), 971–981 (2017).
34. Ye, S.: A novel fuzzy flux sliding-mode observer for the sensorless speed and position tracking of PMSMs. Optik 171, 319–325 (2018).
35. Kim, H., Son, J., Lee, J.: A high-speed sliding-mode observer for the sensorless speed control of a PMSM. IEEE Trans. Ind. Electron. 58(9), 4069–4077 (2001).
36. Lu, X., et al.: Soft switching sliding mode observer for PMSM sensorless control. Trans. China Electrotech. Soc. 30(2), 106–113 (2015).
37. Harnefors, I., Nee, H.P.: A general algorithm for speed and position estimation of AC motors. IEEE Trans. Ind. Electron. 47(1), 77–83 (2000).
38. Fatu, M., et al.: I-F starting method with smooth transition to emf based motion-sensorless vector control of pm synchronous motor/generator. In: IEEE Annual PESC, Rhodes, Greece, pp. 1481–1487 (2008).

How to cite this article: Ye S, Yao X. An improved permanent-magnet synchronous machine sensorless drive based on the fuzzy-PI phase-locked loop and the adjustable boundary-layer FOSMO. IET Power Electron. 2021;14:468–479. https://doi.org/10.1049/pel2.12058