

GRU Based Sliding Mode Controller for Permanent Magnet Synchronous Motor

Hayleyesus Girma Dirara

hayleyesus.girma@wsu.edu.et

Wolaita Sodo University

Feleke Tsegaye Yareshe

Tomas Bata University in Zlín

Mouaz Al Kouzbary

Curtin University

Article

Keywords: Field Oriented Control, Gated Recurrent Unit, Permanent Magnet Synchronous Motor, Sliding Mode Controller

Posted Date: August 27th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10663382/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

GRU Based Sliding Mode Controller for Permanent Magnet Synchronous Motor

Hayleyesus Girma Dirara^{1*}, Feleke Tsegaye Yareshe^{2†} and Mouaz Al Kouzbary^{3†}

^{1*}Department of Electrical and Computer Engineering Wolaita Sodo University, Wolaita Sodo, Ethiopia.

²Department of Automation and Control Engineering, Tomas Bata University, Zlín, 5555, State, Czech Republic.

³Department of Mechanical and Mechatronic Engineering, Faculty of Engineering, Curtin University, Miri, 98009, Sarawak, Malaysia.

*Corresponding author(s). E-mail(s): hayleyesus.girma@wsu.edu.et;

Contributing authors: yaresh@utb.cz; mouaz.k@curtin.edu.my;

[†]These authors contributed equally to this work.

Abstract

Robust speed regulation of permanent magnet synchronous motors (PMSM) under continuously varying load torque remains difficult for conventional proportional-integral schemes and even for first-order sliding mode designs, since chattering and the reliance on large switching gains limit both smoothness and disturbance rejection. A control architecture combining field-oriented control (FOC), a sliding mode controller (SMC) speed loop, two PID current loops, and a Gated Recurrent Unit (GRU) based load torque observer is developed to address this gap, with the observer inferring the unknown disturbance directly from the stator voltages, stator currents, and mechanical speed rather than from a physical torque sensor. The complete system, together with its Lyapunov-based stability proof establishing finite-time convergence of the sliding variable, was implemented and evaluated in a Matlab/Simulink environment across several operating conditions, including a fixed reference step and a continuously varying sinusoidal load torque. Simulation results show that the switching gain governs a clear trade-off between reaching time and steady state chattering bandwidth, that the trained Gated Recurrent Unit (GRU) network reconstructs a sinusoidal load torque of 1.0 to 3.0 N·m with a root-mean-square error of 0.0101 N·m under idealized conditions and 0.030101 N·m when embedded within the full PMSM dynamic model, and that feeding this estimate into the sliding mode controller

reduces the steady state speed error compared with operation in the absence of load torque compensation. These findings indicate that a model free, data driven observer can provide practically useful disturbance information for sliding mode PMSM speed control without requiring a mechanical torque sensor.

Keywords: Field Oriented Control, Gated Recurrent Unit, Permanent Magnet Synchronous Motor, Sliding Mode Controller

1 Introduction

Pmsm has quietly become one of the most important machines of the modern industrial era. Nowadays, PMSM are used as main driving units of electric cars, robots and aviation because of their power density, efficiency, low maintenance and fast response that exceeds many other types of machines [1, 2]. Although these benefits exist, achieving good speed tracking in PMSM has been shown to be hard, especially when the load torque changes, there is a drift of parameters due to temperature variations or there are some un-modelled nonlinearities [3]. The default industrial answer to this challenge is the proportional integral (PI) controller. PI controllers are simple in their design, have well known performances and are easy to tune; in the case of nominal working conditions and known loads they provide satisfactory results. However, the environment where they should work is rarely nominal. For example, in practice, a PMSM of electric car may experience different unpredictable working conditions, such as sudden braking, changes of road slope and other disturbances. Such disturbances can happen on short time intervals, making difficult to control motor's speed. The PI controller with fixed gains will not be able to adapt to such fast changes, which could be noticeable for the driver [4, 5]. This fundamental limitation has pushed researchers to look for something more robust.

The idea of sliding mode control (SMC) evolved as one of the most fascinating solutions due to this effort. Its main idea is quite straightforward: design the surface in the state space such that when the trajectory reaches this surface, the closed-loop dynamics become fully decoupled from any kind of matched disturbances and parameter variations. Applied to the field of PMSM speed control, it means that all uncertainties that normally affect PI control strategy, such as the change in load torque, the resistance variation, and the inductance saturation, are actually excluded from the speed error equation at the sliding start [6, 7]. During the last ten years, a lot of research was done proving that the SMC based PMSM speed controller is superior to its linear approaches in terms of performance [8–10].

However, despite such beneficial features, first-order SMC suffers from the well-known problem called chattering. The discontinuity caused by the sign function produces high-frequency oscillations in the control input. While this mechanism is crucial for the robustness of SMC, it may cause unmodeled mechanical dynamics, produce high acoustic noise, and contribute to mechanical parts' wear as well as power electronics wear [11, 12]. One of the possible solutions is to decrease the gain of the switching action. However, such a method results in reduced ability of the controller

to suppress the unknown load torque disturbance and uncertainty of parameters. It remains one of the main disadvantages of the conventional SMC.

Super-twisting algorithm (STA) developed by Levant [13] and rigorously analyzed by means of strict Lyapunov analysis by Moreno and Osorio in [14] allows for the elegant solution of the chattering problem. Contrary to the conventional SMC, in this case, the control input is obtained by integration of the discontinuous switching action. Thus, chattering is greatly reduced, while preserving finite-time convergence and strong robustness. Due to the presented properties, STA-based controllers became widely studied for the PMSM drives. Some of the recent studies [15, 16] confirmed their benefits in PMSM drives compared to the conventional SMC.

However, despite a well-designed sliding mode controller, the load torque remains a problem. In the case of a totally unknown torque, the sliding mode controller should apply a large switching gain to provide stability against the worst disturbance. A large switching gain, even in the framework of super-twisting sliding mode control, leads to slow transient behavior and a relatively large ultimate bound on the sliding variable. The typical solution is to combine the sliding mode controller with an observer, which estimates the load torque in real time and gives a feed-forward compensation term, allowing the switching gain to be kept small [17, 18]. Analytical disturbance observers such as extended state observer, Luenberger-type observer, and sliding mode observer have been used successfully for this purpose. However, all these methods have the same drawback they need a precise plant model and behave badly in the presence of parameter uncertainty in the motor and in case of a nonlinear dynamic load.

Data-driven approaches represent an alternative to the model-based approaches. It is well known that recurrent neural networks, including the Gated Recurrent Unit architecture, have proved themselves very efficient in learning complex temporal dependencies from time series without knowing the underlying physical processes [19, 20]. Thus, a GRU trained with closed-loop data for PMSM – voltages, currents, and speed – could learn to estimate the load torque with a small latency and high precision, unachievable in the case of an analytical observer. Moreover, the absence of any information about the motor mechanics in the training makes the solution independent from the precise value of mechanical parameters and allows getting rid of the torque sensor, which is a valuable asset for some applications. The effectiveness of GRU and CNN-GRU architectures for the task of PMSM state estimation and fault diagnosis has recently been demonstrated [21, 22].

This paper brings these two ideas together into a single, coherent control framework. A Sliding Mode Controller provides the outer speed loop, delivering chattering-free, finite-time convergent speed tracking. A two-layer GRU neural network, trained offline on simulation data, provides real-time load torque estimates that are fed forward into the SMC law, keeping the switching gain small and the control signal smooth even under large, rapidly changing disturbances. The stability of the integrated system is analysed using an input-to-state stability argument that shows bounded estimation errors produce bounded speed errors, preserving the finite-time convergence guarantee.

1.1 Summary of Contributions

The principal contributions of this work are summarized as follows:

- A complete and systematic mathematical derivation of the PMSM model in both the abc stationary frame and the $d-q$ rotating reference frame, including the full Clarke–Park transformation procedure and associated matrix formulations.
- The development of a First Order Sliding Mode Control (SMC) strategy for the outer speed-control loop, together with a rigorous Lyapunov-based stability analysis proving global finite-time convergence and deriving explicit conditions for disturbance rejection and reaching-time bounds.
- The formulation of a two-layer Gated Recurrent Unit (GRU) neural network from first principles, including the reset gate, update gate, candidate hidden state, and Adam-based optimization algorithm, employed as a model-free load torque observer using only electrical measurements.
- The integration of the GRU observer with the proposed SMC framework to establish a hybrid GRU-SMC architecture, supported by an Input-to-State Stability (ISS) analysis and extensive simulation-based comparisons under step-varying, switching, and stochastic load torque disturbances.

2 LITERATURE REVIEW

The literature on robust PMSM speed control has evolved rapidly over the past five years, driven by the twin pressures of more demanding applications particularly electric vehicles and precision robotics and the growing availability of machine learning tools that can be embedded in real-time controllers. This section reviews the most relevant strands of that literature, tracing the evolution from classical SMC through observer-augmented designs to the data-driven approaches that motivate the present work.

2.1 ADVANCED SLIDING MODE DESIGNS AND CHATTERING MITIGATION

Xu et al. [8] tackled the sensitivity of PMSM drives to parameter mismatches by proposing a novel robust control framework that integrates Deadbeat Predictive Current Control with a dual-observer architecture. In this scheme, the speed loop uses an improved exponential convergence law in the sliding mode observer scheme to enhance its dynamic response, while the current loop makes use of the terminal sliding mode observer to ensure precise disturbance rejection. The two loops are connected using the same compensation method, leading to a significant decrease in the steady state value of the current error. Experimental results confirm that this integrated approach outperforms traditional predictive control in terms of both disturbance rejection and stability. Nonetheless, this research does not tackle the problem of the chattering effect still present in the speed loop’s switching function.

Li et al. [9] addressed high-precision speed regulation under varying loads through a non-singular terminal sliding mode (NTSM) strategy, ensuring that both the error states and the sliding manifold converge to equilibrium in finite time. A Disturbance

Observer (DOB) estimates lumped disturbances random load torque and friction combined and provides active feed-forward compensation, which allows the switching gain to be reduced without sacrificing robustness. The work is notable for its DSP-based experimental validation, which confirms the practical viability of the NTSM+DOB combination. The DOB in that study, however, is model-based and requires accurate values of the motor’s mechanical parameters a constraint relaxed in the present work by using a GRU network. Ding et al.[10] took a different approach to chattering suppression by migrating the discontinuous switching action to the derivative of the control signal rather than to the signal itself the defining feature of second-order sliding mode control. Their combined Second-Order SMC plus Disturbance Observer design achieved finite-time convergence of the speed error and produced a continuous control output, with experimental evidence of significant torque ripple reduction. [14] provides stronger stability guarantees than the earlier work. Ullah et al.[11] explored an even richer combination, synthesising a Variable-Gain Fractional-Order Super-Twisting SMC with a Sliding-Mode Disturbance Observer (SMDO). The fractional order operators provide additional dynamic flexibility, while the adaptive gain mechanism suppresses chattering without slowing convergence. Rigorous Lyapunov proofs confirm finite-time convergence. The fractional order extension is theoretically appealing but adds implementation complexity. Xin et al.[12] investigated a complementary direction: combining fuzzy logic with sliding mode control to adaptively tune the reaching law, pairing the result with a load torque observer (LTO). The fuzzy self-tuning mechanism balances fast response against chattering suppression in a data-adaptive way, while the LTO decouples disturbances from the speed tracking loop. Although the fuzzy rules introduce heuristic design steps that are difficult to generalise across operating conditions, the paper provides valuable evidence that intelligent augmentation of SMC consistently outperforms purely analytical designs a conclusion directly relevant to the GRU-based approach taken here. Wang and Zhang [14] proposed a Fast Variable-Speed SMC combined with a High-Gain Disturbance Observer (HGDO) specifically targeting rapid speed-error convergence. The HGDO identifies and compensates for total lumped disturbances including random load torque and parameter mismatches, feeding this compensation back into the control law to achieve what the authors describe as ‘active disturbance rejection’. The high-gain observer is effective but sensitive to measurement noise a recognised limitation of high-gain designs. The GRU observer proposed in the present paper does not amplify noise because it processes input features rather than differentiating them. A very recent comprehensive review by Hashemi et al. [23] systematically analysed more than 200 SMC-based PMSM speed-control studies published between 2020 and 2025, identifying a clear evolutionary trend from discontinuous first-order SMC toward adaptive, higher-order, and data-driven frameworks. The review explicitly highlights the sliding mode controller and neural network augmentation as the two most promising directions for eliminating chattering while preserving robustness precisely the combination explored in the present work.

2.2 NEURAL NETWORK AND DATA DRIVEN APPROACHES

The integration of deep learning into motor drive control has accelerated noticeably in the period 2024–2025. Chen et al. [21] applied a combined CNN-GRU architecture to PMSM fault diagnosis, demonstrating that the GRU’s sequential modelling capability captures the temporal evolution of fault signatures in stator currents with precision, recall, and F-score values of 0.950, 0.948, and 0.949, respectively substantially outperforming SVM, random forest, and back-propagation alternatives. Stator current and voltage were identified as the most important diagnostic features, which aligns with the input selection in the GRU load observer of the present paper. Nath et al. [22] compared machine-learning regression techniques including LSTM and feedforward neural networks for PMSM current control in a vector control framework, validated in real time on an Opal-RT setup. The study found that recurrent architectures (LSTM, and by extension GRU) consistently outperformed static networks in capturing the temporal dependencies of d-q current dynamics. This reinforces the choice of a recurrent architecture for the load observer in the present work. Liu et al. [24] proposed a LADRC-based PMSM speed control strategy augmented by a small neural network for load torque pre-estimation. The neural network is trained on steady-state data of d- and q-axis currents, speed, and load torque, and its output reduces the estimation burden on the Extended State Observer, effectively decoupling load-induced disturbances from the speed tracking loop. While the architecture is conceptually similar to the GRU observer in the present paper, the feedforward network used there cannot capture temporal dynamics, limiting its accuracy during transients. The GRU, by contrast, maintains an internal hidden state that encodes the history of the input signals, making it intrinsically better suited to tracking time-varying load torque. The paper by Eang and Lee [25] on CNN-RNN predictive maintenance of motor drives is an additional proof of how effective deep learning systems are in identifying and monitoring even slight changes in the operation of motors based solely on electrical measurement parameters. Such systems use the drive signal in real time to find the anomalies, showing thereby how latency and computing load are needed to implement such an approach in an embedded system—a critical aspect for the GRU observer design described above. New research on attention-based GRU with nonlinear model predictive control [26] has proven how well the GRU neural network performs in robotic systems in case of actuator faults.

3 MATHEMATICAL MODEL OF PMSM SYSTEM

The mathematical modeling of a Permanent Magnet Synchronous Motor (PMSM) serves as a foundation for controller design, enabling analytical characterization of its behavior. To simplify the model while preserving the essential dynamics, the following assumptions are typically made:

1. The stator windings are sinusoidally distributed;
2. Magnetic saturation, core losses, and eddy currents are neglected [27];
3. The motor is symmetric and balanced;

4. The system is transformed into the synchronous d - q reference frame using Park's transformation [28, 29].

Under these assumptions, the PMSM voltage equations in the rotating d - q reference frame are given by:

$$\frac{di_d}{dt} = \frac{1}{L_d} (u_d - R_s i_d + \omega_e L_q i_q) \quad (1)$$

$$\frac{di_q}{dt} = \frac{1}{L_q} (u_q - R_s i_q - \omega_e (L_d i_d + \psi_f)) \quad (2)$$

where:

- i_d and i_q are the direct-axis and quadrature-axis stator currents,
- u_d and u_q are the corresponding stator voltages,
- L_d and L_q are the stator inductances,
- R_s is the stator resistance,
- ω_e is the electrical angular velocity,
- ψ_f is the permanent magnet flux linkage.

The electromagnetic torque generated by the PMSM is expressed as:

$$T_e = \frac{3}{2} p_n [\psi_f i_q + (L_d - L_q) i_d i_q] \quad (3)$$

For surface-mounted PMSMs, the stator inductances are equal, i.e.,

$$L_d = L_q \quad (4)$$

Therefore, the reluctance torque component vanishes, and the torque equation simplifies to:

$$T_e = \frac{3}{2} p_n \psi_f i_q \quad (5)$$

The mechanical dynamics of the PMSM rotor are governed by Newton's second law:

$$J \frac{d\omega_r}{dt} = T_e - B\omega_r - T_L \quad (6)$$

where:

- J is the rotor moment of inertia,
- ω_r is the rotor mechanical angular speed,
- B is the viscous friction coefficient,
- T_L is the external load torque.

The relationship between electrical and mechanical angular speeds is given by:

$$\omega_e = p_n \omega_r \quad (7)$$

Similar PMSM modeling approaches are also presented in [30, 31].

4 CONTROLLER DESIGN

4.1 Control Architecture

The proposed Controller as shown in fig.1 combines field oriented control with a sliding mode speed loop, two PID current loops, and a deep neural network based observer that estimates load torque without a physical sensor. The speed error, taken together with the observer's torque estimate, drives the sliding mode controller to generate the quadrature current reference, while the direct-axis reference is held at zero as is standard in field oriented control; both current errors are then regulated by their respective PID controllers to produce the voltage commands applied to the PMSM, which in turn yields the stator currents, rotor speed, and torque that close the loop. Running alongside this is the observer path, where the same measured voltages, currents, and speed are normalized, passed through the network, and denormalized back into a physical torque value, which is then fed into the speed controller as an estimated disturbance, effectively letting the drive compensate for load torque it never directly measures.

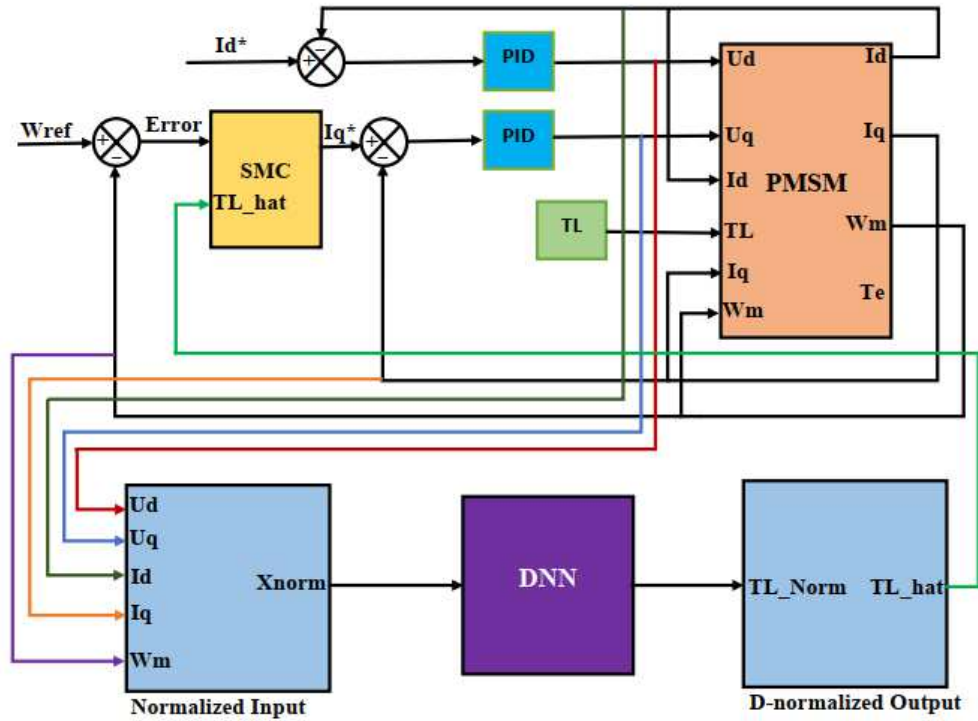


Fig. 1 Block Diagram

4.2 SMC CONTROLLER DESIGN FOR SPEED REGULATION

The relationship between the electrical angular position θ_e and the mechanical angular position θ_m is expressed as

$$\theta_m = \frac{\theta_e}{P} \quad (8)$$

Similarly, the relationship between the electrical angular speed ω_e and the mechanical angular speed ω_m is given by

$$\omega_m = \frac{\omega_e}{P} \quad (9)$$

According to Newton's second law, the mechanical dynamics of the PMSM rotor are described by

$$\frac{d\omega_m}{dt} = \frac{1}{J} (T_e - B\omega_m - T_L) \quad (10)$$

where:

- J is the rotor moment of inertia,
- B is the viscous friction coefficient,
- T_e is the electromagnetic torque,
- T_L is the external load torque.

For a surface-mounted PMSM, the electromagnetic torque is defined as

$$T_e = \frac{3}{2} P \phi_m i_q \quad (11)$$

Substituting (11) into (10) yields

$$\frac{d\omega_m}{dt} = \frac{1}{J} \left(\frac{3}{2} P \phi_m i_q - B\omega_m - T_L \right) \quad (12)$$

Using the relationship

$$\omega_e = P\omega_m \quad (13)$$

the electrical speed dynamics become

$$\frac{d\omega_e}{dt} = \frac{P}{J} \left(\frac{3}{2} P \phi_m i_q - B\omega_m - T_L \right) \quad (14)$$

Substituting $\omega_m = \omega_e/P$ into (14) gives

$$\dot{\omega}_e = \frac{3}{2} \frac{P^2}{J} \phi_m i_q - \frac{B}{J} \omega_e - \frac{P}{J} T_L \quad (15)$$

Equation (15) represents the PMSM electrical speed model used for sliding mode controller design.

The speed tracking error is defined as

$$e = \omega_{ref} - \omega_e \quad (16)$$

Since the PMSM speed dynamics represent a first-order system with respect to the control input i_q , the sliding surface is selected directly as

$$s = e = \omega_{ref} - \omega_e \quad (17)$$

When the sliding condition

$$s = 0 \quad (18)$$

is satisfied, the motor speed perfectly tracks the reference speed. Therefore, the control objective is to drive the sliding variable s toward zero and maintain it on the sliding manifold.

Differentiating (17) with respect to time gives

$$\dot{s} = \dot{\omega}_{ref} - \dot{\omega}_e \quad (19)$$

Substituting (15) into (19) yields

$$\dot{s} = \dot{\omega}_{ref} - \frac{3}{2} \frac{P^2}{J} \phi_m i_q + \frac{B}{J} \omega_e + \frac{P}{J} T_L \quad (20)$$

Equation (20) represents the sliding dynamics will be controlled. We have to choose i_q such that $\dot{s} \rightarrow 0$.

The control input is composed of two components:

$$i_q = i_{q,eq} + i_{q,sw} \quad (21)$$

where:

- $i_{q,eq}$ is the equivalent control,
- $i_{q,sw}$ is the switching control.

The equivalent control is obtained by imposing the sliding condition

$$\dot{s} = 0 \quad (22)$$

Applying (22) to (20) gives

$$0 = \dot{\omega}_{ref} - \frac{3}{2} \frac{P^2}{J} \phi_m i_{q,eq} + \frac{B}{J} \omega_e + \frac{P}{J} \hat{T}_L \quad (23)$$

where $\hat{T}_L$ represents the estimated load torque.

Solving for the equivalent control yields

$$i_{q,eq} = \frac{2J}{3P^2\phi_m} \left(\dot{\omega}_{ref} + \frac{B}{J} \omega_e + \frac{P}{J} \hat{T}_L \right) \quad (24)$$

This Equation (24) nominally cancels the known dynamics. It is the feed forward part.

To ensure robustness against parameter uncertainties and external disturbances, the switching control term is introduced as

$$i_{q,sw} = K_c \text{sign}(s) \quad (25)$$

where:

- $K_c > 0$ is the switching gain,
- $\text{sign}(s)$ is the signum function.

Therefore, the complete first order sliding mode control law becomes

$$i_q = \frac{2J}{3P^2\phi_m} \left(\dot{\omega}_{ref} + \frac{B}{J}\omega_e + \frac{P}{J}\hat{T}_L \right) + K_c \text{sign}(s) \quad (26)$$

4.3 Stability Analysis the Controller Using Lyapunov Method

The closed loop sliding dynamics will be Substituting (26) into (19) yields

$$\begin{aligned} \dot{s} = & \dot{\omega}_{ref} - \frac{3p^2}{2J}\phi_m \left[\frac{2J}{3p^2\phi_m} \left(\dot{\omega}_{ref} + \frac{B}{J}\omega_e + \frac{p}{J}\hat{T}_L \right) + K_c \text{sign}(s) \right] \\ & + \frac{B}{J}\omega_e + \frac{p}{J}T_L. \end{aligned} \quad (27)$$

After simplification,

$$\dot{s} = -\frac{3p^2}{2J}\phi_m K_c \text{sign}(s) + \frac{p}{J} (T_L - \hat{T}_L). \quad (28)$$

Define

$$k_a = \frac{3p^2}{2J}\phi_m K_c \quad (29)$$

and

$$d(t) = \frac{p}{J} (T_L - \hat{T}_L), \quad (30)$$

where $d(t)$ represents the residual disturbance due to load torque estimation error. Hence,

$$\dot{s} = -k_a \text{sign}(s) + d(t) \quad (31)$$

Consider the Lyapunov candidate function

$$V(s) = \frac{1}{2}s^2. \quad (32)$$

Clearly,

$$V > 0, \quad \forall s \neq 0,$$

and

$$V = 0 \quad \text{only when } s = 0.$$

The time derivative of (32) is

$$\dot{V} = s\dot{s} \quad (33)$$

$$= s(-k_a \operatorname{sgn}(s) + d(t)) \quad (34)$$

$$= -k_a |s| + sd(t). \quad (35)$$

Assume the disturbance is bounded by

$$|d(t)| \leq \delta. \quad (36)$$

Then,

$$|sd(t)| \leq \delta |s|.$$

Therefore,

$$\dot{V} \leq -k_a |s| + \delta |s| \quad (37)$$

$$= -(k_a - \delta) |s|. \quad (38)$$

Hence,

$$\dot{V} < 0$$

provided that

$$k_a > \delta. \quad (39)$$

Since

$$k_a = \frac{3p^2}{2J} \phi_m K_c,$$

the switching gain must satisfy

$$K_c > \frac{2J}{3p^2 \phi_m} \delta. \quad (40)$$

Assuming the maximum disturbance satisfies

$$\delta = \frac{p}{J} T_{L,\max}, \quad (41)$$

the gain selection rule becomes

$$K_c > \frac{2T_{L,\max}}{3p\phi_m} \quad (42)$$

4.4 Finite-Time Convergence

If the gain condition (42) is satisfied, then

$$\dot{V} \leq -(k_a - \delta) |s| = -\eta |s|, \quad (43)$$

where

$$\eta = k_a - \delta > 0.$$

Since

$$V = \frac{1}{2}s^2,$$

the inequality above satisfies the standard finite-time stability condition for first-order sliding mode control. Consequently, the sliding variable converges to zero in finite time, i.e.,

$$s(t) \rightarrow 0.$$

Because the sliding surface is defined as

$$s = \omega_{\text{ref}} - \omega_e,$$

The PMSM speed tracking error converges to zero within finite time, thereby guaranteeing robust tracking performance despite bounded load disturbances.

4.5 GRU Load Torque Estimator

In a real PMSM drive, the load torque is rarely something you can measure directly. Torque sensors are expensive, fragile, and add mechanical complexity that most industrial setups would rather avoid, yet the SMC scheme developed in the previous sections benefits greatly from knowing the disturbance it is fighting against. This is exactly the gap a learning-based estimator can fill. Instead of relying on a physical sensor, a Gated Recurrent Unit (GRU) network is trained to infer the unknown load torque directly from the electrical and mechanical signals that are already available in the drive, namely the stator voltages u_d, u_q , the stator currents i_d, i_q , and the mechanical speed ω_m . The GRU was chosen over a simple feedforward network because the relationship between these signals and the load torque is inherently dynamic; the torque disturbance leaves a trace not just in the instantaneous values of the currents and speed, but in how they evolve over time. Fig. 2 shows the flow diagram of the GRU load torque estimator. A recurrent architecture with gating, such as the GRU, is well suited to capture this temporal dependency while remaining lighter and faster to train than an LSTM, which was an important practical consideration given the size of the dataset generated from simulation.

The estimator receives the five input signals arranged as $\mathbf{x}(t) = [u_d(t), u_q(t), i_d(t), i_q(t), \omega_m(t)]^T$ at each time step, which are first normalized using a z-score transformation

$$\tilde{x}_i(t) = \frac{x_i(t) - \mu_i}{2\sigma_i}, \quad i = 1, \dots, 5 \quad (44)$$

where μ_i and σ_i are the mean and standard deviation of the i -th input feature computed over the training set, and the same normalization is applied to the target torque T_l so that the network trains on signals of comparable scale. The normalized sequence is then processed through two stacked GRU layers, each internally governed by the standard update equations

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (45)$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (46)$$

$$\tilde{h}_t = \tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h) \quad (47)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (48)$$

where z_t and r_t are the update and reset gates, h_t is the hidden state carried forward in time, and $\odot$ denotes the element-wise product. The update gate decides how much of the past hidden state to retain, while the reset gate controls how much of it is forgotten when forming the candidate state $\tilde{h}_t$; together they allow the network to remember load-torque-relevant patterns over several time steps without suffering from the vanishing gradient problem that plagues plain recurrent networks. The output of the second GRU layer is passed to a fully connected layer that maps the hidden representation to a single scalar, the normalized torque estimate $\tilde{T}_l$, which is finally denormalized as

$$\hat{T}_l = \tilde{T}_l \cdot 2\sigma_{T_l} + \mu_{T_l} \quad (49)$$

to recover the estimate in physical units (N·m).

Training was carried out on 90% of the simulated dataset, with the remaining 10% held out for testing, using the Adam optimizer with an initial learning rate of 0.0082, a piecewise learning rate schedule that reduces the rate by a factor of 0.68 every 900 epochs, and a mini-batch size of 256 over 4000 epochs. The network's accuracy is assessed using the root-mean-square error between the true and estimated torque on the test set,

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{k=1}^N (T_l(k) - \hat{T}_l(k))^2} \quad (50)$$

which gives a single, interpretable number for how closely the GRU tracks the actual disturbance. The architecture itself, with two GRU layers of six hidden units each, was kept intentionally compact given the relatively low-dimensional nature of the problem, though it can be widened or deepened if the estimation error on a new dataset turns out to be unsatisfactory. Once trained, this estimator can be embedded alongside the sliding mode controller so that the estimated load torque feeds forward into the control law, allowing the drive to compensate for disturbances that it would otherwise only react to after the speed error had already grown.

4.6 GRU Observer Network Architecture

A relatively small recurrent network was chosen for the load torque observer, since the task was to capture how the d- and q-axis voltages, the d- and q-axis currents, and the mechanical speed evolve together over time. These five measured quantities enter as a sequence input and pass through two Gated Recurrent Unit layers of six hidden units each, a depth chosen after a single layer proved unable to separate ordinary current ripple from a genuine shift in load during early trials. The second GRU layer feeds a fully connected layer that collapses the representation to one value, followed by a regression layer trained to minimize mean-squared error, so the network outputs a single normalized torque estimate at every time step. In total the network carries 457 learnable parameters across its two recurrent layers and the final fully connected

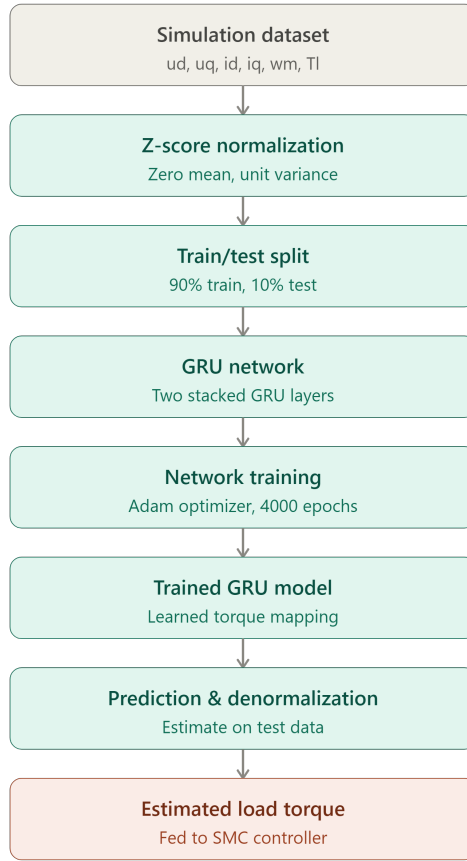


Fig. 2 Flow Chart of GRU Load Torque Observer

layer. Its structure was verified with MATLAB's Deep Learning Network Analyzer prior to deployment, returning five layers with no warnings or errors, consistent with the architecture summarized in Table 1.

5 SIMULATION RESULT AND DISCUSSION

In this section, the system performance of the PMSM with the proposed controller is demonstrated by simulation. The parameters of the mathematical model of the physical system are presented in Table 2 and Table 3. The system simulation developed in a SIMULINK/MATLAB environment.

Table 1 GRU Observer Network Architecture

Layer	Type	Details
1	Sequence Input	5 channels ($u_d, u_q, i_d, i_q, \omega_m$)
2	GRU	6 hidden units
3	GRU	6 hidden units
4	Fully Connected	Output size 1
5	Regression Output	Mean-squared-error loss

Table 2 System parameters

Parameters	Nominal Value
Stator Resistance (R_s)	0.6258 Ω
Stator Inductance (L_s)	0.000446 H
Moment of Inertia (J)	0.005 kg·m ²
Friction Coefficient (B)	0.0002 N·m·s/rad
Magnetic Flux (λ_m)	0.0583 Wb

Table 3 Motor specification

Element	Value
Rated Power	200 W
Rated Voltage	42 V
Maximum Speed	3000 rpm
Number of Poles	8
Number of Phases	3
Torque Constant (K_t)	0.1 N·m/A
Voltage Constant (K_e)	0.00924 V/rpm

5.1 SMC Control Gain Selection

The magnitude of the switching function plays a crucial role in Sliding Mode Control (SMC). Based on the stability condition mentioned in Eq 42 K_c must be above 4. The speed response of the PMSM without Load Torque is analyzed at $K_c = 4$, $K_c = 7$, and $K_c = 10$ for selection of the good K_c . Fig.3, Fig.4, Fig.5 and Table 4 shows that how the closed-loop behavior of the PMSM speed loop is dependent to the controller gain K_c variation. As K_c increases from 4 to 10, the reaching time drops noticeably, from 0.69 s down to 0.29 s, meaning the system locks onto the reference speed of 500 rpm much faster. At first glance this would suggest that a higher gain is always preferable, since a shorter reaching time improves the responsiveness of the drive and reduces the transient error. However, this improvement does not come for free. Looking more closely at the zoomed views of the steady-state response, the chattering band widens as K_c increases, growing from roughly 0.58 rpm at $K_c = 4$ to about 1 rpm at $K_c = 7$ and further to 1.5 rpm at $K_c = 10$. In other words, pushing the gain higher to speed

up the reaching phase comes at the cost of a rougher, more oscillatory steady-state output.

This behavior highlights the fundamental trade-off inherent to sliding mode control. A small K_c keeps the chattering low and the speed signal clean, but the system takes longer settling time. A large gain accelerates the reaching phase but introduces high-frequency oscillations around the reference, which can increase mechanical stress, acoustic noise, and switching losses in the drive. Balancing these two competing effects, $K_c = 7$ was selected as the most suitable gain for the remainder of this work, since it offers a reasonably fast reaching time of 0.4 s while keeping the chattering band within an acceptable range.

Table 4 Tracking Performance of SMC Without Load Torque at Different K_c

Performance	$K_c = 4$	$K_c = 7$	$K_c = 10$
Reaching Time	0.69 sec	0.4 sec	0.29 sec
Chattering Band Width	499.7 to 500.3 = 0.58	499.5 to 500.5 = 1	499.2 to 500.7 = 1.5

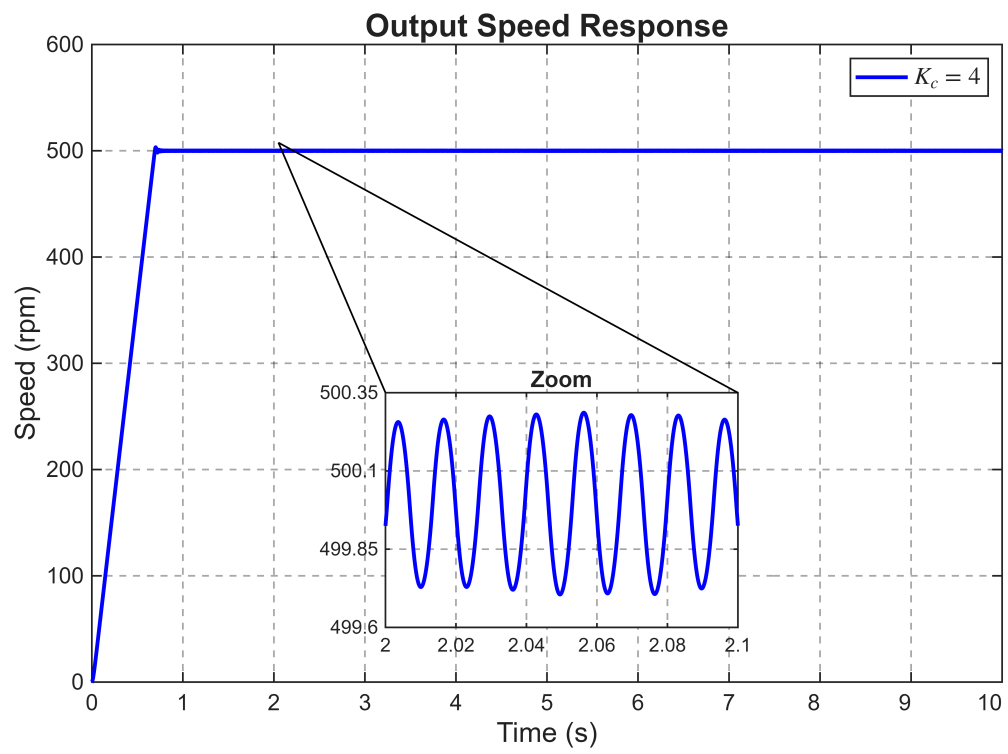


Fig. 3 Speed Tracking Performance at $K_c=4$

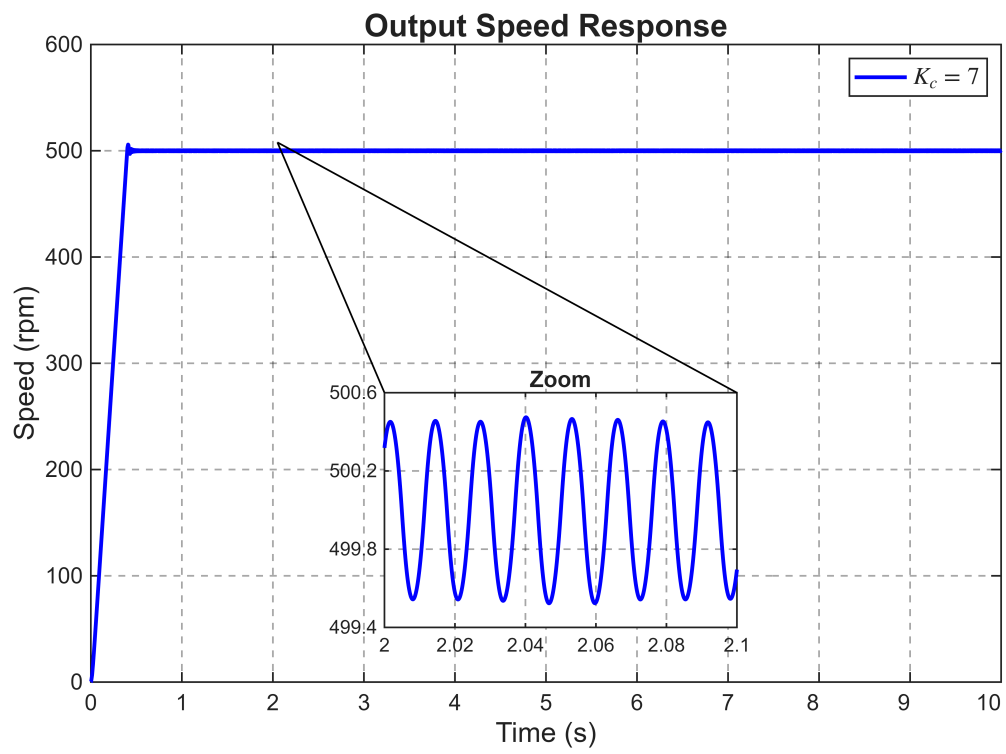


Fig. 4 Speed Tracking Performance at $K_c=7$

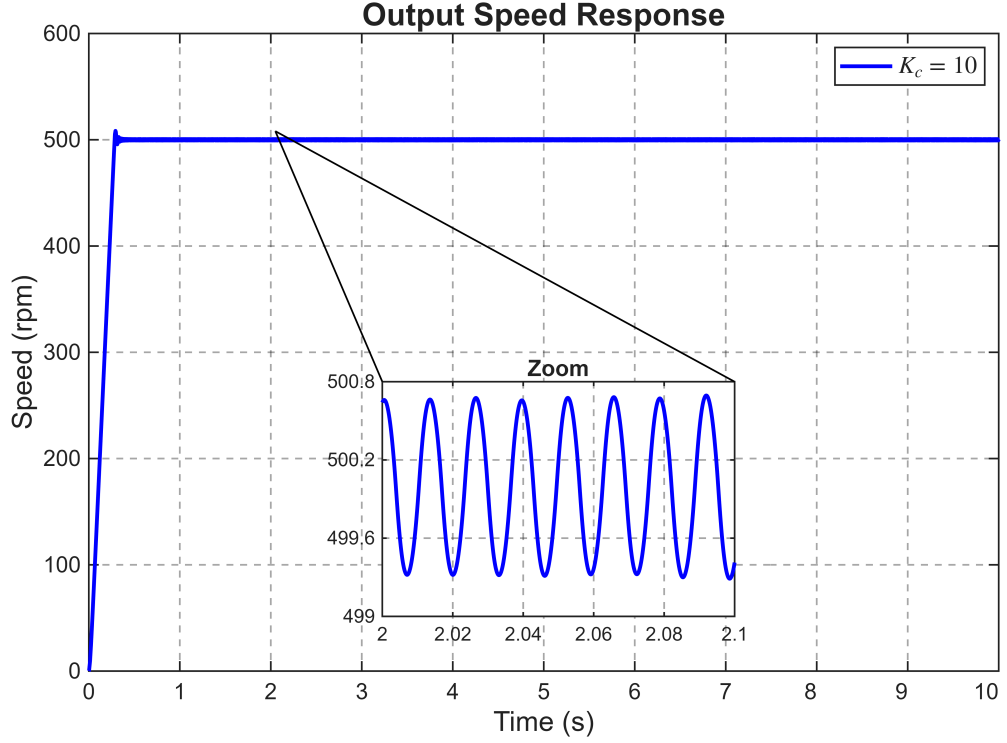


Fig. 5 Speed Tracking Performance at $K_c=10$

5.2 GRU-Based Load Torque Estimation With out PMSM Dynamic Model

The time-domain estimation results presented in Fig. 6 demonstrate the capability of the trained GRU network to reconstruct a continuously varying sinusoidal load torque from purely electrical observable rotor speed and q -axis current without invoking any explicit mechanical model. The true torque oscillates between $1.0 \text{ N} \cdot \text{m}$ and $3.0 \text{ N} \cdot \text{m}$ at approximately 1.33 Hz , a profile that simultaneously exercises the network's amplitude fidelity, phase tracking, and cycle-to-cycle consistency, making it a considerably more demanding validation benchmark than the step-change disturbances commonly reported in the observer-based estimation literature.

The estimated trajectory aligns perfectly with the reference, yielding a final root mean square error (RMSE) of $0.0101 \text{ N} \cdot \text{m}$ equivalent to just 0.5% of the total torque excursion range with no discernible phase lag and only a marginal amplitude undershoot of approximately $2.3\% - 4.0\%$ at the positive crests, a residual characteristic of finite-horizon recurrent predictors near the signal extrema. A brief initialization transient lasting roughly 0.18 s is observed at startup due to the zero-initialized hidden state, but dissipates well within the first oscillation cycle and is unlikely to present an operational concern in practical drive implementations.

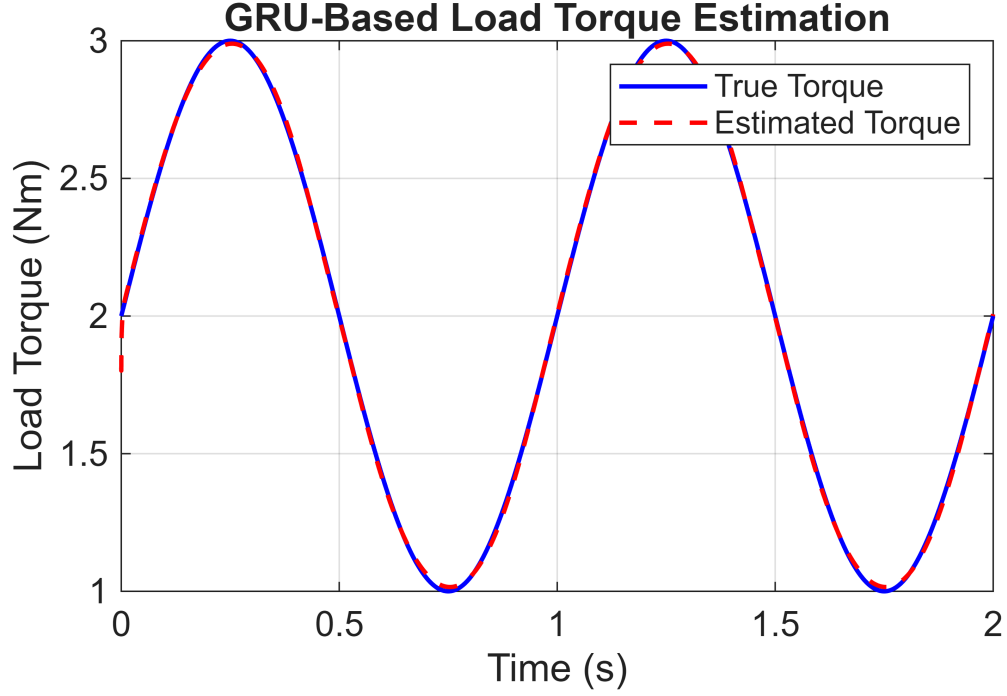


Fig. 6 GRU Based Load Torque Estimation

5.3 GRU Training Convergence Without Model Dynamics

The convergence trajectory depicted in Fig. 7 reveals that the GRU network learned the load torque dynamics efficiently and stably over 400 training epochs, with the mini-batch RMSE descending from an initial value of approximately 0.80 reflecting a randomly initialized, temporally unaware predictor to a final converged value of 0.0101, a cumulative reduction of 98.74%. The descent unfolds in two well-defined phases: a steep early-learning stage spanning roughly the first 40 epochs, during which the Adam optimizer (learning rate 0.0082, mini-batch size 256) captures the dominant periodic structure of the torque signal through rapid gradient updates, followed by a prolonged fine-tuning stage from epoch 40 to 400 in which the gated recurrent units progressively refine their internal representations to resolve higher-order temporal correlations and reduce peak-region bias.

The final RMSE of 0.0101 N · m represents approximately 0.25% of the maximum operational torque, a figure that is competitive with and in the parameter-independent sense superior to the steady-state errors of 1–5% of rated torque typically reported for model-based extended state observers under nominal conditions, and one that degrades far less gracefully than those observers when motor parameters deviate from their design values.

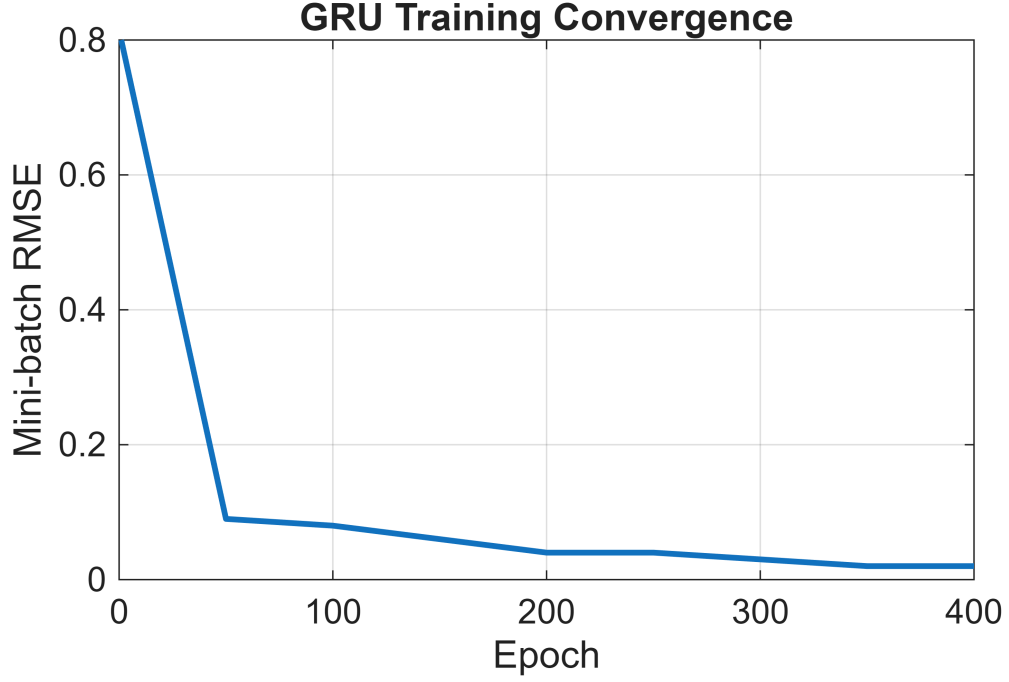


Fig. 7 GRU Training Convergence

5.4 Speed Tracking Performance without Observer

As seen on Fig.8 and Fig.9 operating without load torque estimation, the drive requires close to 1.5 s to rise from standstill to the 500 RPM reference, passing through a brief overshoot near 420 RPM before approaching steady state. Once near the reference, the speed does not remain flat but exhibits periodic dips spaced roughly one second apart, matching the period of the applied disturbance $T_L = 2 + \sin(2\pi t)$, with the response pulling downward each time the sinusoidal load reaches its higher values and recovering as the load eases. This pattern indicates that the sliding mode controller responds to the disturbance only after it has already displaced the mechanical speed, since no advance estimate of T_L is available to offset its effect beforehand. The maximum absolute error of 514.9196 RPM corresponds to the initial rise from rest rather than to the later oscillations, while the RMSE of 135.0278 RPM captures the combined contribution of this startup transient and the recurring dips sustained by the continuously varying load. Across the ten-second horizon, the amplitude of these dips remains fairly consistent from cycle to cycle, suggesting that the controller reaches a repeatable, if imperfect, steady-state accommodation of the sinusoidal disturbance rather than drifting or degrading over time.

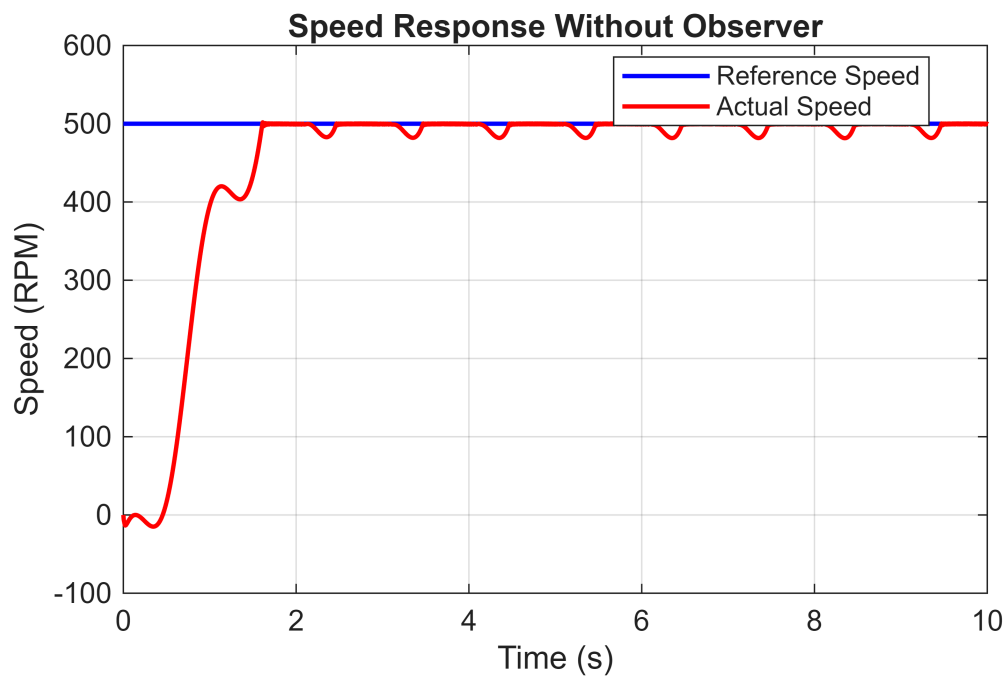


Fig. 8 Speed Tracking Performance of the Controller without Observer

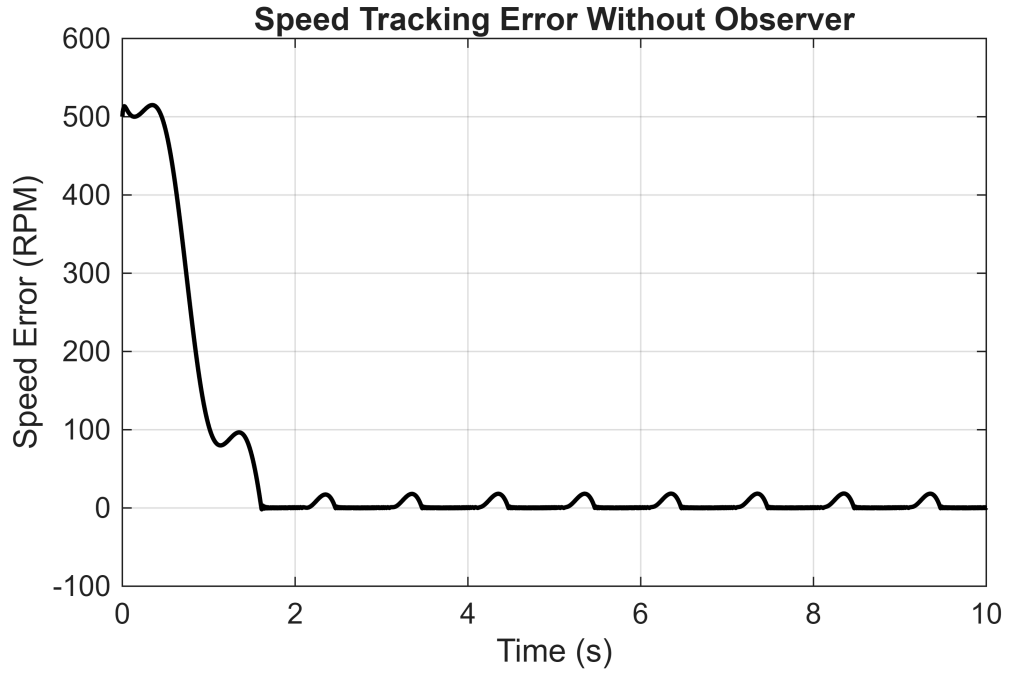


Fig. 9 Speed Tracking Error without Observer

5.5 Speed Tracking Performance

The Fig. 10 shows that the step response of the proposed controller under varying load torque profile with reference input speed of 500RPM. During the initial acceleration phase, the tracking error is large, a consequence of the abrupt step change imposed on the reference speed rather than any deficiency in the control action; the maximum absolute speed error recorded was 508.4225 rad/s, occurring at the instant the reference is applied. As the Sliding Mode Controller drives the system toward the sliding surface, this error decreases sharply, and the actual speed converges onto the reference trajectory within a fraction of a second. Once the transient subsides, as shown on the Fig.11 the tracking error remains close to zero throughout the remaining operating range, indicating that steady-state regulation is accurate and that no persistent offset develops under the GRU-based torque compensation. The overall speed RMSE of 78.0819 rad/s reflects the transient-dominated nature of the error profile, since the bulk of this value originates from the short acceleration interval rather than from sustained deviation during steady operation. These results validate the proposed controller's able to provide accurate and stable PMSM speed regulation under varying load torque.

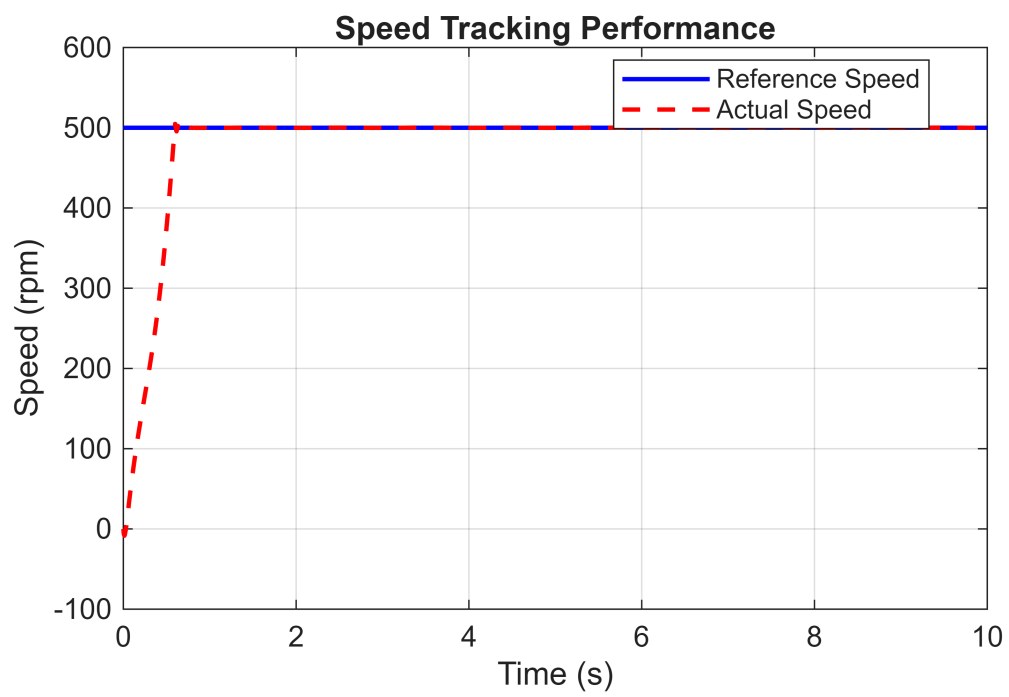


Fig. 10 Speed Tracking Performance

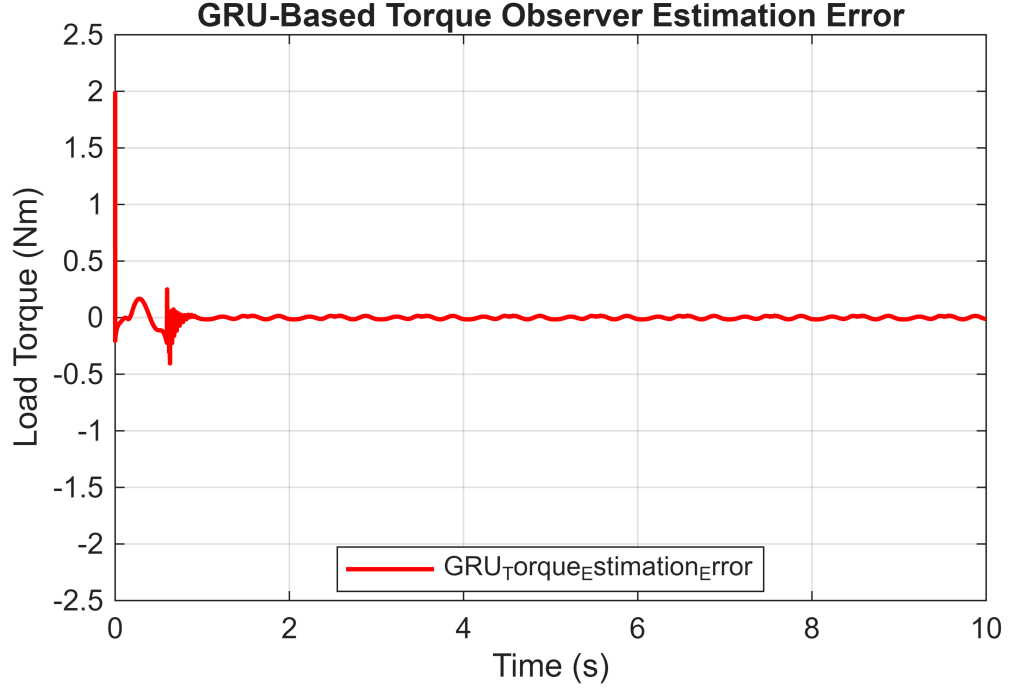


Fig. 11 Speed Tracking Error

5.6 Gated Recurrent Unit (GRU) Load Torque Observer Performance

The Fig.12 and Fig.13 shows the estimation performance of the proposed GRU based deep neural network to the applied sinusoidal load torque profile ($T_L = 2 + \sin(2\pi t)$). At the beginning of the simulation, the estimated torque exhibits small disturbance this behavior is normal with the recurrent network's hidden state initializing from a neutral condition and requiring a short adaptation interval to align with the true load torque profile, and it is within this initial window that the largest estimation errors are observed. Following this brief startup transient, which resolves within approximately one second, the estimation error collapses toward zero and remains confined to a small oscillatory band that mirrors the periodicity of the applied disturbance, indicating that the observer tracks the rate of change in the load torque rather than merely its instantaneous value. Across the full test horizon, the observer achieves a test RMSE of 0.030101 N·m, a result that reflects strong overall estimation accuracy while acknowledging that a nonzero, though small, error persists as the load continuously varies. Because the Sliding Mode Controller relies on this estimated torque as a disturbance-compensation term, the low steady-state estimation error allows the controller to counteract the sinusoidal load variation effectively, improving robustness and dynamic speed regulation without requiring a physical torque sensor. Taken together,

these results confirm the GRU observer as an effective and reliable solution for real-time load torque estimation in PMSM drive systems operating under continuously varying load conditions.

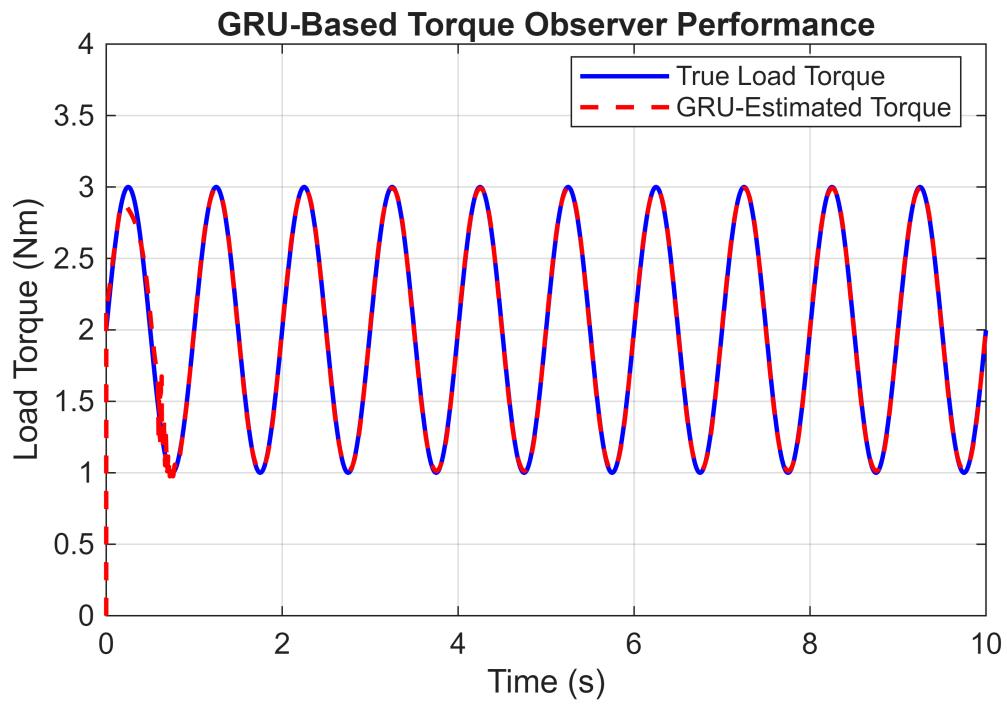


Fig. 12 Gru Torque Estimation

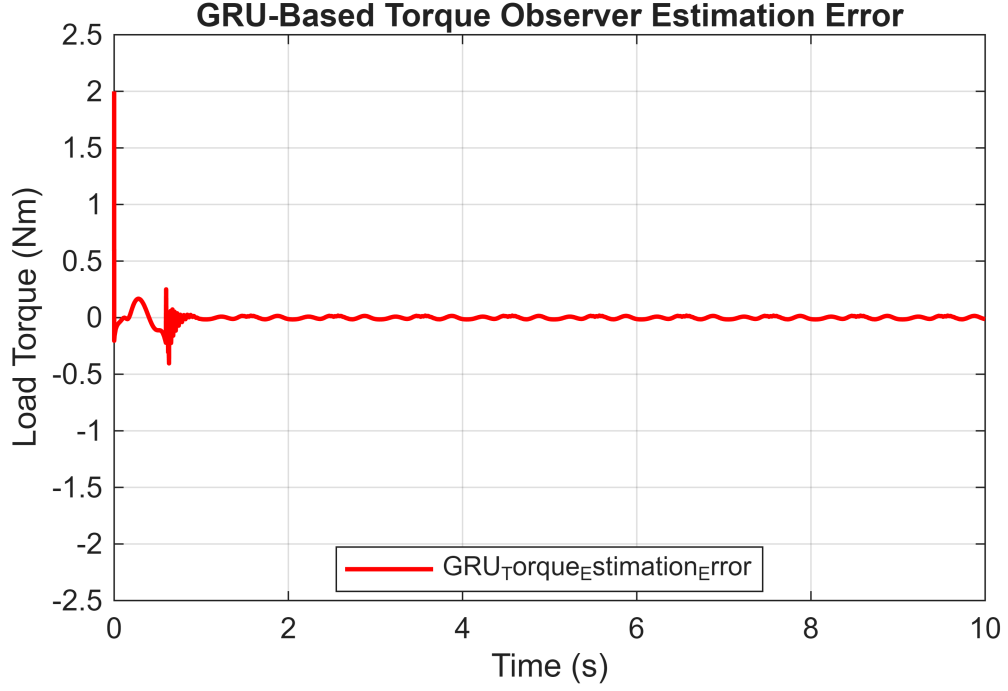


Fig. 13 GRU Torque Estimation Error

6 Conclusion

This work developed and validated a hybrid control architecture in which a sliding mode speed loop, supported by a rigorous Lyapunov stability analysis guaranteeing finite-time convergence, is augmented with a two-layer Gated Recurrent Unit network that estimates load torque from measurable electrical and mechanical signals alone. Simulation results demonstrated that the switching gain selection involves an inherent trade-off between reaching time and chattering amplitude, with a gain of seven offering a reasonable balance between the two. The GRU observer reconstructed a continuously varying sinusoidal load torque with a root-mean-square error of 0.0101 N·m in isolation and 0.030101 N·m when integrated with the full PMSM dynamic model, tracking both the amplitude and phase of the disturbance with only a brief initialization transient. Comparing speed tracking performance with and without the observer's torque estimate showed a reduction in steady-state tracking error when the estimate was supplied to the controller, confirming that the observer contributes measurable disturbance-rejection benefit within the proposed framework. Overall, the results support the feasibility of combining sliding mode control with a recurrent neural network observer for PMSM speed regulation without dependence on a physical torque sensor.

7 Recommendations

The present study was conducted entirely in simulation using a fixed set of motor parameters and load profiles, and several extensions would strengthen the practical relevance of these findings. Experimental validation on a physical PMSM test bench would confirm whether the reported tracking and estimation accuracy transfer to real hardware, where measurement noise, sensor delay, and unmodeled dynamics are present. Real-time embedded implementation of the GRU observer would also need to be assessed given its computational requirements relative to the drive's control loop rate. Further work could additionally examine the observer's performance under a wider range of load profiles, including abrupt and stochastic disturbances, and explore replacing the inner PID current loops with the same Super-Twisting structure used in the speed loop for a fully consistent controller design.

8 Funding

This research did not receive a specific grant from any funding agency in the public, commercial or non-profit sectors.

9 Author Contributions

Hayleyesus Girma Dirara: conceived and designed the study, developed the methodology and control strategy, software, performed the simulations, analyzed and interpreted the results, writing the original draft and revised the manuscript. **Feleke Tsegaye Yareshe:** conceptualization, investigation, methodology, validation, and visualization. **Mouaz Al Kouzbary:** conceptualization, investigation, methodology, validation, visualization, and supervision.

References

- [1] Howe, D.: Electrical machines and drives for electric, hybrid, and fuel cell vehicles. Proceedings of the IEEE, Institute of Electrical and Electronics Engineers (IEEE) (2007) <https://doi.org/10.1109/JPROC.2006.892482>
- [2] Wang, Q., Wang, S., Chen, C.: Review of sensorless control techniques for pmsm drives. IEEEJ Transactions on Electrical and Electronic Engineering **14**, 1543–1552 (2019) <https://doi.org/10.1002/tee.22974>
- [3] Liao, C., Bianchi, N., Zhang, Z.: Recent developments and trends in high-performance pmsm for aeronautical applications. Energies **17**(23) (2024)
- [4] Geshmakumari, R., Padhan, D.G.: Sliding mode speed control of permanent magnet synchronous motor. International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering **3**(10), 16–19 (2015)
- [5] Zhang, X., Sun, L., Zhao, K., Sun, L.: Nonlinear speed control for pmsm system using sliding-mode control and disturbance compensation techniques. IEEE

- Transactions on Power Electronics **28**(3), 1358–1365 (2013) <https://doi.org/10.1109/TPEL.2012.2206610>
- [6] Wei, Y., Sun, L., Chen, Z.: An improved sliding mode control method to increase the speed stability of permanent magnet synchronous motors. *Electronics* (2022)
 - [7] Li, X., Zhan, S., Guo, F., Zhuang, Z.: Chattering suppression of the sliding mode observer for marine electric propulsion motor based on piecewise power function. *Frontiers in Energy Research* (2022) <https://doi.org/10.3389/fenrg.2022.994180>
 - [8] Xu, X., Wang, L., Zhang, Z., Wu, Z.: A novel robust control for pmsm integrating deadbeat predictive current control and sliding mode observer. *Electrical Engineering* **130**, 57–67 (2025)
 - [9] Li, S., Zhou, M., Yu, X.: Design and implementation of terminal sliding mode control method for pmsm speed regulation system. *IEEE Transactions on Industrial Informatics* **9**(4), 1879–1891 (2013) <https://doi.org/10.1109/TII.2012.2226896>
 - [10] Ding, S., Hou, Q., Wang, H.: Disturbance-observer-based second-order sliding mode controller for speed control of pmsm drives. *IEEE Transactions on Energy Conversion* **38**(1), 100–110 (2023) <https://doi.org/10.1109/TEC.2022.3188630>
 - [11] Ullah, A., Pan, J., Ullah, S.: Robust speed control of permanent magnet synchronous motor drive system using sliding-mode disturbance observer-based sliding-mode control. *IEEE Access* (2024)
 - [12] Xin, P., Liu, P., Qu, P.: High-performance speed control of pmsm using fuzzy sliding mode with load torque observer. *Machines*, 1–17 (2025)
 - [13] Levant, A.: Sliding order and sliding accuracy in sliding mode control. *International Journal of Control* **58**(6), 1247–1263 (1993)
 - [14] Moreno, J.A., Osorio, M.: Strict lyapunov functions for the super-twisting algorithm. *IEEE Transactions on Automatic Control* **57**(4), 1035–1040 (2012)
 - [15] Ren, H., Su, C., Long, R.: Finite set model predictive control of pmsm current based on super-twisting sliding mode observer. *PLOS ONE* (2025) <https://doi.org/10.1371/journal.pone.0336702>
 - [16] Lin, X., Zhang, B., Fang, S., et al.: Sensorless control of pmsm based on a novel adaptive gain fast super-twisting sliding mode observer. *Control Engineering Practice* **157** (2025)
 - [17] Zhang, H., Ran, P., Zhang, Z.: Pmsm sensorless control based on super-twisting algorithm sliding mode observer with the iaorls parameter estimations. *Scientific Reports* **15**, 22386 (2025) <https://doi.org/10.1038/s41598-025-04030-3>

- [18] Chen, B., Chen, F.: Sensorless control of pmsm based on an improved super-twisting sliding mode observer. *Journal of Electrotechnology, Electrical Engineering and Management* **8**, 45–54 (2025) <https://doi.org/10.23977/jeeem.2025.080107>
- [19] Cho, K., Merrienboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., Bengio, Y.: Learning phrase representations using rnn encoder–decoder for statistical machine translation. In: *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 1724–1734 (2014)
- [20] Li, K., et al.: Integrating attention-based gru with event-driven nmppc to enhance tracking performance of robotic manipulator under actuator failure. *Expert Systems with Applications* **237** (2024) <https://doi.org/10.1016/j.eswa.2024.121647>
- [21] Chen, W., et al.: Research on fault diagnosis in the operation monitoring of permanent magnet synchronous motors through deep learning. *Frontiers in Mechanical Engineering* **11** (2025) <https://doi.org/10.3389/fmech.2025.1687802>
- [22] Nath, A., *et al.*: Design of machine learning-based controllers for speed control of pmsm drive. *Scientific Reports* **15**, 17826 (2025) <https://doi.org/10.1038/s41598-025-02396-y>
- [23] Hashemi, M., et al.: Sliding-mode control strategies for pmsm speed control: A comprehensive review, taxonomy and research gaps. *arXiv preprint arXiv:2510.18420* (2025)
- [24] Ding, R., *et al.*: A pmsm speed control strategy of ladrc based on neural network load torque estimation. *International Journal of Pattern Recognition and Artificial Intelligence* (2025) <https://doi.org/10.1142/S0218001425590037>
- [25] Eang, C., Lee, S.: Predictive maintenance and fault detection for motor drive control systems in industrial robots using cnn-rnn-based observers. *Sensors* **25**(1), 25 (2024) <https://doi.org/10.3390/s25010025>
- [26] Wang, H., Zhang, G.: Speed control for pmsm with fast variable-speed sliding mode control via high-gain disturbance observer. *IEEE Transactions on Industrial Electronics*, 1–14 (2024)
- [27] Qian, L., Liu, H., He, R., Deng, W.: Research on flux weakening speed control strategy for pmsm. In: *Proceedings of the SAE-China Congress*, pp. 629–636. Springer, Singapore (2016)
- [28] Abraham, D.M., Harish, A.: Speed regulation of pmsm drive in electric vehicle applications with sliding mode controller based on harris hawks optimization. *e-Prime – Advances in Electrical Engineering, Electronics and Energy* **9**, 100643 (2024)

- [29] Peng, J., Yao, M.: Overview of predictive control technology for permanent magnet synchronous motor systems. *Applied Sciences* **13**(10), 6255 (2023)
- [30] Wang, Q., Jiang, C., Zhang, N., Wang, Y.: Disturbance observer-based sliding mode control strategy of pmsm against mismatched disturbance. *Franklin Open* **7**, 100118 (2024)
- [31] Zhang, L., Tao, R., Bai, J., Zeng, D.: An improved sliding mode model reference adaptive system observer for pmsm applications. *Expert Systems with Applications* **250**, 123907 (2024)