Arabian Journal for Science and Engineering (2026) 51:8285–8297
https://doi.org/10.1007/s13369-025-10644-6

RESEARCH ARTICLE-ELECTRICAL ENGINEERING

An Adaptive Filter-Based Online Parameter Identification Method for Permanent Magnet Synchronous Motors

Faruk Erken[1] · Salahddin Ramadan Omran Albedwi[2]

Received: 8 January 2025 / Accepted: 7 September 2025 / Published online: 22 September 2025

Abstract

The reliable and high-performance operation of permanent magnet synchronous motors (PMSMs) fundamentally depends on the accurate estimation of their electrical parameters. These parameters are affected by various operational factors like temperature and current, and their precise estimation is key to optimizing motor performance. In particular, the winding resistance and rotor flux in PMSMs vary with temperature, whereas stator inductances exhibit nonlinear behavior due to magnetic saturation influenced by the operating current. In this study, a novel online parameter estimation method is introduced, which leverages an adaptive filter based on the normalized least mean square (N-LMS) algorithm. The approach utilizes the voltage equations expressed in the d-q reference frame, which is commonly used for modeling PMSM dynamics. To facilitate the convergence of the parameter values, a low-value sinusoidal current is injected into the d-axis current. This excitation ensures that the system converges quickly and provides accurate parameter estimates. The results obtained under different load conditions and varying scenarios demonstrate the effectiveness of the proposed method, with high estimation accuracy achieved for motor parameters. The proposed N-LMS-based online estimation framework offers a substantial solution for online parameter estimation, enhancing the control and performance of PMSM drive systems.

Keywords Adaptive filters · Parameter identification · Permanent magnet synchronous motor (PMSM)

1 Introduction

The utilization of permanent magnet synchronous motor (PMSM) has grown substantially in industrial applications owing to their high efficiency, compact size, and excellent performance [1, 2]. In advanced control applications such as sensorless control and direct torque control (DTC), accurate knowledge of motor parameters is crucial to achieving reliable and high-performance PMSM drives [3]. Motor parameters vary depending on operating conditions such as temperature and current. Specifically, winding resistance changes with temperature, while the inductances vary with current due to magnetic saturation effects [4, 5]. In PMSMs, these variations can be substantial—for example, stator winding resistance and rotor flux can vary by up to 200% and 20% of their nominal values, respectively. Such parameter variations directly affect the performance of control methods that rely on accurate motor parameters, including sensorless speed and position control, and DTC. Therefore, the online estimation of key motor parameters including winding resistance, inductance, and permanent magnet (PM) flux linkage becomes essential under varying operating conditions [6]. PMSMs are typically controlled using either scalar or vector-based methods. While scalar control methods such as v/f control are suitable for applications that do not require high performance, advanced vector control methods, field-oriented control (FOC) and DTC are favored for high-performance servo applications. To support these advanced control strategies, both offline and online estimation methods are employed for the estimation of PMSM parameters. One commonly used offline method involves the application of finite element analysis (FEA) to model the electromagnetic behavior of the motor [7]. Another conventional offline method estimates parameters using data obtained from no-load and locked-rotor tests. However, these methods are inherently limited in their ability to reflect dynamic changes in motor parameters during actual operation.

✉ Faruk Erken
ferken@kastamonu.edu.tr

1 Department of Electrical and Electronics Engineering, Kastamonu University, 37150 Kastamonu, Turkey

2 General Electricity Company of Libya, Tripoli, Libya

Since the parameter accuracy is crucial for both the electrical and mechanical models—as well as for condition monitoring, fault detection, speed regulation, and control system tuning—parameter identification in PMSM systems has been extensively investigated in recent research. [3] proposed a current injection-based multi-parameter estimation method for dual three-phase interior permanent magnet synchronous motors (IPMSMs), incorporating an enhanced recursive least squares (RLS) algorithm. The method is designed to address inverter nonlinearity and magnetic saturation effects by injecting tailored current signals into the motor's *d*–*q* subspaces. The proposed approach enables accurate estimation of key parameters including winding resistance, *d*–*q* axis inductances, and rotor flux linkage, under varying thermal and load conditions. Experimental results demonstrated superior performance compared to conventional techniques, particularly in terms of estimation accuracy and robustness against voltage source inverter (VSI) distortions. Online parameter identification typically relies on voltage equation-based schemes, supplemented by techniques such as back-electromotive force (EMF) analysis, harmonic speed detection, and direct current (DC) signal injection. Some studies aim to estimate temperature effects or detect demagnetization by partially identifying key parameters, mainly stator resistance and magnetic flux linkage. In related works [8–13], various algorithms have been developed for parameter identification and estimation, including the extended Kalman filter (EKF), model reference adaptive system (MRAS), recursive least squares (RLS), neural networks, and artificial intelligence (AI)-based approaches. The core principle of the model reference adaptive system (MRAS) is to employ a mathematical model incorporating the unknown parameters as an adjustable system, while using the actual motor as the reference. Although artificial intelligence (AI)-based approaches have gained increasing attention due to their strong adaptability and learning capabilities, their widespread adoption remains constrained by significant computational demands.

Both the measurements and the estimation model play a critical role in accurate parameter estimation. In particular, measurement uncertainty can significantly affect estimation accuracy. The highly nonlinear and time-varying nature of the PMSM drive system makes it essential to automatically assess whether the voltage measurements are sufficiently informative. [14] propose a comprehensive online method for full parameter estimation of permanent magnet synchronous motors (PMSMs). The method estimates stator resistance, d- and q-axis inductances, permanent magnet flux linkage, and rotor position simultaneously. An extended Kalman filter (EKF)-based framework is used, with improved modeling and observability. Both simulation and experimental results validate the method's high accuracy and robustness under various operating conditions. A reliable and efficient incremental Bayesian learning method for PMSM parameter estimation is introduced in [15]. The proposed approach incorporates a layered noise model to enable accurate estimation of nonlinear flux linkage. Remarkably, it demonstrates strong robustness and maintains high estimation accuracy even under non-Gaussian, time-varying noise and in the presence of outliers, adapting effectively to dynamic operating conditions. To address the issue of core loss, [16] proposes a differential modeling technique known as differential measurement, which calculates incremental values from actual measurements taken under two different speed conditions. This approach enhances the accuracy of flux linkage estimation by compensating for errors caused by core losses through the use of multiple differential measurements. Validated on a laboratory-scale interior PMSM, the method demonstrates improved estimation accuracy, particularly in the deep magnetic saturation region, without requiring explicit core loss data. In addition to model-based methods, there have been efforts to develop model-free control strategies to circumvent the parameter estimation challenge. One such method is the power-oriented modeling and map-based estimation presented in [17], which addresses PMSM parameters identification in both the electrical and in the mechanical energy domains. The method utilizes a generalized PMSM superblock that accepts model parameters as inputs. The effectiveness of the approach is demonstrated through a strong match between the desired and actual performance characteristics.

For PMSMs, precise electrical parameters are critical for achieving high-performance control. [18] propose a hybrid estimation method for permanent magnet synchronous motor (PMSM) drives that simultaneously identifies electrical parameters and voltage source inverter (VSI) nonlinearity. The method utilizes the recursive least squares (RLS) algorithm in an online framework to estimate stator resistance, *d*–*q*-axis inductances, and PM flux linkage, while also compensating for VSI-induced voltage errors. Experimental results on a 300-kW PMSM system show that the approach achieves high estimation accuracy and robustness under temperature and frequency variations, outperforming conventional methods. Similarly, in [19], VSI nonlinearity is estimated in real time along with motor parameters using a novel chaotic particle swarm optimization with dynamic self-optimization (DSCPSO) algorithm. Experimental results confirm that the method outperforms traditional techniques in tracking time-varying parameters and VSI nonlinearity under different operating conditions. In another study [20], an active disturbance rejection control (ADRC) with integrated parameter identification is designed for current control of PMSM servo system. A Kalman filter-based technique is used to create an approximate model of the motor that accounts for nonlinear uncertainties. The experimental outcomes demonstrate the method's suitability for controlling highly coupled and nonlinear systems. The cross-coupling angle and the $d-q$ axis inductances are determined using a new method in [21], involving high-frequency signal injection into a virtual rotary axis. This method also incorporates the impact of magnetic saturation, enabling accurate identification of the PM flux linkage. [22] introduces a model capable of achieving parameter estimation errors below 10%, regardless of variations in inverter dead time. Transient response tests show that the method estimates parameters with less than 9% error, demonstrating its effectiveness under dynamic conditions. In addition to these model-based techniques, various alternative approaches have also been proposed. Particle swarm optimization (PSO)-based methods have been applied to parameter identification to enhance optimization performance [23]. Model reference adaptive system (MRAS)-based techniques for stator resistance and speed estimation are presented in [24, 25] showing reliable performance for sensorless vector control. Meanwhile, artificial intelligence (AI)-based methods have gained increasing attention for their capacity to capture nonlinear and time-varying dynamics. These include early adaptive neural network approaches [26, 27] as well as recent deep learning-based estimation frameworks [28], demonstrating the evolution of AI-driven parameter identification techniques for PMSMs.

In this study, an online identification method for circuit parameters of PMSM based on N-LMS algorithm is proposed. The method offers high accuracy, robustness, fast convergence, and strong noise tolerance. Unlike model-based approaches such as MRAS, it does not require a predefined model. The estimation process is performed using measurable motor quantities—currents, voltages, speed, and position—under a field-oriented control (FOC) scheme. For surface-mounted PMSMs, setting the d-axis current to zero ensures maximum torque per ampere (MTPA), reduces losses, and simplifies control. However, in the study, a low-amplitude sinusoidal signal is deliberately injected into the d-axis current reference to introduce a dynamic excitation. This controlled perturbation enhances the identifiability of parameters by decoupling their effects in the voltage equations. To evaluate the effectiveness and robustness of the proposed method, simulations are conducted on three PMSMs a variety of operating conditions, including constant and dynamic loads, multiple speed levels, and parameter variations caused by temperature and magnetic saturation. These scenarios demonstrate the generalizability and practical viability of the approach for a wide range of real-world motor applications. Detailed descriptions of the proposed method and the simulation results are presented in Sect. 2 and 3, respectively.

2 PMSM Online Parameter Identification Method

The equivalent circuit parameters of the PMSM are estimated using the N-LMS adaptive filtering method. This adaptive filter operates by iteratively adjusting its weights based on the incoming data to minimize the estimation error. The algorithm operates online, continuously updating its weights as new data becomes available, allowing it to adapt dynamically to changes in motor behavior during operation. Because the N-LMS algorithm is inherently online and adaptive, it is highly responsive to parameter variations, ensuring accurate and timely estimation throughout the motor's operation. The R_s, L_d, L_q, and λ_m parameters of the PMSM are estimated using the applied method. $d-q$ axis voltage relations are used to estimate the equivalent circuit parameters of PMSM. The voltage equations of the PMSM according to the $d-q$ reference frame are given as follows:

$$V_d = R_s i_d + L_d \frac{d}{dt} i_d - \omega_r L_q i_q \tag{1}$$

$$V_q = R_s i_q + L_q \frac{d}{dt} i_q + \omega_r L_d i_d + \omega_r \lambda_m \tag{2}$$

In the equations, each circuit parameter is considered as a weight (w_i) and the expressions that multiply the circuit parameters are referred to as input values (X_i). In case (y_i) values show the estimated values of $d-q$ axis voltages:

$$y_1 = w_1.X_1 + w_2.X_2 - w_3.X_3 \tag{3}$$

$$y_2 = w_4.X + w_5.X_5 + w_6.X_6 + w_7.X_7 \tag{4}$$

In these equations, w_1 and w_4 represent R_s, w_2 and w_6 represent L_d, w_3 and w_5 represent L_q, and w_7 represents λ_m. Initially, all weights can be set to zero, or the estimation process can begin with known parameter values. Using known initial values helps reduce the convergence time and allows the algorithm to reach accurate estimates more fast. In this study, the weights are initially set to zero to evaluate the effectiveness of the proposed algorithm. Subsequently, the impact of starting with known parameter values on the convergence time is demonstrated. During each sampling interval, V_d and V_q values are computed from the updated weights and the gradient of the difference between the estimated and actual voltage values is taken as the error term. The estimation process is then refined using the arithmetic mean of the weights corresponding to the same parameter across multiple updates. This approach is intended to enhance the accuracy of the estimation. The schematic of the proposed parameter identification algorithm for the PMSM under field-oriented control is given in Fig. 1.

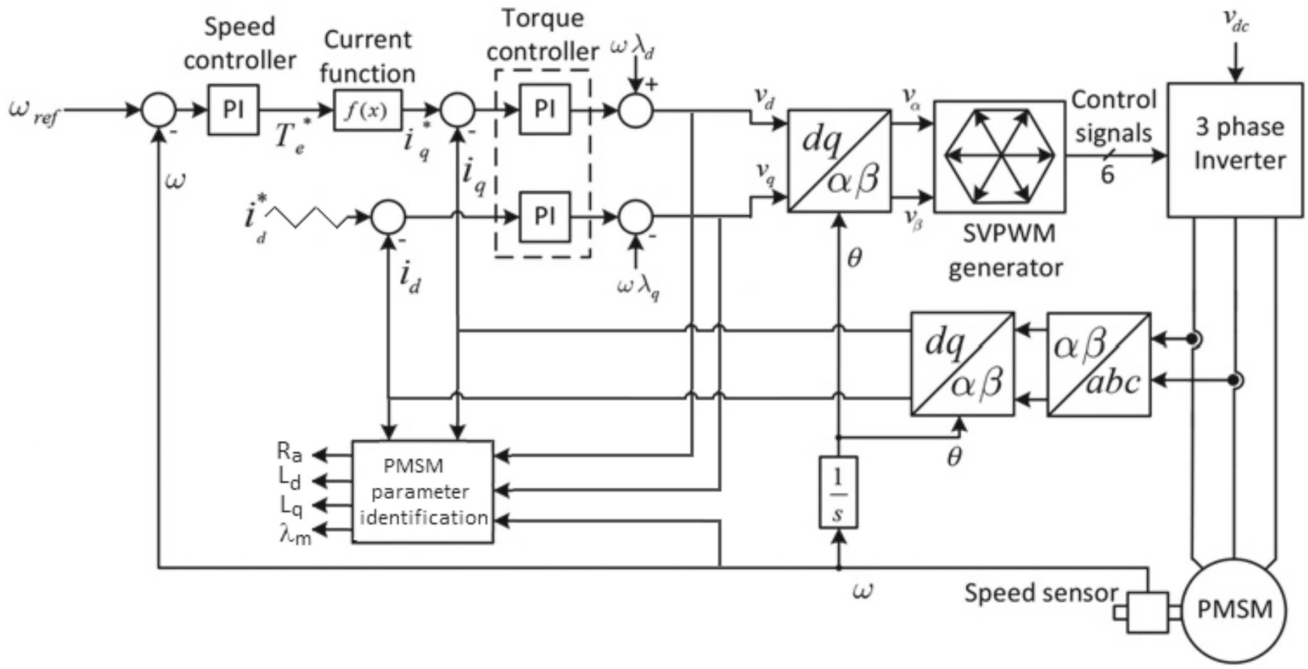

Fig. 1 The scheme of the proposed parameter identification algorithm

In the proposed method, the current, voltage, and speed signals in the $d-q$ reference frame are utilized, which remain relatively constant except for the high-frequency harmonics they contain. In conventional FOC of PMSMs, the d-axis current reference is typically set to zero. However, to guarantee the convergence of the algorithm, a zero-mean sinusoidal reference signal with a peak amplitude of 1.5 V is applied as the d-axis current reference. This intentional excitation enhances system observability and enables the estimation algorithm to reliably converge to a unique solution.

The weights, which representing the equivalent circuit parameters of the PMSM, are continuously updated using the N-LMS adaptive filter. This filter operates by linearly combining input variables to iteratively refine parameter estimates online. The N-LMS algorithm operates over a convex error surface derived from the linearized voltage equations in the d-q reference frame. This convexity ensures that the algorithm converges to the global minimum, not local minima, provided that persistent excitation conditions are satisfied. The use of a zero-mean sinusoidal current in the d-axis introduces the necessary excitation, ensuring observability and convergence to the global solution.

2.1 Weight Update Algorithm

The least mean square (LMS) filter is a type of adaptive filter that updates its coefficients based on the instantaneous error signal, using a gradient descent algorithm to minimize the mean squared error.

Let us assume that the sub-data consist of N subentries $X_1, X_2, \ldots X_N$. At n time steps, each sub-input creates the input value ($X(n) \in \mathbb{R}$) for a sample. The expression $X(n) = [X_1(n) \ldots X_N(n)]^T$ refers to the vector of the values of the sub-inputs at n time steps. $w(n) = [w_1(n) \ldots w_M(n)]^T$ can be expressed as the weight vector at that moment. In this case, the estimate of the value $y(n)$ can be defined as the product of the input values and their weights as follows [1]:

$$\widehat{y}(n) = X^T(n)w(n) = \sum_i w_i(n)X_i(n) \tag{5}$$

There will be a difference between the predicted $\widehat{y}(n)$ and the expected value $y(n)$. This difference is defined as error as follow:

$$e(n) = y(n) - \widehat{y}(n) \tag{6}$$

The weight vector values of each entry are updated by minimizing the mean square error (MSE) value:

$$\min_{w_i} E[(y(n) - \widehat{y}(n))]^2,\ i = 1, \ldots, N \tag{7}$$

Here E is the expectation operator. If the derivative of Eq. (7) with respect to weight is taken and equalized to zero;

$$\frac{\partial E}{\partial w} = -2E[(y(n) - \widehat{y}(n))H_i(n)] = -2E(e(n)X_i(n)),\ i = 1, \ldots, N \tag{8}$$

In this case, a series of N equations is obtained. The gradient in Eq. (8) can be used in a type of optimization algorithm called the steepest descent algorithm to obtain an iterative solution to minimize Eq. (7).

$$w(n+1) = w(n) + \lambda e(n) X_i(n) \tag{9}$$

The term λ in Eq. (9) can be replaced with the following expression

$$\frac{\mu}{\|X(n)\|^2} \tag{10}$$

An expression is obtained as in the N-LMS method. Here μ is called update parameter or adaptation gain and if $0 < \mu < 2$, it converges to the Wiener solution.

$$w(n+1) = w(n) + \mu \frac{e(n)}{\|X(n)\|^2}(X(n)) \tag{11}$$

This algorithm's greatest benefit is that the weights are updated fastly based on the error term. This establishes an effective feedback system.

2.2 Key Parameter Selection

The selection of key parameters in the proposed adaptive filter-based online parameter identification method significantly impacts the accuracy and stability of the estimation process. In this study, parameter values are chosen based on prior research, practical considerations, fundamental system characteristics, and empirical validation to ensure effective performance across different motor configurations. The primary parameters in the N-LMS adaptive filtering algorithm include the adaptation gain (μ), the reference current waveform used for convergence, and the initial values of estimated parameters.

The adaptation gain μ significantly influences both the convergence speed and the stability of the algorithm. A smaller μ ensures stable but slow adaptation, whereas a larger μ accelerates convergence but may induce instability. Although there is no universally accepted method in the literature for precisely selecting μ, the theoretical stability condition for LMS-based algorithms is given by $0 < \mu < 2$ [29]. However, for practical applications, much smaller values are typically used to ensure robust performance. Based on extensive studies in adaptive filtering applications and preliminary testing with PMSM systems, μ values in the range of 0.005 to 0.025 have been shown to provide good performance for motor parameter estimation applications. For this study, μ = 0.01 is selected as it provides a good balance between convergence speed and stability across the range of tested motors.

A low-amplitude sinusoidal current injection in the d-axis is chosen to ensure effective excitation of the system while minimizing distortions in normal operation. According to established practices in PMSM parameter identification literature, low-amplitude sinusoidal excitation provides adequate parameter observability while maintaining acceptable torque quality. A 1.5 V peak value with zero-mean value sinusoidal current injection is selected based on common practices reported in parameter identification studies, as it enhances parameter observability without introducing DC bias or affecting the motor's steady-state behavior. The current frequency is set to 10 Hz to prevent excessive amplification of derivative terms in the voltage equations while ensuring adequate excitation bandwidth for parameter estimation. At higher frequencies (> 20 Hz), the derivative term becomes significantly larger, amplifying measurement noise and numerical differentiation errors, which can severely degrade parameter estimation accuracy. At lower frequencies (< 5 Hz), while derivative errors are minimized, the excitation bandwidth becomes insufficient for adequate parameter observability, particularly for inductance estimation.

Initial parameter values can be set based on available motor specifications or initialized to zero to evaluate the algorithm's robustness. When approximate initial values (e.g., within ± 20% of nominal values) are used, the convergence speed improves significantly. In this study, the algorithm is evaluated using both zero-initialized and known initial values under varying load and speed conditions, demonstrating its adaptability and robustness across different operational scenarios.

3 Results and Discussions

FOC is a widely adopted high-performance vector control strategy for three-phase motors, including PMSMs. In parameter estimation studies, PMSMs are typically operated under FOC to ensure stable and dynamic control, while measured current, voltage, and speed signals are utilized for real-time parameter identification. The sampling time T_s is set to 20 μs to capture the system dynamics with sufficient temporal resolution.

To evaluate the effectiveness of the proposed approach, it is applied to three PMSMs with varying power levels. Detailed specifications of the motors are presented in Table 1. Although the d-axis and q-axis inductances are typically assumed to be equal in surface-mounted PMSMs due to their symmetric magnetic structure, they are estimated independently in this study to account for possible deviations arising from manufacturing tolerances and operating conditions.

In this study, three distinct parameter scenarios are constructed for each motor while maintaining a constant speed

Table 1 Motor parameters

	Motor1	Motor2	Motor3
Rated power (kW)	2	8	12
Rated speed (rpm)	2000	3000	1700
Armature resistance (Ω)	0.9485	0.11	0.085
Armature inductance (mH)	5.25	0.97	0.95
PM flux linkage (Wb)	0.1827	0.1119	0.192

of 200 rad/s and a fixed load torque of 3 Nm. In the first scenario, motor parameters are estimated using their nominal (actual) values. In the second scenario, the stator resistance is increased by 10% to simulate the thermal effects commonly observed during motor operation. In the third scenario, both the d- and q-axis inductances and the permanent magnet (PM) flux linkage are reduced by 10%, reflecting the degradation that may occur over time due to increased temperature and current-induced magnetic saturation. The parameter estimation algorithm is initiated at $t = 0.1$ s in the simulation.

Figures 2, 3 and 4 illustrate the estimated values of R_s, L_d, L_q, and λ_m for three motors across the three scenarios. These figures provide a comparative evaluation of key electrical parameters, highlighting the variation in characteristics across different machines. The differences observed are attributed to variations in design, manufacturing tolerances, and operational dynamics. This comparative analysis not only underscores the effectiveness of the proposed estimation method but also offers valuable insights into the factors influencing parameter identification performance. Moreover, evaluating the consistency or divergence of estimated parameters across different machines can guide future improvements in estimation accuracy and robustness.

A comparison of the estimated values of R_s, L_d, L_q, and λ_m for the three motors indicates that the maximum convergence time is 0.6 s. In the simulations, the estimation process is initialized with zero values for all parameters, representing a worst-case scenario. If the estimation process initiates with predetermined parameter values, the computational time required for convergence will approach zero.

Temperature significantly affects PMSM performance, particularly through its influence on winding resistance. In the second scenario, only the stator resistance is increased by 10% to simulate thermal effects. Considering temperature-related parameter changes is essential for accurate estimation and reliable motor control. Figure 3 presents the estimated values of R_s, L_d, L_q, and λ_m for Scenario 2, to simulate temperature effects. Analysis of the curves indicates that estimation time decreases as motor power increases. These results highlight the importance of accurate parameter estimation for improving motor performance, reliability, and thermal management.

Figure 4 presents the estimation results under scenario 3, where both the PM flux linkage and the d–q-axis inductances are reduced by 10%. The curves indicate that Motor3, which has the highest power rating, exhibits the shortest settling time. Since the motor's behavior in the synchronous reference frame is governed by the d–q axis inductances, analyzing these reductions offers insight into their impact on electromagnetic performance, torque generation, and dynamic response. These findings highlight the importance of considering such parameter variations in motor design, control, and optimization to achieve target performance levels.

Figures 2, 3 and 4 collectively highlight the notable differences in parameter estimates among the three motors, emphasizing the need for motor-specific estimation strategies to improve modeling accuracy and control effectiveness. These insights contribute to the development of more robust and efficient electromechanical systems for industrial and automotive applications. Figure 5 compares the estimated and actual values of stator resistance (R_s), d–q-axis inductances (L_d, L_q), and permanent magnet flux (λ_m) under all three scenarios and across all motors. The close alignment between the red (actual) and blue (estimated) curves indicates high estimation accuracy. Specifically, the results demonstrate effective tracking of temperature-induced changes in R_s accurate characterization of magnetic properties through L_d and L_q and reliable estimation of λ_m, which is essential for torque generation. These results validate the robustness and generalizability of the proposed method, supporting its applicability in fault diagnosis, adaptive control, and energy-efficient motor drive systems.

To evaluate the accuracy of the estimation results, the average values of the estimated parameters and their respective errors are presented in Table 2. Among the parameters, the PM flux linkage λ_m exhibits the highest accuracy, with a maximum error of less than 0.12% across all scenarios. The q-axis inductance (L_q) is also estimated with high precision, showing errors between 0.004% and 0.77%. The stator resistance (R_s), which is known to be highly sensitive to temperature, is estimated with an error range of 0.33% to 1.84%. In contrast, the d-axis inductance (L_d) shows a relatively higher maximum estimation error of 8.18%, indicating greater uncertainty in its identification. Notably, the motor with the highest power rating consistently exhibits the smallest estimation errors across all parameters. The elevated estimation error in L_d can be attributed to the sinusoidal current injection applied to the d-axis to ensure observability and convergence of the algorithm. When examining the PMSM voltage equations, Eq. (1) and (2), this injection leads to oscillatory behavior in i_d, described by $i_d(t) = i_d \sin(\omega t)$, which results in a derivative term $di_d/dt = \omega i_d \sin(\omega t)$. These

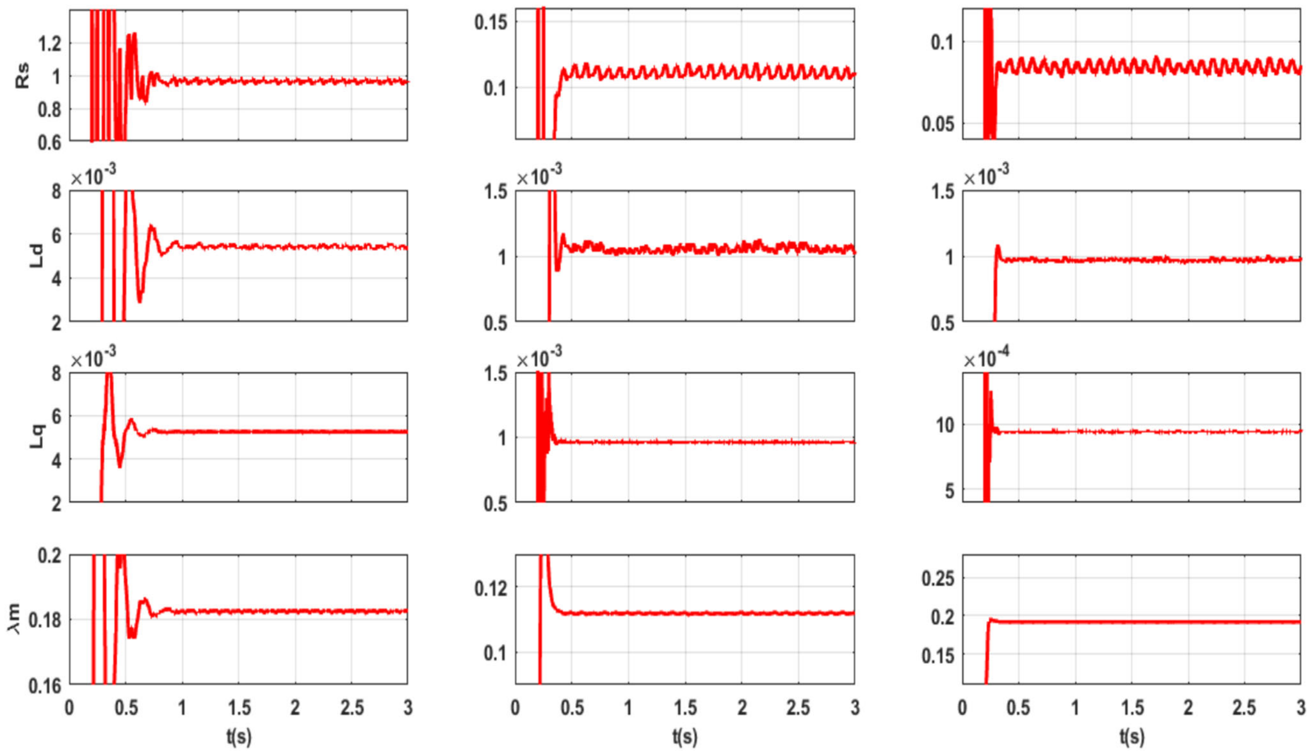

Fig. 2 R_s, L_d, L_q, and λ_m values estimated for the scenario 1 for Motor1 (right column), Motor2 (middle column), and Motor3 (left column)

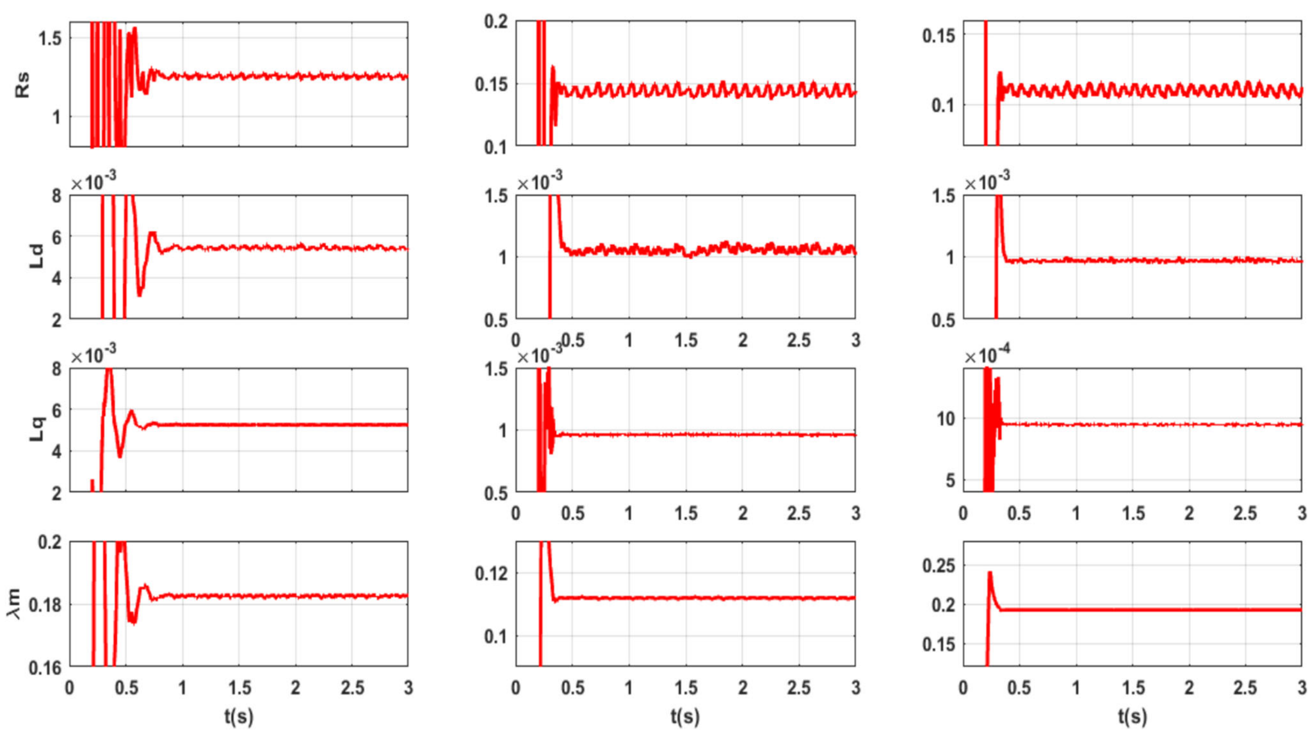

Fig. 3 R_s, L_d, L_q, and λ_m values estimated for the scenario 2 for Motor1 (right column), Motor2 (middle column), and Motor3 (left column)

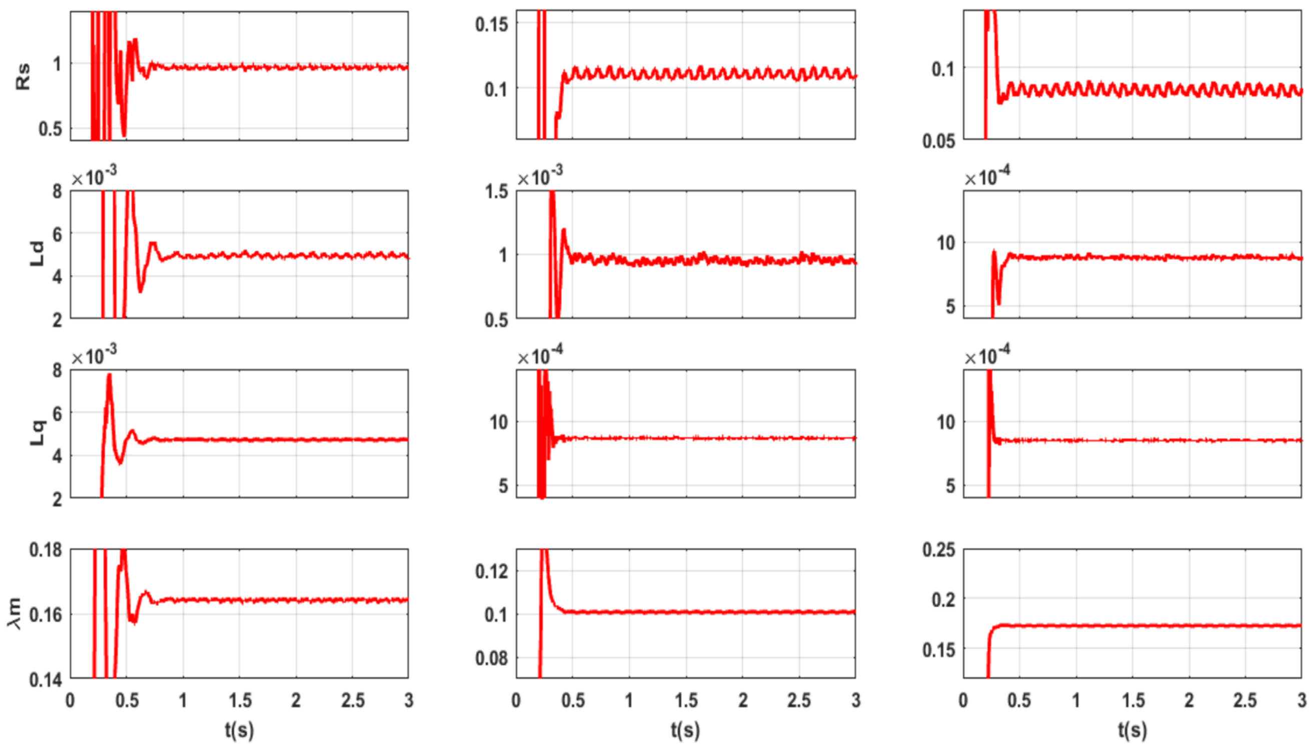

Fig. 4 R_s, L_d, L_q, and λ_m values estimated for the scenario 3 for Motor1 (right column), Motor2 (middle column), and Motor3 (left column)

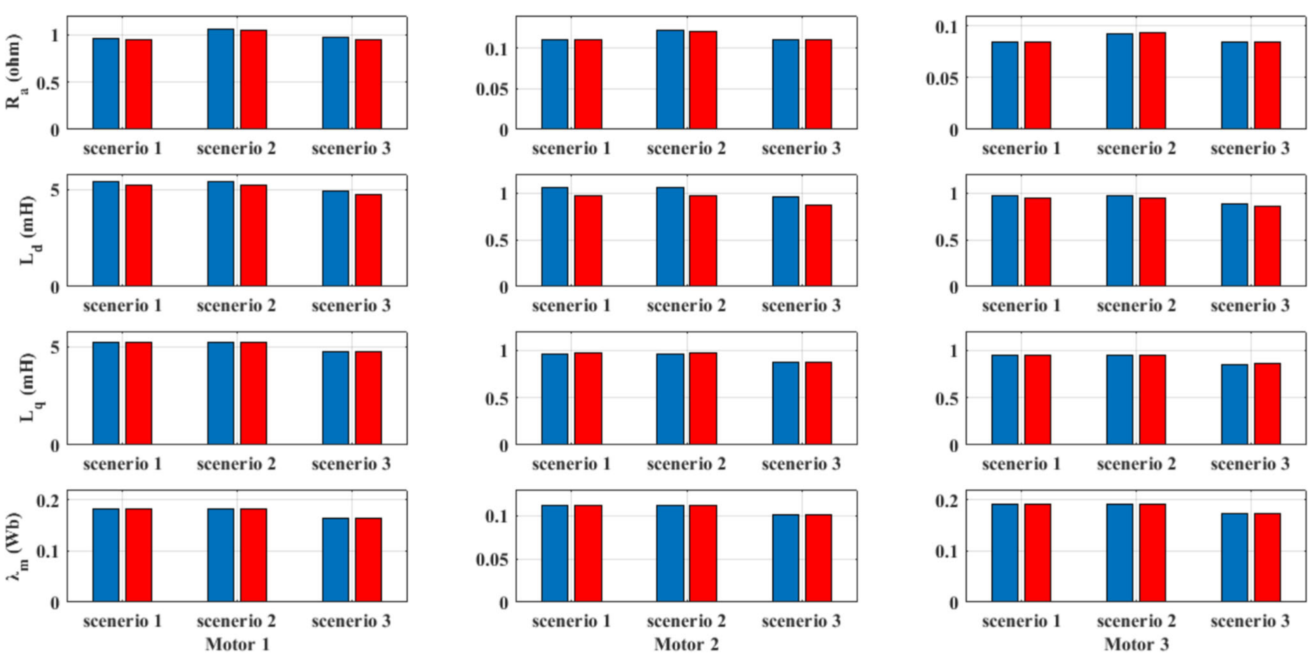

Fig. 5 The actual (red) and the estimated values (blue) for R_s, L_d, L_q, and λ_m for three scenarios and motors

Table 2 Estimated values and estimation errors

	Motor1	Error (%)	Motor2	Error (%)	Motor3	Error (%)
Scenario 1						
R_s	0.96442	1.65	0.11099	0.89	0.084085	1.09
L_d	5.41697	3.08	1.05390	7.96	0.968566	1.92
L_q	5.25232	0.04	0.963167	0.70	0.943369	0.70
λ_m	0.18249	0.12	0.111846	0.048	0.192027	0.014
Scenario 2						
R_s	1.06009	0.609	0.122074	0.88	0.092569	1.01
L_d	5.41477	3.04	1.05637	8.18	0.967693	1.83
L_q	5.25283	0.004	0.962597	0.77	0.943323	0.71
λ_m	0.18250	0,12	0.111842	0.05	0.192029	0.015
Scenario 3						
R_s	0.96627	1.84	0.11036	0.33	0.084272	0.86
L_d	4.93590	4.27	0.951248	8.23	0.876404	2.44
L_q	4.72374	0.027	0.867001	0.69	0.848896	0.72
λ_m	0.16443	0.18	0.100684	0.026	0.172824	0.014

oscillations magnify the impact of L_d in both the instantaneous and differential terms of the model, thereby increasing estimation uncertainty.

This analysis suggests that the identification of L_d is particularly sensitive to excitation conditions and highlights the need for careful signal design in improving estimation robustness. Furthermore, the propagation of estimation error can be formulated analytically as follows:

$$\Delta L_d = \left|\frac{\partial L_d}{\partial V_d}\right|\Delta V_d + \left|\frac{\partial L_d}{\partial i_d}\right|\Delta i_d + \left|\frac{\partial L_d}{\partial\left(\frac{di_d}{dt}\right)}\right|\Delta\left(\frac{di_d}{dt}\right) \tag{12}$$

where the sensitivity to measurement errors in di_d/dt is particularly high. It is concluded that this situation may cause a relatively high estimation error in L_d. This situation also contributed to the increase in error in the estimates of other parameters.

To further validate the effectiveness of the proposed algorithm under realistic operating conditions, the method is tested under dynamic load variations. Specifically, to assess the adaptability of the algorithm to sudden and gradual load changes commonly encountered in practical applications, a stepwise load variation is applied to all three motors. Additionally, to observe the algorithm's behavior when initialized with true parameter values, the estimation process is started using actual values, with the algorithm activated at $t = 0.1$ s. For all cases, the initial load is set to 3 Nm, increased to 6 Nm at $t = 1$ s, and further to 10 Nm at $t = 2$ s. The corresponding parameter estimation results under these conditions are presented in Fig. 6.

As illustrated in Fig. 6, initializing the estimation with actual parameter values eliminates any estimation delay. The figure presents the online estimation of four key PMSM parameters for three different motors under dynamic load variations. The results indicate exceptional stability, with all parameters maintaining nearly constant values throughout the simulation, and only minimal disturbances observed at load transition points.

This stability, observed consistently across all motor types and loading conditions, highlights the robustness and adaptability of the proposed estimation algorithm. The negligible impact of load changes on estimation accuracy confirms the method's effectiveness in decoupling parameter estimation from mechanical disturbances. Furthermore, the absence of visible settling times following abrupt load changes demonstrates the algorithm's strong real-time tracking capability and its suitability for practical applications involving dynamic operating environments.

To evaluate the performance of the proposed algorithm under varying speed conditions, step changes in motor speed are applied to all three motors. The estimation algorithm is activated at $t = 0.1$ s. For each motor, the initial speed is set to 100 rad/s, increased to 300 rad/s at $t = 1$ s, and further to 600 rad/s at $t = 2$ s. Figure 7 illustrates the variation in estimated parameters under these conditions.

Figure 7 illustrates the robust performance of the proposed algorithm in estimating four PMSM parameters across three different motors under dynamic speed conditions. Following activation at $t = 0.1$ s, the algorithm quickly converges, exhibiting only brief and expected transients during speed transitions. A slight decrease in the estimated stator resistance (R_s) is observed for Motor2 and Motor3 as speed

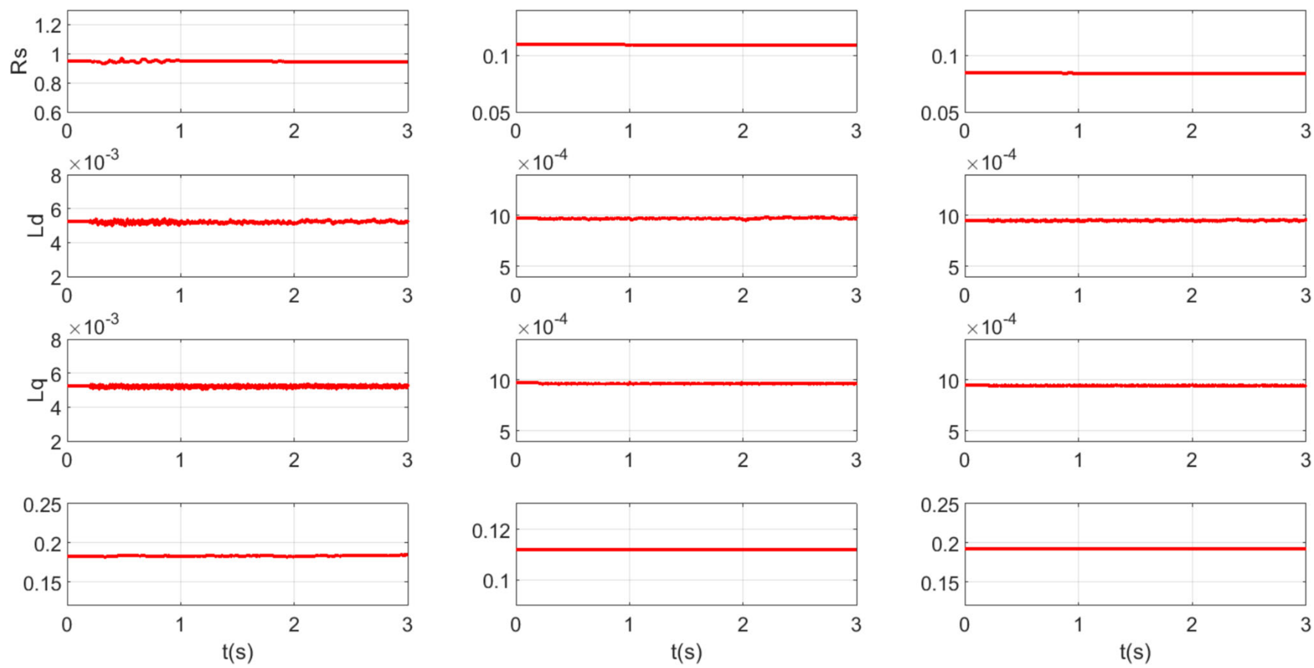

Fig. 6 R_s, L_d, L_q, and λ_m values estimated for different loads for Motor1 (right column), Motor2 (middle column), and Motor3 (left column)

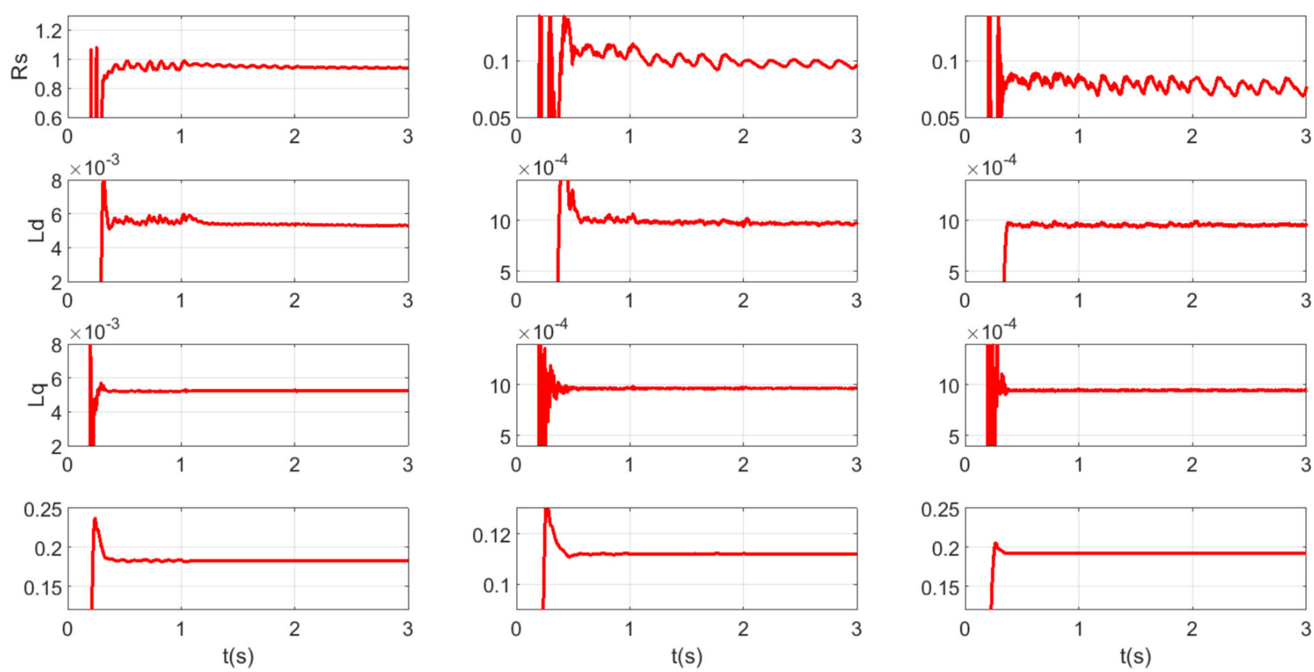

Fig. 7 R_s, L_d, L_q, and λ_m values estimated for different speeds for Motor1 (right column), Motor2 (middle column), and Motor3 (left column)

increases, while the remaining parameters remain stable. These results confirm the algorithm's ability to maintain high estimation accuracy despite speed fluctuations. The consistent convergence behavior across all motor types highlights the method's adaptability and practical applicability for real-time PMSM control under varying operating conditions.

The proposed N-LMS method presents a practical trade-off between estimation accuracy and computational efficiency for online PMSM parameter identification. Compared to conventional methods such as MRAS, RLS, Kalman filters, PSO-based approaches, and AI-based estimators, it offers notable advantages in terms of algorithmic simplicity,

Table 3 Comparative analysis of the current study and the previous studies

Method	Representative studies	Algorithm type	Complexity	Convergence time	Key advantages	Main limitations	Parameter accuracy
Proposed N-LMS	Current Study	Adaptive Filter	Low	≤ 0.6 s ≈ 0 (with known values)	Simple implementation, no model required, real-time adaptation	Higher L_d error, requires excitation	λm: < 0.12%, Rs: 0.33–1.84%, Lq: 0.004–0.77%, Ld: up to 8.18%
PSO-based	[4, 19, 23]	Optimization	High	Variable	Global optimization, handles multimodal problems	High computational load, stochastic convergence	< 10% typical
RLS-based	[3, 8, 18]	Recursive Estimation	Medium–High	Fast	Well-established theory, fast convergence, current injection for excitation	Matrix inversions, numerical instability	Varies by implementation
Kalman Filter	[12, 13, 20]	State Estimation	High	Medium	Uncertainty estimates, optimal under Gaussian noise	Requires noise statistics, complex tuning	Good with proper tuning
MRAS	[24, 25]	Model Reference	Medium	Medium	Established technique, stable convergence	Requires reference model, limited adaptability	Moderate, good for Rs estimation
AI-based	[5, 26–28]	Machine Learning	Very High	Training dependent	High adaptability, handles nonlinear relationships, real-time identification capability	Training data requirements, computational complexity, black box nature	Very good for Rs, Ld, Lq, λm with proper training

real-time feasibility, and robustness across multiple motors and operating conditions.

Among all estimated parameters, the method achieves the highest accuracy in PM flux linkage estimation, with errors consistently below 0.12%. Stator resistance is estimated with errors between 0.33 and 1.84%, outperforming or matching MRAS and PSO-based alternatives. While the d-axis inductance shows relatively higher errors (up to 8.18%)—likely due to excitation-induced dynamic effects—the q-axis inductance is estimated with excellent accuracy (0.004–0.77%). In terms of computational load, the N-LMS method significantly outperforms Kalman filters, PSO, and AI-based approaches, while offering faster convergence (≤ 0.6 s) than most alternatives. When initialized with known parameter values, the convergence time becomes negligible. Its low complexity and deterministic execution make it well-suited for real-time embedded applications. Unlike model-based or optimization-heavy methods, it requires no predefined motor model and avoids complex tuning procedures.

The method's robustness under varying speed and load conditions further highlights its reliability for practical use. While it requires current injection for convergence, this trade-off is justified by its overall performance and adaptability. As detailed in Table 3, the N-LMS method provides the best overall cost-performance ratio, making it a strong candidate for real-time PMSM drive applications requiring accurate and adaptive parameter estimation.

The quantitative comparison reveals that the N-LMS method achieves the best balance of implementation simplicity, computational efficiency, and estimation accuracy among existing approaches. While it may not yield the lowest error for all parameters—especially d-axis inductance—its overall strengths, such as low algorithmic complexity, rapid convergence, and consistent accuracy across key parameters, make it highly suitable for real-time industrial applications. The method's ability to estimate permanent magnet flux linkage with exceptional precision, coupled with its robustness under varying operating conditions, supports its applicability in adaptive control, fault diagnostics, and energy optimization. Therefore, the N-LMS approach presents a compelling solution for embedded PMSM drive systems requiring reliable and efficient online parameter identification.

4 Conclusions

This study introduces and validates an online parameter estimation method for permanent magnet synchronous motors (PMSMs) based on the normalized least mean square (N-LMS) algorithm. The proposed approach represents a meaningful advancement in enhancing the adaptability and real-time intelligence of electric drive systems, particularly under dynamically changing operating conditions.

The method enables continuous and accurate estimation of critical motor parameters including stator resistance, *d–q*-axis inductances, and permanent magnet flux linkage by utilizing the voltage equations in the *d–q* reference frame. This adaptive capability is especially beneficial in real-world applications where motors are exposed to varying speeds, fluctuating loads, thermal effects, and magnetic saturation, such as electric vehicles or automated industrial systems.

To assess the method's performance, simulations are conducted on three different PMSMs with varying power ratings under diverse scenarios, including dynamic load changes, speed transitions, and parameter deviations. The results demonstrate fast convergence (≤ 0.6 s), low computational cost, and high accuracy across most parameters, with particularly strong performance in estimating permanent magnet flux linkage. Although higher errors are observed in d-axis inductance due to signal sensitivity, the overall estimation performance remained robust and reliable.

The findings confirm that the N-LMS-based parameter estimation method strikes an effective balance between implementation simplicity, estimation accuracy, and computational efficiency. Its generalizability and real-time capability make it a strong candidate for deployment in advanced motor control strategies, adaptive systems, and fault-tolerant applications where performance and reliability are essential.

Acknowledgements This study is supported by Kastamonu University Scientific Research Projects Coordination Unit grant no KÜ–BAP01/2019–51 project.

Author Contributions Faruk Erken was involved in investigation, algorithm design and analysis, writing draft, and writing—review; Salahddin Ramadan Omran Albedwi was involved in algorithm design and analysis and writing—review.

Data Availability The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding authors.

References

1. Erken, F.; Öksüztepe, E.; Kürüm, H.: Online adaptive decision fusion based torque ripple reduction in permanent magnet synchronous motor. IET Electr. Power Appl. **10**(3), 189–196 (2016)
2. Hassan, A.A.; Kassem, A.M.: Modeling, simulation and performance improvements of a PMSM based on functional model predictive control. Arab. J. Sci. Eng. **38**, 3071–3079 (2013)
3. Li, Z.; Feng, G.; Lai, C.; Banerjee, D.; Li, W.; Kar, N.C.: Current injection-based multi-parameter estimation for dual three-phase IPMSM considering VSI nonlinearity. IEEE Trans. Transp. Electrif. **5**(2), 405–415 (2019)
4. Liu, Z.; Wei, H.; Zhong, Q.; Liu, K.; Xiao, X.; Wu, L.: Parameter estimation for VSI-fed PMSM based on a dynamic PSO with learning strategies. IEEE Trans. Power Electron. **32**(4), 3154–3165 (2017)
5. He, L.; Feng, Y.; Yan, Z.; Cai, M.: Rotor temperature prediction of PMSM based on LSTM neural networks. Arab. J. Sci. Eng. **49**, 16685–16696 (2024)
6. Krishnan, R.: Electric motor drives modeling, analysis, and control. Prentice Hall, New Jersey (2001)
7. Vaseghi, B.; Takorabet, N.; Meibody-Tabar, F.: Fault analysis and parameter identification of permanent-magnet motors by the finite-element method. IEEE Trans. Magn. **45**(9), 3290–3295 (2009)
8. Ma, X.; Bi, C.: A technology for online parameter identification of permanent magnet synchronous motor. CES Trans. Electr. Mach. Syst. **4**(3), 237–242 (2020)
9. Wu, C.; Zhao, Y.; Sun, M.: Enhancing low-speed sensorless control of PMSM using phase voltage measurements and online multiple parameter identification. IEEE Trans. Power Electron. **35**(10), 10700–10710 (2020)
10. Yao, Y.; Huang, Y.; Peng, F.; Dong, J.: Position sensorless drive and online parameter estimation for surface-mounted PMSMs based on adaptive full-state feedback control. IEEE Trans. Power Electron. **35**(7), 7341–7355 (2020)
11. Wang, Q.; Wang, G.; Zhao, N.; Zhang, G.; Cui, Q.; Xu, D.: An impedance model-based multiparameter identification method of PMSM for both offline and online conditions. IEEE Trans. Power Electron. **36**(1), 727–738 (2021)
12. Li, X.; Kennel, R.: General formulation of Kalman-filter-based online parameter identification methods for VSI-fed PMSM. IEEE Trans. Ind. Electron. **68**(4), 2856–2864 (2021)
13. Candelo-Zuluaga, C.; Riba, J.-R.; Garcia, A.: PMSM parameter estimation for sensorless FOC based on differential power factor. IEEE Trans. Instrum. Meas. **70**, 1–12 (2021)
14. Yu, Y.; Huang, X.; Li, Z.; Wu, M.; Shi, T.; Cao, Y.; Yang, G.; Niu, F.: Full parameter estimation for permanent magnet synchronous motors. IEEE Trans. Ind. Electron. **69**(5), 4376–4386 (2022)
15. Huang, K.; Feng, G.; Lai, C.; Kar, N.C.: Robust incremental Bayesian learning based online flux linkage estimation for PMSM drives. IEEE Trans. Transp. **8**(4), 4509–4522 (2022)
16. Feng, G.; Lai, C.; Tan, X.; Peng, W.; Kar, N.C.: Multi-parameter estimation of PMSM using differential model with core loss compensation. IEEE Trans. Transp. Electrif. **8**(1), 1105–1115 (2022)
17. Tebaldi, D.: Efficiency map-based PMSM parameters estimation using power-oriented modeling. IEEE Access **10**, 45954–45961 (2022)
18. Lian, C.; Xiao, F.; Liu, J.; Gao, S.: Parameter and VSI nonlinearity hybrid estimation for PMSM drives based on recursive least square. IEEE Trans. Transp. Electrif. **9**(2), 2195–2206 (2023)

19. Feng, W.; Zhang, W.; Huang, S.: A novel parameter estimation method for PMSM by using chaotic particle swarm optimization with dynamic self-optimization. IEEE Trans. Veh. Technol. **72**(7), 8424–8432 (2023)
20. Shi, S.; Guo, L.; Chang, Z.; Zhao, C.; Che, P.: Current controller based on active disturbance rejection control with parameter identification for PMSM servo systems. IEEE Access **11**, 46882–46891 (2023)
21. Liu, S.; Wang, Q.; Wang, G.; Li, B.; Ding, D.; Zhang, G.; Xu, D.: Virtual-axis injection based online parameter identification of PMSM considering cross coupling and saturation effects. IEEE Trans. Power Electron. **38**(5), 5791–5802 (2023)
22. Lee, J.; Seo, H.; Lee, J.S.; Han, B.K.; Mok, H.S.: Electrical parameter estimation method for surface-mounted permanent magnet synchronous motors considering voltage source inverter nonlinearity. IEEE Access **11**, 16288–16296 (2023)
23. Liu, Z.H.; Wei, H.L.; Li, X.H.; Liu, K.; Zhong, Q.C.: Global identification of electrical and mechanical parameters in PMSM drive based on dynamic self-learning PSO. IEEE Trans. Power Electron. **33**(12), 10858–10871 (2018)
24. Khlaief, A.; Boussak, M.; Châari, A.: A MRAS-based stator resistance and speed estimation for sensorless vector controlled IPMSM drive. Electr. Power Syst. Res. **108**, 1–15 (2014)
25. Badini, S.S.; Verma, V.: MRAS-based speed and parameter estimation for a vector-controlled PMSM drive. Electrica. **20**(1), 28–40 (2020)
26. Rahman, M.; Hoque, M.: On-line adaptive artificial neural network based vector control of permanent magnet synchronous motors. IEEE Trans. Energy Convers. **13**(4), 311–318 (1998)
27. Kumar, R.; Gupta, R.A.; Bansal, A.K.: Identification and control of PMSM using artificial neural network. In: 2007 IEEE International Symposium on Industrial Electronics, Vigo, Spain, (2007)
28. Bui, M.X.; Dutta, R.; Rahman, F.: Application of deep learning in parameter estimation of permanent magnet synchronous machines. IEEE Access **12**, 40710–40721 (2024)
29. Haykin, S.: Adaptive Filter Theory, Prentice Hall, (2014)