FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 1 | Pages 138-142 | e-ISSN: 2347-470X

Inductance Estimation of PMSM Using Extended Kalman Filter

Komal Naikawadi[1], Sudhir Madhav Patil[2*], Kapil Kalantri[3], Maneetkumar R. Dhanvijay[4] and Atul V. Karanjkar[5]

[1]PG Student (M.Tech. Mechatronics), Department of Manufacturing Engineering and Industrial Management, College of Engineering Pune (COEP), Shivaji Nagar, Pune: 411005, Maharashtra State, INDIA. naikawadikm20.mfg@coep.ac.in
[2]Associate Professor, Department of Manufacturing Engineering and Industrial Management, College of Engineering Pune (COEP), Shivaji Nagar, Pune: 411005, Maharashtra State, INDIA. smp.prod@coep.ac.in
[3]Head, Design and Development, HELLA eMobionics, Hella India Automotive Pvt. Ltd., Baner, Pune: 411045, Maharashtra State, INDIA. kapil.kalantri@forvia.com
[4]Associate Professor, Department of Manufacturing Engineering and Industrial Management, College of Engineering Pune (COEP), Shivaji Nagar, Pune: 411005, Maharashtra State, INDIA. mrd.mfg@coep.ac.in
[5]Associate Professor, Department of Mechanical & Mechatronics Engineering (Additive Manufacturing), ZSCT's Thakur College of Engineering and Technology, Kandivali (E), Mumbai: 400101, Maharashtra State, INDIA. avk.mechanical@gmail.com

***Correspondence:** smp.prod@coep.ac.in; Tel.: +91-20-25507712

ABSTRACT- Estimation of parameters of Permanent Magnet Synchronous Motor (PMSM) plays an important role for motor controller tuning in Electric Vehicle (EV) application. Under running condition motor parameters vary due to different effects such as temperature, saturation and Voltage Source Inverter (VSI) non-linearities. Identification of parameters in running condition increases the control performance of system. This paper uses Extended Kalman Filter (EKF), which allows estimation of d-q axis inductances of PMSM. The control algorithm considered here is Field Oriented Control (FOC) for EV system having position sensor. The simulation is performed using MATLAB- Simulink software. The simulation results show that EKF identifies the d- and q- axis inductances L_d, L_q considering measurement and process noise using a state space model of motor equations for implementation.

General Terms: Electric Vehicle, Motor Characterization, Motor Controller
Keywords: Extended Kalman Filter, MATLAB-Simulink, PMSM, Parameter Estimation, Simulation.

ARTICLE INFORMATION
Author(s): Komal Naikawadi, Sudhir Madhav Patil, Kapil Kalantri, Maneetkumar R. Dhanvijay and Atul V. Karanjkar;
Received: 03-08-2022; Accepted: 30-01-2023; Published: 15-03-2023;
E- ISSN: 2347-470X;
Paper Id: IJEER220735;
Citation: 10.37391/IJEER.110119
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-11/ijeer-110119.html

Publisher's Note: FOREX Publication stays neutral with regard to jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

Permanent Magnet Synchronous Motor (PMSM) is becoming popular in Electric Vehicle (EV) domain because of its merits such as good dynamic performance [1], high efficiency [2], high power density [3] and almost no maintenance [4-7]. Under running condition different effects such as temperature [8], saturation effects [9, 10] and Voltage Source Inverter (VSI) non-linearities [11] affect the performance of the EV system. To tune the motor controller and to increase the control performance of the accurate motor parameter identification is necessary [12]. Generally, one gets motor value from the datasheet of motor. Most of the time datasheet is not available so identifying motor parameters is the first task required for tuning the controller. There are different online [13] and offline methods available for parameter estimation. Classification of offline methods can be done as per frequency domain, time domain-based methods. Online methods can be classified as observer-based methods, Artificial Intelligence-Machine Learning (AI-ML) based methods [14] and deep learning-based methods. Generally, for sensor less parameter estimation observer-based methods are used. Deep learning based multi-modal Long Short-Term Memory (LSTM) method has proved its suitability for time varying parameter identification of PMSM [15].

There are various online numerical methods available for parameter estimation such as Recursive Least Square (RLS), Extended Kalman Filter (EKF), High frequency injection method, Recursive Prediction Error Method (RPEM), fractional order method, Model Reference Adaptive System (MRAS) method, runge kutta method. In RLS algorithm the squared error is minimized recursively. It has less computational time but it is sensitive to noise [16]. RLS algorithm treats the system as linear so it has less accuracy compared to EKF. EKF converts the non-linear system into linear using mathematical approach called Taylor series. Section 2 discusses the explanation of EKF in detail. MRAS algorithm has slow convergence speed but it has advantage of less computational complexity [17]. High frequency injection method is more sensitive to noise and has disadvantage of ripples. The advantages and disadvantages of different numerical based methods are given in below table 1.

Table 1: Comparative Table

Method Name	Advantages	Disadvantages
RLS	• Simple theoretical derivation and implementation. • Less execution time compared to EKF.	• Sensitive to disturbances and noises. • Data saturation.
MRAS	• Less implementation complexity. • Suitable for nonlinear systems.	• Sensitive to noises. • Difficult to be used in multi parameter identification.
EKF	• Enable to reject measurement noise. • Non-linearities can be added.	• More computational burden. • More Complex.

Field Oriented control (FOC) is used as a control strategy. The fundamental principle behind FOC strategy is that it converts 3 phase system to 2 phase rotating system by Clark transformation. Further it converts 2 phase rotating system into DC system by Park transformation. Using Clark and Park transformation, the system is converted into α-β and d-q frame respectively. *Figure 1* shows the working of FOC algorithm.

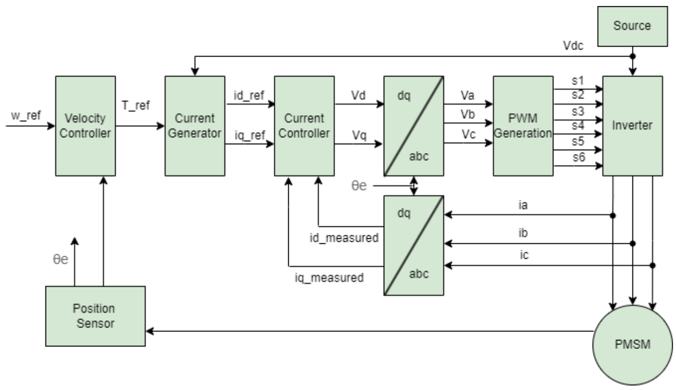

Figure 1: FOC for PMSM

The electric equation of three phase abc rotating frame can be represented as below:

$$V_a = i_a \times R_s + \frac{d\psi_a}{dt} \quad (1)$$

$$V_b = i_b \times R_s + \frac{d\psi_b}{dt} \quad (2)$$

$$V_c = i_c \times R_s + \frac{d\psi_c}{dt} \quad (3)$$

where, V_a, V_b, V_c are the stator voltage (instantaneous) for phase a, b, c; i_a, i_b, i_c are the stator current (instantaneous) for phase a, b, c; R_s is the stator resistance per phase; and ψ_a, ψ_b, ψ_c are the stator flux linkages (instantaneous) for phase a, b, c. There is one problem in d-q frame that is rank deficiency. The voltage equations have 4 unknowns but for solving it, there are only two equations available, equation 5 and equation 6. This problem can be overcome by decreasing the number of parameters to identify or by increasing the rank of observability matrix.

This article is further organized as follows. Section 2 gives the basic mathematical model of PMSM and d-q axis inductances identification method. Section 3 provides the results for parameter estimation using EKF algorithm. Section 4 includes the discussion based on obtained results and it also discusses about the future scope. Finally section 5 concludes the work.

2. METHODS

2.1 Overview

The paper proposes an algorithm using EKF for obtaining d-q axis inductances of PMSM. The control strategy incorporates FOC for EV system having position sensor. The EKF enabled algorithm with FOC has been simulated using MATLAB-Simulink software. For this, the first step is to build a mathematical model of PMSM. Second step includes selection of algorithm and a method for analysis to obtain the solution for proposed mathematical model thereby helping to estimate targeted parameter, inductance, of the proposed study. The accuracy of the proposed method and its comparative analysis with other models is based on identification error.

2.2 Mathematical Model of PMSM

In this section, the proposed mathematical model of PMSM is discussed. The mathematical model acts as an input to the identified EKF algorithm leading to determination of inductance through simulation, carried out using MATLAB-Simulink software.

For the reference d-q axis frame, which rotates synchronously, the stator voltage can be determined by using the equation 4 and equation 5.

$$V_{sd} = i_{sd} \times R_s + \frac{d\lambda_d}{dt} - \omega_e \times \psi_q \quad (4)$$

$$V_{sq} = i_{sq} \times R_s + \frac{d\lambda_q}{dt} + \omega_e \times \psi_d \quad (5)$$

where, V_{sd} and V_{sq} are stator voltage in the reference d-q axis frame, i_{sd} and i_{sq} are stator current in the reference d-q axis frame, ω_e is the stator angular electrical velocity, ψ_d and ψ_q are d and q axis flux linkage.

The equation 6 is used to determine electromagnetic torque of the motor.

$$T_{em} = (\tfrac{3}{2} \times p_b \times \psi_m \times i_{sq}) + (\tfrac{3}{2} \times p_b \times (L_q - L_d) \times i_{sd} \times i_{sq})) \quad (6)$$

The equation of electromagnetic torque contains two components: torque produced due to the stator current with the Permanent Magnet (PM) flux and other is reluctance torque which is generated due to saliency in the motor. Surface Mounted PMSM (SPMSM) has reluctance equal to zero since $L_d = L_q$ where as in Interior Magnet PMSM (IPMSM) reluctance torque exists as $L_d < L_q$.

The equation 7 represents the mechanical equation of the machine as:

$$T_{em} - T_L - B \times \omega_m = J \times \frac{d\omega_m}{dt} \quad (7)$$

Where, T_L is the load torque, B is the viscous friction coefficient, ω_m is the shaft speed, and J is the moment of inertia.

2.3 Extended Kalman Filter Algorithm

EKF is the optimal recursive estimation algorithm based on least square method used to estimate states of dynamic nonlinear system [18, 19]. The dynamic model of non-linear system is linearized in EKF using Taylor series. Main advantage of EKF is that it rejects the process and measurement noise having similar accuracy as Unscented Kalman Filter (UKF), and Moving Horizon Estimation (MHE). Nonlinear state equations for EKF can be written as:

$$X_{k+1} = f(X_k, u_k) + w_k \quad (8)$$
$$Y_k = H(X_k) + v_k \quad (9)$$

Here, f is a system function, u is the control. w and v are zero mean process and measurement noises respectively. Basically, in EKF there are two main steps: 1. Prediction step; and 2. Correction step. The steps for estimation of X vector parameters are:

Initialization:

$$X, P$$

Prediction step:

$$X_p = f(X)$$
$$P_p = A \times P \times A^T + Q$$

Kalman Gain:

$$K = P_p \times H^T \times (H \times P_p \times H^T + R)^{-1}$$

Correction step:

$$X_e = X_p + K(Y - H(X_p))$$
$$P_e = P_p - K \times H \times P_p$$
$$A = \frac{\partial f(X,u)}{\partial X} \; at \; X = \widehat{X_k}$$
$$H = \frac{\partial h(X)}{\partial X} \; at \; X = \widehat{X_k}$$

Here, X is the vector containing the parameters to be estimated, P is the covariance matrix, A and H are the Jacobian matrices.

Execution time for EKF is longer than RLS and MRAS. [20, 21]. It has better optimization capability, good convergence in simultaneously estimating PMSM electrical parameters [10, 22]. R. Kerid has considered temperature variation while implementing EKF algorithm for parameter estimation [23]. EKF with Gradient correction has less calculation, high accuracy, and fast convergence speed. It has been observed that EKF has a complex structure with high computational burden and comparative longer execution time than MRAS and RLS. It is difficult to design the algorithm for multi parameter measurement [10, 24].

Initialization of P_0 is done using trial and error method to get better stability and convergence time. The process and measurement noise Q and R are also taken using trial and error method. A complex part of this algorithm is to choose values of Q and R as they affects convergence stability and performance. If the values of Q matrix increase, the steady state performance of the system gets affected. For increased R the transient response becomes worse.

2.4 Identification Error

The outcome of identification is susceptible to measurement noise. The following equation gives the identification error during motor parameter estimation. Here, identification is the estimated value and true means the actual datasheet value.

$$Identification\ error\ (\%) = (|identification - true|\ /true) \times 100$$

Due to magnetic saturation and fluctuating environmental temperatures, variations in the stator inductance and resistance of PMSM are always there. Thus, there will always be an identification error. Attempts are to be made for elimination of identification error by realizing the simultaneous identification of multi-parameters. The implementation of EKF algorithm with FOC strategy, as presented in this paper, helps to minimize the identification error and eliminates over computational time.

3. RESULTS

In this section the implemented EKF algorithm for field oriented controlled PMSM motor is given. Implementation of algorithm is done using the MATLAB function and the FOC motor model is developed using the Simulink. *Figure 2* shows the overall model. Switching frequency and sampling period are 10 kHz and 100 micro seconds respectively. The PMSM parameters are given in table 2.

Table 2: Motor Specification

Parameter	Value
Stator Resistance	4.49 Ohm
d-axis inductance	0.002633 Henry
q-axis inductance	0.0039 Henry
Number of poles	8
Flux linkages	0.55 Weber

Figure 3 gives the estimation of d-axis inductance along with the identification error. *Figure 4* gives the estimation of q-axis inductance along with the identification error. From results it can be seen that algorithm is able to estimate the inductances of IPMSM motor. As the computational time increases the results falls down to zero. In this paper, the initial covariance matrix P_0 and noise matrices Q and R are used as follows:

$$P_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0.003 & 0 \\ 0 & 0 & 0 & 0.004 \end{bmatrix}$$

$$Q = \begin{bmatrix} 0.1 & 0 & 0 & 0 \\ 0 & 0.1 & 0 & 0 \\ 0 & 0 & 300 & 0 \\ 0 & 0 & 0 & 200 \end{bmatrix}, \quad R = \begin{bmatrix} 0.05 & 0 \\ 0 & 0.05 \end{bmatrix}$$

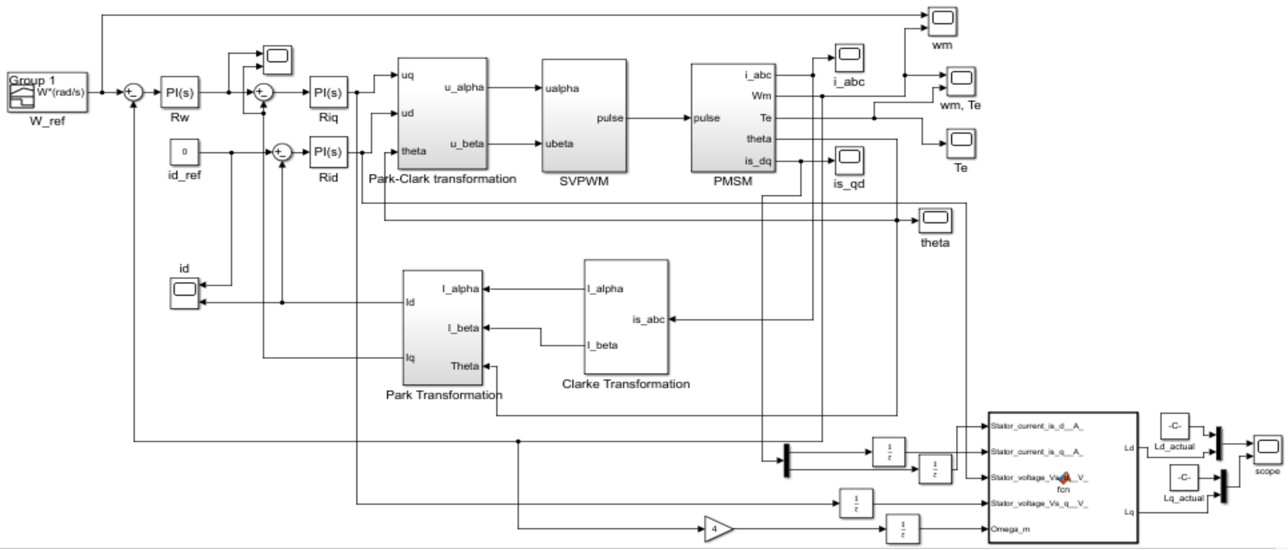

Figure 2: Simulation Model for Inductance

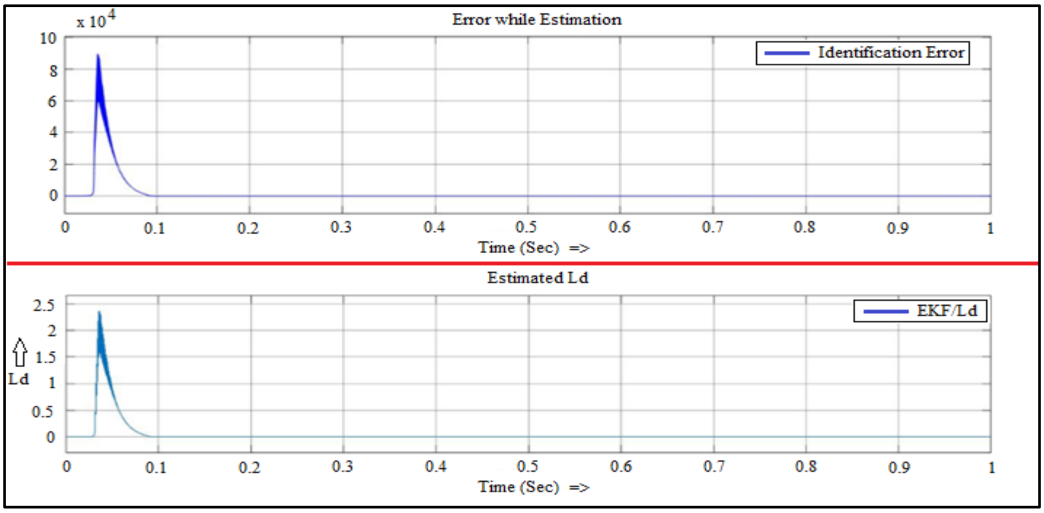

Figure 3: L_d Estimation

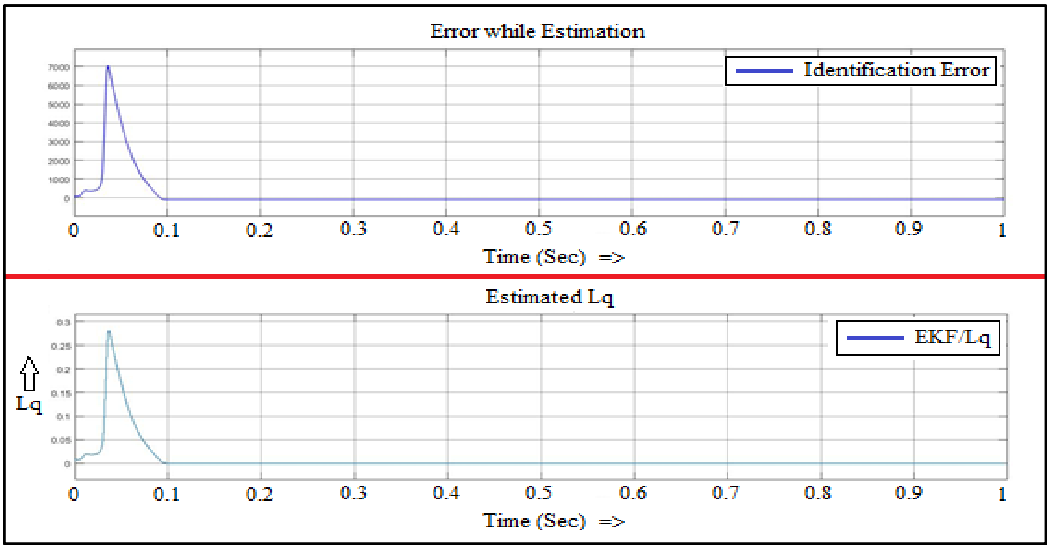

Figure 4: Lq Estimation

Research Article | Volume 11, Issue 1 | Pages 138-142 | e-ISSN: 2347-470X

4. DISCUSSION

From results it can be seen that the EKF algorithm converges to the actual value within a very small time. The performance of the EKF algorithm strongly gets affected due to initialization matrices such as P_0, Q and R. To get the exact results trial and error method is used. The increase in value of process noise matrix Q increases the Kalman gain which gives quick filter dynamics. The increase in value of measurement noise matrix states that current measurements are influenced by noise and Kalman gain of algorithm decreases.

5. CONCLUSION

This paper presents the implementation of EKF algorithm for inductance estimation of PMSM. The EKF algorithm considers the noise effects due to which it is generally used for identification of PMSM parameters. Trial and error method is used to get the initialization matrices such as P_0, Q and R. During implementation of EKF it is required to take care of computational time. As increased computational time results into the null element matrices. Further scope is to go for joint estimation of both inductances as well as the noise matrices to get more accuracy of system's inductance estimation.

REFERENCES

[1] Shahapure S. B., Kulkarni (Deodhar) V. A., and Shinde S. M. A technology review of energy storage systems, battery charging methods and market analysis of EV based on electric drives. International Journal of Electrical and Electronics Research (IJEER). 10(1), (March 2022), 23-35. https://doi.org/10.37391/IJEER.100104.

[2] Liu H., Gao Z., Wu W., Chow L. and Wu T. 2015. Design of a high-efficiency permanent magnet synchronous motor and inverter system. In Proceedings of the 41st Annual Conference of the IEEE Industrial Electronics Society (IECON 2015), 004996-005001, IEEE. https://doi.org/10.1109/IECON.2015.7392884.

[3] Lee, C-H., Shin, H-S., and Kim, K-C. Analysis of interior permanent magnet synchronous motor according to winding method. International Journal of Electrical and Electronics Research (IJEER). 10(2), (June 2022), 207-213. https://doi.org/10.37391/IJEER.100227.

[4] Kulkarni, S., and Thosar, A. Performance analysis of fault tolerant operation of PMSM using direct torque control and fuzzy logic control. International Journal of Electrical and Electronics Research (IJEER).10(2), (June 2022), 297-307. https://doi.org/10.37391/ijeer.100240.

[5] Park, S. H., Lee, E. C., Park, J. C., Hwang, S. W., and Lim, M. S. Prediction of mechanical loss for high-power-density PMSM considering eddy current loss of PMs and conductors. IEEE Transactions on Magnetics. 57(2), Art No. 6300205, (Feb. 2021), 1-5. https://doi.org/10.1109/TMAG.2020.3007439.

[6] Jeong, C-L., Kim, Y-K., and Hur, J. Optimized design of PMSM with hybrid-type permanent magnet for improving performance and reliability. IEEE Transactions on Industry Applications. 55(5), (2019), 4692-4701. https://doi.org/10.1109/TIA.2019.2924614.

[7] Fang, S., Liu, H., Wang, H., Yang, H., and Lin H. High power density PMSM with lightweight structure and high-performance soft magnetic alloy core. IEEE Transactions on Applied Superconductivity. 29(2), Art no. 0602805, (March 2019), 1-5. https://doi.org/10.1109/TASC.2019.2891630.

[8] Liu, H., Zhang, C. and Huang, Q. 2021. Model reference adaptive parameter identification of PMSM based on single-loop model predictive control. In Proceedings of the 40th Chinese Control Conference (CCC), 1365-1372, IEEE. https://doi.org/10.23919/CCC52363.2021.9549990.

[9] Liu, Z., Feng, G., and Han, Y. 2021. Extended-kalman-filter-based magnet flux linkage and inductance estimation for PMSM considering magnetic saturation. In Proceedings of the 36th Youth Academic Annual Conference of Chinese Association of Automation (YAC), 430-435, IEEE. https://doi.org/10.1109/YAC53711.2021.9486499.

[10] Zwerger, T. and Mercorelli P. 2019. Combining SMC and MTPA using an EKF to estimate parameters and states of an interior PMSM. In Proceedings of the 20th International Carpathian Control Conference (ICCC), 1-6, IEEE. https://doi.org/10.1109/CarpathianCC.2019.876606.

[11] IEEE guide for test procedures for synchronous machines part I-acceptance and performance testing part II-test procedures and parameter determination for dynamic analysis: in IEEE Std 115-2009 (Revision of IEEE Std 115-1995), (May 2010), 1-219. https://doi.org/10.1109/IEEESTD.2010.5464495.

[12] Jiang, J. W., Chen, Z., Wang, Y. H., Peng, T., Zhu, S. L., and Shi L. M. Parameter estimation for PMSM based on a back propagation neural network optimized by chaotic artificial fish swarm algorithm. International Journal of Computers Communications and Control. 14(6), (December 2019), 615-632. Available at https://univagora.ro/jour/index.php/ijccc/article/view/3705/pdf.

[13] Naikawadi, K. M., Patil, S. M., Kalantri, K., and Dhanvijay M. R. Comparative analysis of features of online numerical methods used for parameter estimation of PMSM. International Journal of Power Electronics and Drive Systems (IJPEDS). 13(4), (December 2022), 2172-2180. http://doi.org/10.11591/ijpeds.v13.i4.pp2172-2180.

[14] Rafaq, M. S., and Jung, J-W. A comprehensive review of state-of-the-art parameter estimation techniques for permanent magnet synchronous motors in wide speed range. IEEE Transactions on Industrial Informatics. 16(7), (July 2020), 4747-4758. https://doi.org/10.1109/TII.2019.2944413.

[15] Cui, M., Khodayar, M., Chen, C., Wang, X., Zhang, Y., Khodayar, M. E. Deep learning-based time-varying parameter identification for system-wide load modeling. IEEE Transactions on Smart Grid. 10(6), (Nov. 2019), 6102-6114. https://doi.org/10.1109/TSG.2019.2896493.

[16] Ye, Z., Liu, T., Fuller, M., and Griepentrog, G. Parameter identification of PMSM based on MRAS with considering nonlinearity of inverter. In Proceedings of the 45th Annual Conference of the IEEE Industrial Electronics Society (IECON 2019), 1255-1260, IEEE. https://doi.org/10.1109/IECON.2019.8927595.

[17] Liu, Z-H., Nie, J., Wei, H-L., Chen, L., Li, X-H., and Lv, M-Y. Switched PI control based MRAS for sensorless control of PMSM drives using fuzzy-logic-controller. IEEE Open Journal of Power Electronics. 3, (June 2022), 368-381. https://doi.org/10.1109/OJPEL.2022.3182053.

[18] Lei, X., and Zhang, Z. Recursive weighted least squares estimation algorithm based on minimum model error principle. Defence Technology. 17(2), (April 2021), 545-558. https://doi.org/10.1016/j.dt.2020.02.003.

[19] Patwardhan, S. C., Narasimhan, S., Jagadeesan, P., Gopaluni, B., Shah, S. L. Nonlinear Bayesian state estimation: A review of recent developments. Control Engineering Practice. 20(10), (October 2012), 933-953. http://dx.doi.org/10.1016/j.conengprac.2012.04.003.

[20] Xu, Y., Yang, K., Liu, A., Wang, X., and Jiang, F. 2019. Online parameter identification based on MTPA operation for IPMSM. In Proceedings of the 22nd International Conference on Electrical Machines and Systems (ICEMS), 1-4, IEEE. https://doi.org/10.1109/ICEMS.2019.8921761.

[21] Li, X., Zhang, P., and Yan, L. Sensorless control of permanent magnet synchronous motor with online parameter identification. Transactions of China Electrotechnical Society. 31(14), (July 2016), 139-147.

[22] Kim, W-H., Kim, M-J., Lee, K-D., Lee, J-J., Han, J-H., Jeong, T-C., Cho, S-Y., and Lee, J. Inductance calculation in IPMSM considering magnetic saturation. IEEE Transactions on Magnetics. 50(1), (Jan. 2014), 1-4. https://doi.org/10.1109/TMAG.2013.2277586.

[23] Kerid, R., Bourouina, H., and Yahiaoui, R. Parameter identification of PMSM using EKF with temperature variation tracking in automotive application. Periodicals of Engineering and Natural Sciences (PEN). 6(2), (2018), 109-119. http://dx.doi.org/10.21533/pen.v6i2.168.

[24] Wang, Q., Wang, G., Zhao, N., Zhang, G., Cui, Q. and Xu, D. An impedance model-based multiparameter identification method of PMSM for both offline and online conditions. IEEE Transactions on Power Electronics. 36(1), (Jan. 2021) 727-738. https://doi.org/10.1109/TPEL.2020.3000896.