Flux Linkage Identification of IPM Motor Through Neural-Network Considering Speed Impact

Zhenghao Liu
Department of Electrical and Computer Engineering
The University of Alabama
Tuscaloosa, USA
zliu99@crimson.ua.edu

Shuhui Li (Corresponding author)
Department. of Electrical and Computer Engineering
The University of Alabama
Tuscaloosa, USA
sli@eng.ua.edu

2024 IEEE Power & Energy Society General Meeting (PESGM) | 979-8-3503-8183-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/PESGM51994.2024.10688723

***Abstract*—An IPM motor is a primary electric motor broadly used in the electric vehicle (EV) industry, in which flux-linkage estimation is critical for the operation and control of the motor. This paper shows that besides the motor current impact, motor operating speed is another factor that should be considered and addressed in the flux linkage estimation of an IPM motor. This is particularly important for IPM motors in EV applications, which typically require for a very broad motor operating speed range from low to very high speed. The paper shows that the conventional estimation method based on motor current information only cannot provide accurate motor flux estimation, especially for motors operating at high-speed conditions. The paper also indicates that introducing additional impact factors could cause significant challenges to the conventional methods in terms of computing complexity and memory needed to store the conventional lookup tables. To overcome the challenges, the paper proposes a neural network (NN) method for flux linkage identification. The proposed NN is trained offline. Therefore, it only requires a small memory size to store the trained network weights and computing efficiency is high, and suitable for online implementation. The evaluation study in this paper demonstrates that compared to the conventional methods, the proposed NN method can provide accurate flux linkage estimation, which further enhances the motor torque estimation based on the proposed NN method.**

Keywords—interior permanent magnet, torque currents (Iq), field weakening currents (Id), Neural-Network (NN), Look-Up-Table (LUT)

I. Introduction

Among the electric traction motors, interior permanent magnet (IPM) motors, which include rotors with embedded magnets, are increasingly being used as the driving motors for electric vehicles (EVs). The advantages of an IPM motor include its wide velocity and torque variation, high power, light weight, and energy efficiency. Flux linkage of an IPM motor is an essential measurement of the linkage of the magnetic field in the motor windings to identify the electromagnetic characteristics and performance of the motor. Accurate identification of motor flux linkage is important for the development and design of motor control and drive systems and for the high performance, safety, and efficiency of the motor [1-3]. It is also important for the motor performance evaluation and torque estimation.

A significant challenge in the identification of motor flux linkage is the magnetic saturation and cross saturation impacts, in terms of motor core losses, that are difficult to determine due to the nonlinear relations of the core loss with motor current, speed, etc. [4-6]. This paper focuses on investigating the motor speed impact to the flux linkage identification, which is especially important for IPM motor applications in EVs, where broad motor operating speed range is typically needed for IPM motors in EVs.

At present, the lookup table (LUT) method is the widely used method for flux linkage identification in the IPM motor and automobile industry for EVs. However, the traditional LUT flux linkage identification methods cannot successfully handle the flaws in correctly identifying motor flux linkages when the motor operates at varying speeds. Especially, the core loss of the motor becomes a non-neglectable aspect as the operating speed increases. The balancing of the accuracy and the size of the LUTs makes it a difficult choice for the LUT methods.

Recently, the development of neural networks has had outstanding results in many complex research areas. It also should have great potential for solving the motor identification problem. This paper focuses on the flux linkage identification of IPM motors by taking a consideration the motor speed impact through a neural network based approach. A comprehensive investigation into the development and validation of the proposed neural network method is presented in the paper. The effectiveness of the proposed approach is demonstrated by comparing the performance of the proposed NN method with the traditional LUT method based on a simulated test motor.

The paper is organized as follows. In Section II, the IPM motor model considering the speed impact is evaluated and its equivalent with and without core loss is analyzed. In Section III, the flux linkage estimation using conventional methods is analyzed and the proposed NN method is presented, including the NN training mechanism for the flux identification. Section IV focuses on the performance investigation of the flux estimation using the conventional LUT method and the proposed NN method as well as their impact on the torque estimation of the motor. Section V gives the conclusions of this paper.

II. IPM Motor Model at Low and High Speed

The IPM motor model is typically defined in the dq reference frame based on the well-known Park transformation [7]. In most IPM motor applications, the speed impact on the magnetic model of the motor is not considered. However, this could become a critical issue when the motor operates at a high speed, such as in the application of EVs, where an IPM motor can operate in a broad speed range from low to high speed.

A. IPM motor model at low speed

When the operating speed is low, the core loss impact of the motor is normally not considered. Therefore, the d- and q-axis flux linkages of the motor are modeled as

$$\begin{bmatrix}\lambda_d\\ \lambda_q\end{bmatrix} = \begin{bmatrix}L_d & 0\\ 0 & L_q\end{bmatrix}\begin{bmatrix}i_d\\ i_q\end{bmatrix} + \begin{bmatrix}\lambda_{pm}\\ 0\end{bmatrix} \tag{1}$$

where L_d, L_q, i_d, i_q are stator d- and q-axis inductance and current, and λ_{pm} is the flux linkage of the rotor magnet. The stator d- and q-axis voltage equations are

$$\begin{bmatrix}v_d\\ v_q\end{bmatrix} = R\begin{bmatrix}i_d\\ i_q\end{bmatrix} + \frac{d}{dt}\begin{bmatrix}\lambda_d\\ \lambda_q\end{bmatrix} + \omega_e\begin{bmatrix}-\lambda_q\\ \lambda_d\end{bmatrix} \tag{2a}$$

$$\begin{bmatrix}v_d\\ v_q\end{bmatrix} = R\begin{bmatrix}i_d\\ i_q\end{bmatrix} + \frac{d}{dt}\begin{bmatrix}L_d & 0\\ 0 & L_q\end{bmatrix}\begin{bmatrix}i_d\\ i_q\end{bmatrix} + \omega_e\begin{bmatrix}-\lambda_q\\ \lambda_d\end{bmatrix} \tag{2b}$$

where ω_e is the motor electric speed. The equivalent circuit representation of (2b) is shown in Fig. 1, in which the core loss of the motor is not included. The electromagnetic torque of the motor is obtained as follows

$$T_{em} = \frac{P}{2}\left(\lambda_d i_q - \lambda_q i_d\right) = \frac{P}{2}\left[\lambda_{pm} + \left(L_d - L_q\right)i_d\right]i_q \tag{3}$$

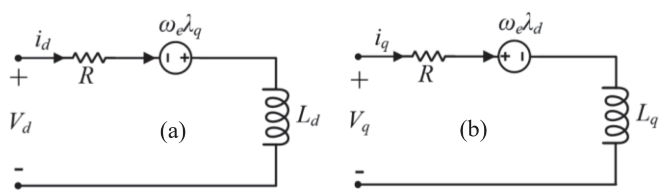

Fig. 1. Equivalent circuit model at low speed: a) d-axis circuit, b) q-axis circuit

B. IPM motor model at high speed

When the operating speed is high, the core loss impact of the motor cannot be ignored, which means that in terms of the equivalent circuit, we need to have a core loss component in the d- and q-axis equivalent circuits of the motor. This can be modeled by adding a variable resistance R_C in the d- and q-axis equivalent circuits of the motor as shown in Fig. 2, where i_{dc}, i_{qc} and i_{do}, i_{qo} are motor currents contributed to the d- and q-axis core loss and flux linkage parts, respectively.

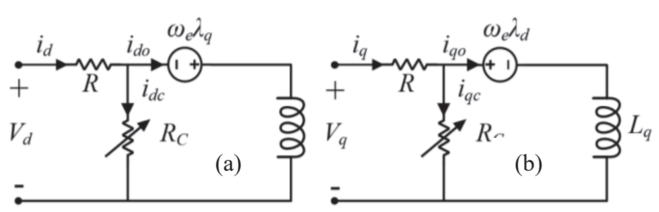

Fig. 2. Equivalent circuit model at high speed: a) d-axis circuit, b) q-axis circuit

Thus, the d-axis and q-axis flux linkages are expressed as:

$$\begin{bmatrix}\lambda_d\\ \lambda_q\end{bmatrix} = \begin{bmatrix}L_d & 0\\ 0 & L_d\end{bmatrix}\begin{bmatrix}i_{do}\\ i_{qo}\end{bmatrix} + \begin{bmatrix}\lambda_{pm}\\ 0\end{bmatrix} \tag{4}$$

and the electromagnetic torque of the motor is described as

$$T_{em} = \frac{P}{2}\left(\lambda_d i_{qo} - \lambda_q i_{do}\right) \tag{5}$$

III. Identification of IPM Motor Flux Linkages

The d- and q-axis flux linkages are important information for controlling and operating an IPM motor with high efficiency and performance. The estimation can affect the accuracy of maximum-torque-per-amp (MTPA), flux weakening, and maximum-torque-per-volt (MTPV) algorithms as well as the development of the motor controller. However, as it is well known, motor flux linkages can be affected by multiple factors. In this section, we first present the current method used in the industry for flux linkage identification based on the motor current information only and then present the proposed method as well as why the proposed method is needed.

A. Traditional Look-up-Table (LUT) Method

The LUT approach is a commonly used technique in many motor drives and EV industries because of its reliability, computing efficiency, etc. In the LUT method, it is assumed that the motor flux linkages depend only on the motor d- and q-axis currents without considering the motor speed impact. The method uses two LUTs to gain d- and q-axis flux linkage relations over all the possible Id and Iq combinations from low to high values as illustrated in Fig. 3. Hence, the LUTs use two-dimensional input variables, Id and Iq, to determine the motor d- and q-axis flux linkages. The size of the LUTs can vary depending on the motor's current range and the resolution of the LUTs. However, these lookup table data are usually pre-made at one a low particular speed condition to decrease the impact of core loss. Therefore, it cannot represent the correct flux linkage at a high speed unless the dimension of its input variables switches from 2 dimensions to larger dimensions. However, a larger multidimensional LUT would significantly increase the size of LUTs and the complexity of the interpolation algorithm. Another flaw with the LUT method is that the operational variation of motor parameters over the motor's lifetime is ignored. In addition to the LUT method, several other identification methods have been developed by others [8-11]. However, critical issues associated with these methods include convergence and accuracy problems under complicated motor operating conditions.

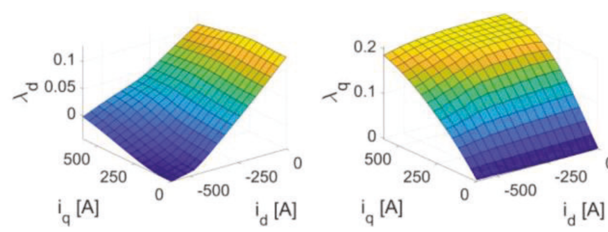

Fig. 3. d-q flux linkages with motor d- and q-axis currents

B. Proposed Neural Network Method

Unlike traditional treatments, we consider that motor speed is an important factor to affect the identification of motor flux linkages. However, this would be difficult to achieve using the LUT approach since the increase of the input variable dimension would generally make the LUTs impractical. To overcome this challenge, we propose a neural network (NN) method to identify motor flux linkages considering the impact of motor speed that can change from low to high-speed range. Therefore, the input variables to the NN will include motor d- and q-axis currents and motor speed. The NN outputs are the identified d- and q-axis flux linkages under a specified input condition. The NN is a typical forward network consisting of one input layer, 2 hidden layers, and one output layer. Each of the 2 hidden layers has 10 nodes. The structure of the NN is shown in Fig. 4.

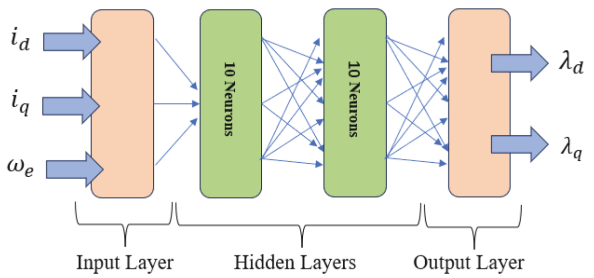

Fig. 4. Structure of the proposed NN for flux linkage estimation

C. Training of Neural Network

For the NN to have the identification capability, training of the NN is required. This involves two stages: 1) training data collection and 2) NN training based on the collected data.

In the training data collection stage, measurements are obtained through either offline or online experiments. In each experiment, voltage applied to the motor as well as motor current and speed are recorded. To get enough training data, the motor speed is slowly increased from a low speed to its maximum speed. For each motor operating speed, motor d- and q-axis currents are obtained over the full motor current ranges. Then, for each measurement of motor voltage, current, and speed at a steady state, the flux linkages are calculated according to (6), which is the steady-state representation of (2b).

$$\lambda_d = (v_q - Ri_q)/\omega_e\,,\ \lambda_q = (-v_d + Ri_d)/\omega_e \qquad (6)$$

Each collected data is saved into the memory in an NN input-output pair as $\{(i_d, i_q, \omega_e) \leftrightarrow (\lambda_{d,}\lambda_q)\}$. After all the data collection and calculation process is completed, the data are presented to train the NN in the training stage.

In the training stage, the NN is trained repeatedly until a stop criterion is reached. The NN is trained offline, meaning there is no online training involved. We used the Levenberg–Marquardt Backpropagation algorithm to train the NN [12]. The objective of the NN training is to minimize the root mean square error between the NN estimated and actual motor flux linkages as follows:

$$C = \frac{1}{N}\sum_{k=1}^{N}\sqrt{\left(\hat{\lambda}_d(k) - \lambda_d(k)\right)^2 + \left(\hat{\lambda}_q(k) - \lambda_q(k)\right)^2} \qquad (7)$$

where N is the total number of training data samples, k stands for the training sample index, $\lambda_d(k)$ and $\lambda_q(k)$ are the motor d- and q-axis flux linkages of the kth training sample, and $\hat{\lambda}_d(k)$ and $\hat{\lambda}_q(k)$ are the corresponding NN estimated flux linkages. Fig. 5 illustrates the training process of the NN for the flux linkage identification.

The NN is trained multiple times and a best trained NN is selected as the finalist. The performance evaluation of the developed NN is shown in the next section.

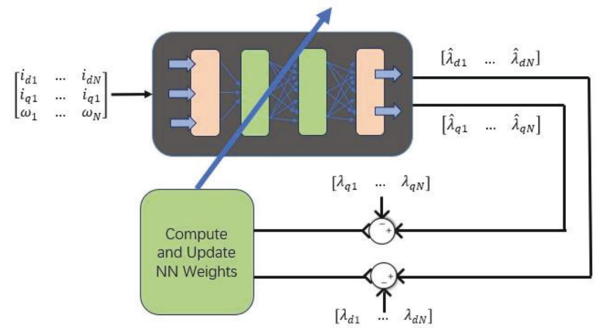

Fig. 5. Training NN for flux linkage identification

IV. SIMULATION EVALUATION

The potentiality of the proposed Neural Network method is verified with the MATLAB/Simulink model. The simulation evaluation is based on an 8-pole, 100 kW IPM motor from [13]. Table 1 shows the parameters of the test motor. The motor parameter variations are built into the model and considered as an unknown black box, which would make the simulation evaluation closer to the situation of a hardware experimental evaluation.

Table I: Parameters of an IPM motor from [13]

Parameter		Units
Rated Power	100	kW
DC voltage	500	V
Maximum Speed	10000	RPM
Permanent magnet flux	0.1266	Wb
Inductance in q-axis	0.59	mH
Inductance in d-axis	0.35	mH
Stator copper resistance	0.5	Ohm
Inertia	0.095	Kg*m^2
Pole pairs	4	

A. Neural network development based on the test motor

First, collection of the training data was conducted for the test motor as follows. The motor operating speed was increased from 500 RPM to 9000 RPM with a 1000 RPM increment interval. The motor current range is set from ±320A to 0A. Then, a simulation experiment was conducted, and the d- and q-axis flux linkages were calculated according to (6) for each speed and current condition. To cover the entire current combination possibilities at each motor operating speed, Id and Iq were alternately changed from 0 to their maximum value.

Second, we conducted 30 NN training experiments based on the above-collected data. In each training experiment, the network has a maximum of 1000 training epochs. However, if the NN training performance in terms of RMS error reduction does not improve by 0.001 for twenty consecutive epochs, the training process stops. From 30 separately trained NNs, the NN with the best performance was picked as the finalist for the flux linkage identification of the IPM motor. For comparison purposes, we also developed flux linkage LUTs based on the collected data obtained at a low speed (500 RPM). Note: the LUTs can only provide flux linkage estimation based on motor d- and q-axis currents.

B. Performance evaluation and comparison

In this subsection, the NN and LUTs, obtained in Section IV.A, are evaluated and compared for arbitrary motor current and running speed.

First, we compared the flux linkage estimation using NN and LUT methods. Note: in the following figures, the 2D method stands for the LUT method. Fig. 6 shows the flux linkages estimation for motor operating speeds at 500 RPM, 5500 RPM, and 8500 RPM, respectively, when the d-axis current changes while the q-axis current is fixed. Fig. 7 shows the flux linkages estimation for the same speed condition when the q-axis current changes while the d-axis current is fixed.

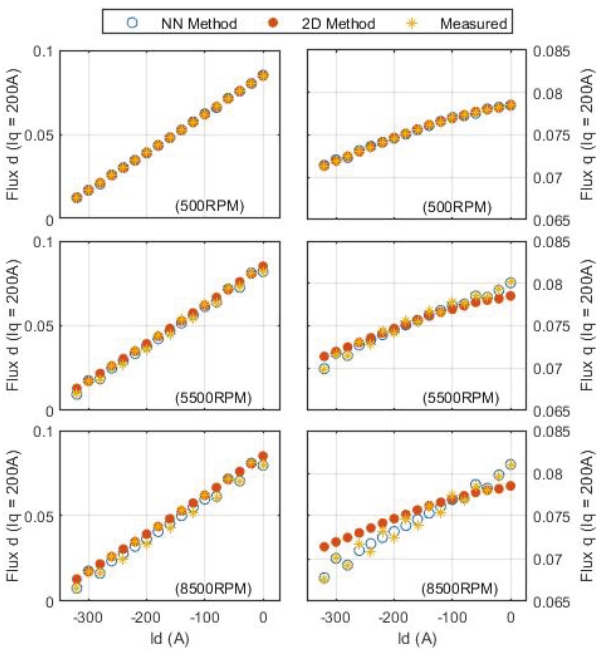

Fig. 6. Comparison results of d- and q- flux under different speed with d-axis current change only. Iq = 200A

From the figures, it can be seen that when the motor running speed is low, there is almost no difference in the flux estimation using the NN and LUT methods. However, when the motor running speed is high, the difference becomes higher and the NN method provides a more accurate estimation. A closer look at Figs. 6 and 7 shows that the change in the q-axis current has a higher impact on the estimation of the d-axis flux linkage. This interesting finding can be better understood from Figs. 2a, 2b, and equation (4), which shows that the product of motor speed and permanent magnet flux linkage can particularly cause a high impact on the core loss in the q-axis circuit (Fig. 2b) and therefore affect the estimation of motor d-axis flux linkage.

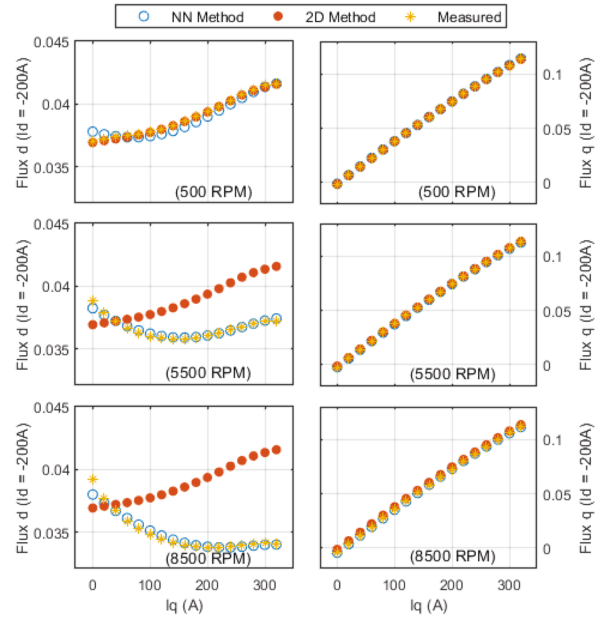

Fig. 7. Comparison results of d- and q- flux under different speed with q-axis current change only. Id = 200A

Fig. 8 shows the absolute error between the measured and estimated flux linkages by using the NN and LUT methods when the motor operating speed is 8500 RPM. The figure further demonstrates that the proposed NN method can provide a much more accurate estimation of motor flux linkage than the LUT method.

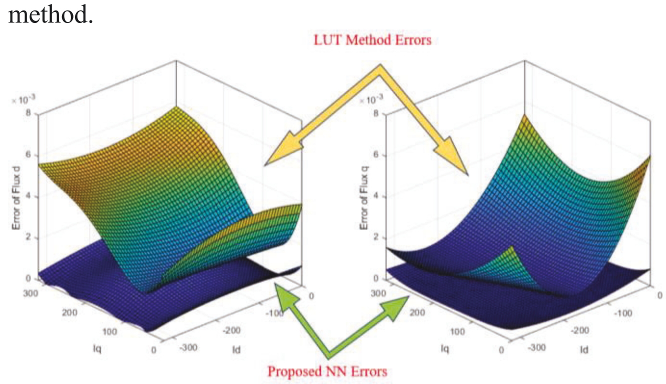

Fig. 8. Estimation error between the LUT and NN methods at 8500 RPM

Fig. 9 shows the actual motor torque compared with the estimated motor torque based on the flux linkages estimated by using the NN and LUT methods. This investigation is important as the estimated motor flux is usually needed for developing MTPA, flux weakening, and MTPV algorithm and for the motor torque diagnosis as well. Therefore, the study would provide an important guideline on whether the speed impact should be considered in the motor flux estimation. As can be seen from the figure, the error between the actual torque and the estimated torque using LUTs becomes larger as the motor speed increases while the NN method can accurately provide the torque estimation.

Overall, all the comparison studies demonstrate that the proposed NN method can provide an accurate estimation of motor flux linkages. On the other hand, the memory needed to store the NN weights is much smaller even than the 2D LUT method. Regarding computing speed, the proposed NN method can provide fast flux linkage estimation since there is no training involved in the online application of the NN method, which would make the NN method easy to implement in practical IPM motor operation and control, such as in EV applications.

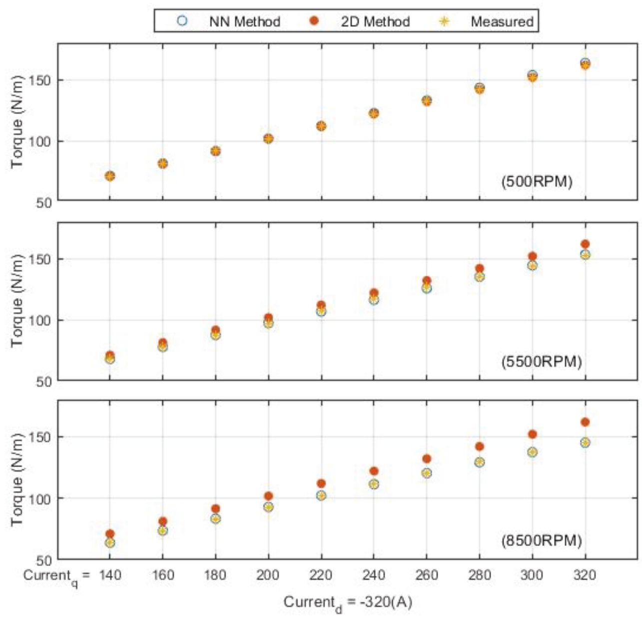

Fig. 9. Torque results under different speed with the q-axis current change only while Id = -320A

V. CONCLUSIONS

IPM motors are important electric motors that are widely used in electric vehicles, in which accurate estimation of the motor flux linkage is critical to ensure the high performance, efficiency, reliability, and safety of the EV electric motor. It is found in this paper that the motor operating speed is a key factor affecting the motor core loss and flux linkages. However, the speed impact has not been properly addressed in the traditional estimation methods, especially the widely used LUT method in the IPM motor industry. A significant challenge is that the consideration of the speed impact would significantly increase the size and complexity of the traditional LUT methods. To overcome the challenge, this paper proposes an NN method for motor flux estimation with full consideration of motor current and speed impacts. The study presented in this paper demonstrates that the proposed NN method can accurately estimate the motor flux linkages while the conventional methods will generate evident estimation error especially when the motor running speed is high. In addition, since the proposed NN is trained offline, it only requires a very small memory size to store the trained network weights and the computing efficiency is adequate to meet the online DSP implementation of the proposed NN method on a practical IPM motor in EVs. In future research, other factors that may affect the motor flux linkage estimation, such as motor's internal temperature, will be further investigated.

REFERENCES

[1] A. Accetta, M. Cirrincione, M. Pucci and A. Sferlazza, "State Space-Vector Model of Linear Induction Motors Including End-Effects and Iron Losses Part I: Theoretical Analysis," in IEEE Transactions on Industry Applications, vol. 56, no. 1, pp. 235-244, Jan.-Feb. 2020, doi: 10.1109/TIA.2019.2952031.

[2] Y. Wang, Y. Xu and J. Zou, "Online Multiparameter Identification Method for Sensorless Control of SPMSM," in IEEE Transactions on Power Electronics, vol. 35, no. 10, pp. 10601-10613, Oct. 2020, doi: 10.1109/TPEL.2020.2974870.

[3] Y. Inoue, Y. Kawaguchi, S. Morimoto and M. Sanada, "Performance improvement of sensorless IPMSM drives in low-speed region using online parameter identification," 2009 IEEE Energy Conversion Congress and Exposition, San Jose, CA, USA, 2009, pp. 1933-1938, doi: 10.1109/ECCE.2009.5316536.

[4] B. Stumberger, G. Stumberger, D. Dolinar, A. Hamler and M. Trlep, "Evaluation of saturation and cross-magnetization effects in interior permanent-magnet synchronous motor," in IEEE Transactions on Industry Applications, vol. 39, no. 5, pp. 1264-1271, Sept.-Oct. 2003, doi: 10.1109/TIA.2003.816538.

[5] E. Armando, R. I. Bojoi, P. Guglielmi, G. Pellegrino and M. Pastorelli, "Experimental Identification of the Magnetic Model of Synchronous Machines," in IEEE Transactions on Industry Applications, vol. 49, no. 5, pp. 2116-2125, Sept.-Oct. 2013, doi: 10.1109/TIA.2013.2258876.

[6] K. M. Rahman and S. Hiti, "Identification of machine parameters of a synchronous motor," in IEEE Transactions on Industry Applications, vol. 41, no. 2, pp. 557-565, March-April 2005, doi: 10.1109/TIA.2005.844379.

[7] Mohan, Ned. Advanced electric drives: analysis, control, and modeling using MATLAB/Simulink. John wiley & sons, 2014.

[8] S. Kallio, J. Karttunen, P. Peltoniemi, P. Silventoinen, and O. Pyrhönen, "Online Estimation of Double-Star IPM Machine Parameters Using RLS Algorithm," IEEE Transactions on Industrial Electronics, vol. 61, no. 9, pp. 4519–4530, Sep. 2014, doi: 10.1109/TIE.2013.2290761.

[9] D. Q. Dang, M. S. Rafaq, H. H. Choi, and J.-W. Jung, "Online Parameter Estimation Technique for Adaptive Control Applications of Interior PM Synchronous Motor Drives," IEEE Trans. Ind. Electron., vol. 63, no. 3, pp. 1438–1449, Mar. 2016, doi: 10.1109/TIE.2015.2494534.

[10] Ozden, G. Manav, and M. Dursun, "ANN based magnetic field and inductance modeling of double sided linear switched reluctance motor," in 2018 5th International Conference on Electrical and Electronic Engineering (ICEEE), Istanbul, May 2018, pp. 133–137. doi: 10.1109/ICEEE2.2018.8391316.

[11] L. Ortombina, F. Tinazzi, and M. Zigliotto, "Magnetic Modeling of Synchronous Reluctance and Internal Permanent Magnet Motors Using Radial Basis Function Networks," IEEE Trans. Ind. Electron., vol. 65, no. 2, pp. 1140–1148, Feb. 2018, doi: 10.1109/TIE.2017.2733502.

[12] C. Lv et al., "Levenberg–Marquardt Backpropagation Training of Multilayer Neural Networks for State Estimation of a Safety-Critical Cyber-Physical System," in IEEE Transactions on Industrial Informatics, vol. 14, no. 8, pp. 3436-3446, Aug. 2018, doi: 10.1109/TII.2017.2777460.

[13] "JMAG-RT Model Library," *Simulation Technology for Electromechanical Design : JMAG*. Available at https://www.jmag-international.com/modellibrary/