

Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Turk J Elec Eng & Comp Sci (2017) 25: 1643 – 1656 © TÜBİTAK doi:10.3906/elk-1505-101

Research Article

Neural network approach on loss minimization control of a PMSM with core resistance estimation

Hüseyin ERDOĞAN^{1,*}, Mehmet ÖZDEMİR²

¹Department of Electrical and Electronics Engineering, Faculty of Engineering, Dicle University, Diyarbakır, Turkey ²Department of Electrical and Electronics Engineering, Faculty of Engineering, Fırat University, Elazığ, Turkey

Received: 13.05.2015	•	Accepted/Published Online: 06.06.2016	٠	Final Version: 29.05.2017
----------------------	---	---------------------------------------	---	----------------------------------

Abstract:Permanent magnet synchronous motors (PMSMs) are often used in industry for high-performance applications. Their key features are high power density, linear torque control capability, high efficiency, and fast dynamic response. Today, PMSMs are prevalent especially for their use in hybrid electric vehicles. Since operating the motor at high efficiency values is critically important for electric vehicles, as for all other applications, minimum loss control appears to be an inevitable requirement in PMSMs. In this study, a neural network-based intelligent minimum loss control technique is applied to a PMSM. It is shown by means of the results obtained that the total machine losses can be controlled in a way that keeps them at a minimum loss control technique is used. Within this context, hysteresis and eddy current losses are primarily obtained under certain conditions by means of a PMSM finite element model, initially developed by CEDRAT as an educational demo. A comprehensive loss model with a dynamic core resistor estimator is developed using this information. A neural network controller is then applied to this model and comparisons are made with analytical methods such as field weakening and maximum torque per ampere control techniques. Finally, the obtained results are discussed.

Key words: Permanent magnet synchronous motor, energy efficiency, neural network, loss model

1. Introduction

When working with limited energy sources, as in electric cars, it is obvious that loss of power has a great effect on overall efficiency and performance. Therefore, it is of the utmost necessity that the losses be reduced as much as possible to prevent the limited power sources of the automobiles from being drained. When reviewing the literature, it is observed that there are many studies on the investigation of losses in permanent magnet synchronous motors (PMSMs). The authors of [1] and [2] considered only the copper losses. Neglecting core losses is the main shortcoming of this work.

To achieve a complete investigation of losses on PMSMs, several authors conducted their research considering iron losses along with copper losses. In electric vehicle applications, motors are generally required to operate in wide speed ranges. The authors of [3–8] performed analyses on iron losses and/or equivalent core loss resistance under fixed rotor speed operation conditions. In fixed speed operations, frequency remains fixed, too. This introduces some simplicity and easiness, especially in loss calculations with frequency-dependent partial differential equation components. However, this type of analysis has limited use and cannot be used in variable speed operations. Furthermore, there is some research in which speed variation was taken into

^{*}Correspondence: erdogan@dicle.edu.tr

account. For example, in [9-16], the authors discussed different particular speed values, but they conducted their research with a fixed core resistance. In these cases, they neglected the variation of core resistance, which is related to frequency. This approach provides advantages in calculations, yet causes certain errors due to neglecting frequency effects. The authors of [17-20] also examined core resistance changes in variable speeds. These authors, like those mentioned above, ran their analyses only for certain speed values; consequently, they neglected speed variations between the selected speed values. Finally, the authors of [21-24] investigated dynamic changes in core resistance with variable speeds by using highly complex analytical calculations.

Besides determining the iron core resistance values, another important issue in the literature concerns the definition of the loss minimization technique.

In electric car drive systems, the amplitude of the voltage of the vehicle battery terminals tends to change under different loads. In the low voltage range, despite the lack of sufficient rotor speed, a force requirement arises for the control mode to enter the field weakening area in order to achieve the desired operating speed. Thus, field weakening (FW) control is very important for electric vehicles. The FW technique was used in many studies to extend the operating speed range.

FW applications were examined and a new analytical method was proposed in [25]. The results of the proposed method were compared to those of the earlier methods. In that paper, highly complex analytical calculations were used and only the FW region was examined. A maximum torque per ampere (MTPA) strategy was used in [26–28] to reduce motor losses. These studies were also based on a single method that included intensive analytical procedures, as in the previous research. In addition to studies that focused only on one method [25–28], there exist several studies [1,5,12,29–32] that use the FW and MTPA strategies jointly. In these studies, the increase in performance using a combination of the two methods is apparent. The methods presented in [1,12,29–32] yield good results but require intensive and complex analytical procedures. To reduce this complexity, the authors of [5] used look-up tables in order to keep procedures as simple as possible. However, the construction of tables is still very time-consuming for researchers.

The continuously evolving processing power of computers can considerably decrease the computing challenges faced by researchers. Smart systems have appeared in every field. The authors of [33,34] based the minimum loss control of a PMSM on a fuzzy logic controller. In these studies, Serga et al. [33] implemented a FW method using a fuzzy logic controller that they designed, and Butt et al. [34] designed a fuzzy logic controller to implement the MTPA method to the motor. Even if studies with a fuzzy logic controller may seem to be sparing researchers from complicated calculations, the creation of tables and membership functions of the controller constitute a challenge, which is completely dependent on experience. Wu et al. [3] chose to make use of the learning skills of computers to gain expertise and experience, and they designed a neural network controller in order to apply only the MTPA method to motors.

Intelligent systems proposed in the literature focus on either MTPA or FW methods. Therefore, it would be interesting to find out what kind of results would be obtained when a smart controller combining both methods is used.

In this paper, a PMSM loss model was built, which can be used in designing a controller to minimize losses and thus increase the efficiency in PMSM. The model does not neglect electrical losses. A neuro-fuzzybased core resistance estimator for an interior permanent magnet synchronous motor has been designed. This estimator was used for estimating the core resistance dynamically as the speed changes. Consequently, a neural network controller was designed and applied to the motor to decrease its losses. At the end, the results were analyzed.

2. PMSM loss model

Primarily, it is necessary to set up a PMSM loss model that does not neglect losses in order to create a minimum loss control simulation in the PMSM. The PMSM dq-reference model was selected as the baseline in this paper, since it is the most appropriate for the control method applied. Saturation effects and inverter switching losses are neglected in this work.

Equivalent circuits of the d and q axes of the PMSM, which do not neglect losses, are presented in Figures 1 and 2 [16].





Figure 1. The d-axes equivalent circuit of a PMSM with core resistance.

Figure 2. The q-axes equivalent circuit of a PMSM with core resistance.

Of the resistors shown in the circuit, R_c stands for equivalent iron core resistance and R_a represents phase winding resistance. Currents i_d and i_q represent the stator d and q axes' current components, i_{dc} and i_{qc} the stator d and q axes' iron core current components, and i_{d0} and i_{q0} the remaining d and q axes' current components. In addition, u_d and u_q represent the d and q axes' voltages, L_d and L_q represent the inductances along the d and q axes, and ψ_M represents the flux density of the permanent magnets.

Instantaneous equations, which represent the PMSM where the losses are also taken into account, can be derived from equivalent circuits shown in Figures 1 and 2, as follows:

$$\frac{di_{d0}}{dt} = \frac{1}{L_d} \left(R_c \frac{u_d + R_c i_{d0}}{R_a + R_c} - R_c i_{d0} + \omega_e L_q i_{q0} \right) \tag{1}$$

$$\frac{di_{q0}}{dt} = \frac{1}{L_q} \left(R_c \frac{u_q + R_c i_{q0}}{R_a + R_c} - R_c i_{q0} + \omega_e \left(\Psi_M + L_d i_{d0} \right) \right)$$
(2)

The impact of the iron core resistance, R_c , on currents can be clearly observed in Eqs. (1) and (2). The generated torque expression of the PMSM adapted to a dq equivalent circuit can be obtained as presented in Eq. (3), where p represents the number of pole pairs:

$$T_e = \frac{3}{2}p\left[\Psi_{PM}i_{q0} + (L_d - L_q)i_{d0}i_{q0}\right]$$
(3)

2.1. Finite element analysis of core losses in PMSM

In loss minimization studies of PMSMs, identifying the iron losses of the motor has great significance in a loss minimization procedure. Analytical methods trying to solve this problem appear quite difficult, because loss equations include partial differential equations [5–7,19–24,35,36]. After investigating some previous studies [4,7,8,13,17,20,22,37], the usage of a motor model developed by the finite elements method (FEM) was chosen as the most suitable solution to the problem.

The FEM is a method used for the solutions of Laplace- and Poisson-type partial differential equations. Using the FEM, the fluxes, generated torque, and iron losses of the PMSM can be calculated in detail once the physical size of the motor and the parameters of the materials used are introduced into the software.

In this study, FEM analysis is carried out with a premade educational demonstration FEM, which was created and released by CEDRAT and embedded in Flux 2D software. For more information about the FEM model, please visit http://www.cedrat.com/; the analysis was carried out under a registered trial license.

Consequently, the hysteresis power loss (W_h) and the eddy current power loss (W_e) defined by Eqs. (4) and (5), respectively [6], as the two main components of total iron losses (W_{fe}) , are found by running FEM analysis at different speeds. The results obtained are shown in Figure 3.

$$W_h = k_h \left[1 + c \left(r - 1 \right) \right] B^2 f \tag{4}$$

Here B is the peak value of the magnetic flux density, k_h is the material constant, c is the magnetic flux density ratio $\left(\frac{B_{\min}}{B_{\max}}\right)$, r is the empirical factor, and f is the fundamental frequency.

$$W_e = k_{ec} \sum_{n=1}^{\infty} B_n^2 \left(nf \right)^2 \tag{5}$$

 B_n is the peak value of the magnetic flux density for the *n*th harmonic order. Here, if the skin effect of the eddy current is neglected, k_{ec} can be written as follows:

$$k_{ec} = \frac{\pi^2 d^2}{6\rho_e \rho} \tag{6}$$

Here d is the sheet thickness, ρ is the sheet density, and ρ_e is the specific electrical resistance of the steel.

From Figure 3, it can be clearly seen that the variation of the eddy current losses has a quadratic shape that responds to a change in frequency, as defined in Eq. (5). Additionally, the change of the hysteresis loss has a linear shape that suits the definition given in Eq. (4).

It is possible to calculate the iron core equivalent resistance, Rc, by means of the total iron losses obtained in Figure 3. In this study, the preformed lossless model was operated at each value of speed given in Figure 3, using the $I_d = 0$ control method to obtain corresponding u_o voltage values. Then the u_o voltage values obtained from the lossless model were used in Eq. (8) together with the W_{fe} values obtained from FEM analyses in order to find the iron core equivalent resistances, R_c , for each speed point, as shown in Figure 4. Eq. (8) can be derived from the d and q axes' equivalent circuits, given in Figures 1 and 2 [14]. The other parameters of the PMSM are given in the Table.

Table. Other PMSM parameters.

Parameter [unit]	Value
\mathbf{p}_p [-]	4
$\mathbf{R}_a \left[\Omega\right]$	0.42
Ψ_{PM} [Wb]	0.5052
J [kgm ²]	0.0637
$L_d [mH]$	2.11e-3
$L_q [mH]$	8.98e-3



Figure 3. Core losses on the PMSM.

Figure 4. Core resistance derivation vs. speed.

$$u_0^2 = u_{d0}^2 + u_{q0}^2 \tag{7}$$

$$W_{fe} = W_h + W_e = \frac{\omega_e^2 \left(\rho L_q i_{q0}\right)^2}{R_c} + \frac{\omega_e^2 \left(L_d i_{d0} + \psi_M\right)^2}{R_c} = \frac{u_0^2}{R_c}$$
(8)

2.2. Core resistance estimation with adaptive neuro-fuzzy interference system

For carrying out loss analysis on variable speed drive systems, core resistance values for all corresponding speed values must be known. The FEM cannot be used in dynamic analysis because FEM models are required to work with constant values. In this regard, intelligent systems are emerging as the most appropriate solution to dynamically determine the core resistance. The results obtained by FEM using fixed-speed simulations can be used as the required training data for developing a neuro-fuzzy intelligent prediction model.

In the case of limited access to the required training data, results obtained by ANN may not be satisfactory. In such a case, a fuzzy logic controller can be used as an auxiliary element to improve the results obtained by an ANN controller [38].

As defined in detail in [39,40], ANFIS is a prediction system that can be used in a wide range of applications. In [40], Jang identified the modeling of nonlinear multivariable functions, identification of nonlinear components in the control of dynamic systems, and identification of irregular time series as possible areas of application.

When designing a neuro-fuzzy controller for existing problems, rotor speed values were taken as input parameters and core resistance values corresponding to these rotor speeds were taken as output parameters. The design was performed with the Adaptive Neuro-Fuzzy Interference System (ANFIS) toolbox in MATLAB. Within this design triangle (trimf), the membership function type was used. The number of membership functions was chosen as three, and the input membership functions were formed as shown in Figure 5.

The results obtained from the neuro-fuzzy estimation system are shown in Figure 6. The neuro-fuzzy estimation system estimated the core resistance values with great accuracy. Thus, this system can be used in variable speed operations with high accuracy.

3. PMSM minimum loss control with neural network

Technological developments and advances in artificial intelligence applications have allowed modern analytical methods to replace analytical solutions. As a result of the studies, it is observed that modern methods are just as successful as classical methods in the analysis of electrical machinery; thus, iterative applications that require a great deal of calculations are replaced by trained systems.



Figure 5. Membership functions for core resistor estimator.



Figure 6. Comparison of estimated core resistance values obtained from finite element results to those obtained from the neuro-fuzzy estimator.

For control actions based on analytical calculations, it is necessary to compare and contrast many parameters again and again and generate reference currents using many parameters again. However, by utilizing the designed neural network, it is possible to generate desired reference currents using a small number of parameters and without complex calculations after the training procedure. In this context, when designing a neural network controller for the present problem, it was primarily developed as an analytical loss minimization controller model. This controller was initially developed in a previous study in [12] as a combination of the MTPA and FW control methods. The operation of this controller can be summarized by the flow diagram given in Figure 7. In this diagram, U_s and U_{sm} represent the inverter output voltage and the maximum phase voltage of the inverter, respectively; ω_r represents measured rotor speed; ω_{rc} represents critical angular frequency, which can be calculated as U_{sm}/ψ_m ; and ω_{rA} represents the maximum speed at positive constant torque limit.



Figure 7. MTPA and FW controller flow chart.

The reference $i_q *$ current, obtained from the analytical model, and the measured rotor speed were taken as the input for the neural network controller. As for the output, the $i_d *$ reference current, generated by the analytical method, was taken. A total of 5022 samples were taken and were used for training (3516 samples, 75%), verification (753 samples, 15%), and testing (753 samples, 15%). As shown in Figure 8, the design was developed comprising two layers and was planned to have 10 neurons in the hidden layer.



Figure 8. Design of neural network minimum loss controller.

Training was conducted with the Levenberg–Marquardt backpropagation method. The outputs obtained in the training are shown in Figure 9.



Figure 9. Neural network training results.

The simulation model, including the designed neural network controller, was developed as described in Figure 10. Additionally, an operation scenario was applied to the simulation. In this scenario, during the first 0.2 s, the motor is operated at 70 rad/s constant speed value, which is below the nominal speed (94.28 rad/s) of the motor. Then, in order to examine the effects of speed changes on motor behavior between 0.2 and 0.3 s, the speed is increased linearly with a 550 rad/s² slope value. Between 0.3 and 0.45 s, the slope value is decreased to 125 rad/s². In addition to examining the motor's dynamic response to load changes, a dynamic load torque, whose value is defined as $T_L = 3\omega_m$, is applied to the motor from the beginning of the operation.

To make an overall assessment, the results obtained are given in Figures 11–18. The results are compared to those of the MTPA and FW control methods.



Figure 10. PMSM minimum loss control simulation model.



Figure 11. Core resistance estimation during an operation scenario with neural network and MTPA and FW methods.



Figure 13. Comparison of generated torque responses between neural network and MTPA and FW control methods.



Figure 12. Comparison of rotor speed responses between neural network and MTPA and FW control methods.



Figure 14. Comparison of d axes component current variation, i_d , between neural network and MTPA and FW control methods.





Figure 15. Comparison of q axes component current responses, i_q , between neural network and MTPA and FW control methods.

Figure 16. Comparison of iron power loss variation between neural network and MTPA and FW control methods.



Figure 17. Comparison of total power loss variations between neural network and MTPA and FW control methods.

The dynamic change of the core resistance is given in Figure 11. When the torque and rotor speed variations given in Figures 12 and 13 are examined, it is observed that the motor variables follow their references with great success and show a good dynamic response. Besides, the neural network controller successfully adjusts the values of the d and q currents, as can be seen from Figures 14 and 15. Consequently, the applied neural network controller clearly produces lower core losses than the MTPA and FW controller, as can be seen from Figure 16. When Figure 17 is investigated in detail around the high-speed region, it can be observed that the MTPA and FW controller causes lower values of total power loss, which is the sum of the iron losses and copper losses; however, in the low-speed region, the neural network controller becomes more advantageous. This situation can be clearly seen in efficiency derivation as given in Figure 18. Again, in the low-speed region, the neural network is more advantageous than the MTPA and FW.



Figure 18. Comparison of motor efficiency variations between neural network and MTPA and FW control methods.

4. Conclusion

This paper carried out a study on minimizing the electrical losses of the PMSM with intelligent systems. In this context, as a novel approach, a neuro-fuzzy-based estimator was designed in order to eliminate an important deficiency found in the literature about determining the dynamic core resistance. Once the dynamic core resistance is available, it is possible to reduce the core losses of the machine by means of a controller. For this reason, a neural network controller, which is a novel approach employing the dynamic core resistance, was designed and applied to the motor. The simulation results show clearly that minimum loss control can be obtained by the proposed control technique. These steps are shown in the flow chart in Figure 19. Finally, the obtained results were compared to the results of the MTPA and FW control methods.

Because iron loss in the constant torque zone increases in direct proportion to speed increase, the effects of reducing iron loss assure better results in the high-speed zone; this can be seen clearly in Figure 16.



Figure 19. Steps of the loss minimization procedure in this study.

ERDOĞAN and ÖZDEMİR/Turk J Elec Eng & Comp Sci

When the results in Figures 11–18 are examined, it is clear that the neural network method can be successfully applied for minimum loss control in PMSMs. Again, the proposed neural network controller can be used with great accuracy instead of controllers based on intensive load of mathematical operations and with the feedbacks and comparisons they include, as seen in Figure 7. It can be said that the MTPA and FW control methods give lower total losses, especially in the high-speed region. However, operating a motor with the MTPA and FW control methods is more complex and time-consuming compared to the neural network controller. Once trained, a neural network controller makes the solution significantly easier to reach, because it does not have to calculate the speed to decide which method should be used compared to the MTPA and FW control methods, where this is a requirement. All this can clearly be seen from Figure 7. Finally, based on this study, a neural network controller will provide a great advantage to researchers in application as it can produce the required output signal depending only on two parameters.

Both given loss control methods have been found to increase motor efficiency significantly by 5%–6%, where the efficiency was 87% before applying the loss control techniques to the motor. Furthermore, the most significant result of this study is the obvious decrease in the motor's iron losses. As can be clearly seen from Figure 16, the motor's iron losses decrease significantly, especially in the high-speed region, when compared to the MTPA and FW control methods.

References

- Asaei B, Rahrovi B. Minimum-copper-loss control over full speed range of an IPMSM drive for hybrid electric vehicle application. In: IEEE 2010 Vehicle Power and Propulsion Conference; 1–3 September 2010; Lille, France. New York, NY, USA: IEEE. pp. 1-6.
- [2] Jeong YS, Sul SK, Hiti S, Rahman KM. Online minimum-copper-loss control of an interior permanent-magnet synchronous machine for automotive applications. IEEE T Ind Appl 2006; 42: 1222-1229.
- [3] Wu Z, Li G, Zhu Y. Efficient optimization control of permanent magnet synchronous motor using artificial neural network. Adv Inf Sci Serv Sci 2011; 3: 260-267.
- [4] Almandoz G, Ugalde G, Poza J, Escalada AJ. MATLAB-Simulink coupling to finite element software for design and analysis of electrical machines. In: Katsikis VN, editor. MATLAB—A Fundamental Tool for Scientific Computing and Engineering Applications. Rijeka, Croatia: InTech, 2012. pp. 161-184.
- [5] Aorith H, Wang J, Lazari P. A new loss minimization algorithm for interior permanent magnet synchronous machine drives. In: IEEE 2013 International Electric Machines and Drives Conference; 12–15 May 2013; Chicago, IL, USA. New York, NY, USA: IEEE. pp. 526-533.
- [6] Gracia MH, Lange E, Hameyer K. Numerical calculation of iron losses in electrical machines with a modified postprocessing formula. In: Proceedings of the 16th International Symposium on Electromagnetic Fields COMPUMAG; 24–28 June 2007; Aachen, Germany. New York, NY, USA: IEEE. pp. 1-2.
- [7] Han SH, Soong WL, Jahns TM. An analytical design approach for reducing stator iron losses in interior PM synchronous machines during flux-weakening operation. In: IEEE 2007 Industry Applications Annual Meeting; 23–27 September 2007; New Orleans, LA, USA. New York, NY, USA: IEEE. pp. 103-110.
- [8] Ugalde G, Almandoz G, Poza J, Gonzalez A. Computation of iron losses in permanent magnet machines by multidomain simulations. In: 13th European Conference on Power Electronics and Applications; 8–10 September 2009; Barcelona, Spain. New York, NY, USA: IEEE. pp. 1-10.
- [9] Bernal FF, Garefa-Cerrada A, Faure R. Loss-minimization control of synchronous machines with constant excitation. In: IEEE 1998 Annual Power Electronics Specialists Conference; 22 May 1998; Osaka, Japan. New York, NY, USA: IEEE. pp. 132-138.

- [10] Cavallaro C, Di Tommaso AO, Miceli R, Raciti A, Galluzzo GR, Trapanese M. Analysis a DSP implementation and experimental validation of a loss minimization algorithm applied to permanent magnet synchronous motor drives. In: 29th Annual Conference of the IEEE Industrial Electronics Society; 2–6 November 2003; Roanoke, VA, USA. New York, NY, USA: IEEE. pp. 312-317.
- [11] Cavallaro C, Di Tommaso AO, Miceli R, Raciti A, Galluzzo GR, Trapanese M. Efficiency enhancement of permanentmagnet synchronous motor drives by online loss minimization approaches. IEEE T Ind Electron 2005; 52: 1153-1160.
- [12] Erdoğan H, Gümüş B, Özdemir M. Minimum loss control of permanent magnet synchronous motor. In: Elektrik, Elektronik, Bilgisayar ve Biyomedikal Mühendisliği Sempozyumu ve Sergisi; 27–29 November 2014; Bursa, Turkey. Ankara, Turkey: TMMOB. pp. 27-29 (in Turkish with abstract in English).
- [13] Küttler S, Benkara KEK, Friedrich G, Vangraefschèpe F, Abdelli A. Impact of the flux weakening on the iron losses in an internal permanent magnet synchronous machine. In: IEEE 2014 Energy Conversion Congress and Exposition; 14–18 September 2014; Pittsburgh, PA, USA. New York, NY, USA: IEEE. pp. 4188-4195.
- [14] Morimoto S, Tong Y, Takeda Y, Hirasa T. Loss minimization control of permanent magnet synchronous motor drives. IEEE T Ind Electron 1994; 41: 511-517.
- [15] Uddin MN, Member S, Zou H, Azevedo F. Online loss minimization based adaptive flux observer for direct torque and flux control of PMSM drive. In: IEEE 2014 Industry Applications Society Annual Meeting; 5–9 October 2014; Vancouver, BC, Canada. New York, NY, USA: IEEE. pp. 1-7.
- [16] Watanabe Y, Kim TW, Mushi A, Kawamura A. Research on overall efficiency improvement of electric vehicles by MTHDPAM control method. In: IEEE 2012 15th International Power Electronics and Motion Control Conference; 4–6 September 2012; Novi Sad, Serbia. New York, NY, USA: IEEE. pp. LS5c.2–1-LS5c.2–6.
- [17] Krings A, Nategh S, Wallmark O, Soulard J. Local iron loss identification by thermal measurements on an outerrotor permanent magnet synchronous machine. In: IEEE 2012 15th International Conference on Electrical Machines and Systems; 21–24 October 2012; Sapporo, Japan. New York, NY, USA: IEEE. pp. 1-5.
- [18] Dutta R, Chong L, Rahman FM. Analysis and experimental verification of losses in a concentrated wound interior permanent magnet machine. Pr Electromagn Res B 2013; 48: 221-248.
- [19] Shchur I, Rusek A, Makarchuk O, Mandzyuk M. Definition of parameters of mathematical model of pmsm for electric vehicles on the basis of computer and experimental research. Maszyny Elektryczne Zeszyty Problemowe 2014; 1: 147-152.
- [20] Soulard J. Modeling of iron losses in permanent magnet synchronous motors with field-weakening capability for electric vehicles. Int J Auto Tech 2003; 4: 87-94.
- [21] Lee JY, Lee SH, Lee GH, Hong JP, Hur J. Determination of parameters considering magnetic nonlinearity in an interior permanent magnet synchronous motor. IEEE T Magn 2006; 42: 1303-1306.
- [22] Lee BH, Kwon SO, Sun T, Hong JP, Lee GH, Hur J. Modeling of core loss resistance for d-q equivalent circuit analysis of IPMSM considering harmonic linkage flux. IEEE T Magn 2011; 47: 1066-1069.
- [23] Vaez S, John VI. Minimum loss operation of PM motor drives. In: IEEE 1995 Canadian Conference on Electrical and Computer Engineering; 5–8 September 1995; Montreal, QC, Canada. New York, NY, USA: IEEE. pp. 284-287.
- [24] Zarei AH, Abbaszadeh K, Safari K. The analytical analysis of the rotor losses in the PMSM motors. In: Proceedings of the World Congress on Engineering and Computer Science; 24–26 October 2012; San Francisco, CA, USA. New York, NY, USA: IEEE. pp. 1044-1048.
- [25] Chen JJ, Chin KP. Minimum copper loss flux-weakening control of surface mounted permanent magnet synchronous motors. IEEE T Power Electr 2003; 18: 929-936.
- [26] Solomon O, Famouri P. Control and efficiency optimization strategy for permanent magnet brushless AC motors. In: 2009 IEEE International Symposium on Industrial Electronics; 5–8 July 2009; Seoul, South Korea. New York, NY, USA: IEEE. pp. 505-512.

- [27] Sue SM, Hung TW, Liaw JH, Li YF, Sun CY. A new MTPA control strategy for sensorless V/f controlled PMSM drives. In: IEEE 2011 Conference on Industrial Electronics and Applications; 21–23 June 2011; Beijing, China. New York, NY, USA: IEEE. pp. 1840-1844.
- [28] Wang W, Fahimi B, Kiani M. Maximum torque per ampere control of permanent magnet synchronous machines. In: IEEE 2012 International Conference on Electrical Machines; 2–5 September 2012. New York, NY, USA: IEEE. pp. 1013-1020.
- [29] Liaw JH, Liao YH, Tung CW, Sue SM, Huang YS. A robust field-weakening control strategy for IPMSM drives. In: IEEE 2010 International Power Electronics Conference; 21–24 June 2010; Sapporo, Japan. New York, NY, USA: IEEE. pp. 605-611.
- [30] Bolognani S, Calligaro S, Petrella R, Pogni F. Flux-weakening in IPM motor drives: comparison of state-of-art algorithms and a novel proposal for controller design. In: IEEE 2011 European Conference on Power Electronics and Applications; 30 August–1 September 2011; Birmingham, UK. New York, NY, USA: IEEE. pp. 1-11.
- [31] Pan CT, Liaw JH. A robust field-weakening control strategy for surface-mounted permanent-magnet motor drives. IEEE T Energy Conver 2005; 20: 701-709.
- [32] Toosi S, Mehrjou MR, Karami M, Zare MR. Increase performance of IPMSM by combination of maximum torque per ampere and flux-weakening methods. ISRN Power Eng 2013; 2013: 1-11.
- [33] Sergaki ES, Georgilakis PS, Kladas a. G, Stavrakakis GS. Fuzzy logic based online electromagnetic loss minimization of permanent magnet synchronous motor drives. In: IEEE 2008 International Conference on Electrical Machines; 6–9 September 2008; Vilamoura, Portugal. New York, NY, USA: IEEE. pp. 1-7.
- [34] Butt CB, Hoque MA, Rahman MA. Simplified fuzzy-logic-based MTPA speed control of IPMSM drive. IEEE T Ind Appl 2004; 40: 1529-1535.
- [35] Ducar I, Marinescu C. The PMSM efficiency at variable speed for pumping applications. In: IEEE 2014 International Conference and Exposition on Electrical and Power Engineering; 16–18 October 2014; Iasi, Romania. New York, NY, USA: IEEE. pp. 16-18.
- [36] Fernandez-Bernal F, Garcia-Cerrada A, Faure R. Determination of parameters in interior permanent magnet synchronous motors with iron losses without torque measurement. IEEE T Ind Appl 2001; 37: 1265-1272.
- [37] Finken T, Hameyer K. Computation of iron and eddy-current losses in IPM motors depending on the field weakening angle and current waveform. In: IEEE 2009 International Symposium on Electromagnetic Fields in Mechatronics, Electrical and Electronic Engineering; 17–19 September 2009; Arras, France. New York, NY, USA: IEEE. pp. 123-128.
- [38] Blair JC. Book reviews. B Med Libr Assoc 1980; 68: 250.
- [39] Valčić M, Antonić R, Tomas V. ANFIS based model for ship speed prediction. Brodogradnja 2011; 62: 373-382.
- [40] Jang JSR. ANFIS: adaptive-network-based fuzzy inference system. IEEE T Syst Man Cyb 1993; 23: 665-685.