Minimization of Losses in Permanent Magnet Synchronous Motors Using Neural Network

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Abstract

In this paper, maximum efficiency operation of two types of permanent magnet synchronous machine drives, namely, surface type permanent magnet synchronous machine (SPMSM) and interior type permanent magnet synchronous machine (IPMSM), are investigated. The efficiency of both drives is maximized by minimizing cupper and iron losses. Loss minimization is implemented using flux weakening. A neural network controller (NNC) is designed for each drive, to achieve loss minimization at different speeds and load torque values. Data for training the NNC are obtained through off-line simulations of SPMSM and IPMSM at different operating conditions. Accuracy and fast response of each NNC is proved by applying sudden changes in speed and load and tracking the NNC output. The motors' efficiency obtained by flux weakening is compared with the efficiency obtained when setting the d-axis current component to zero, while varying the angle of advance "φ" of the PWM inverter supplying the PMSM drive. Equal efficiencies are obtained at different values of φ, derived to be function of speed and load torque. A NN is also designed, and trained to vary φ following the derived control law. The accuracy and fast response of the NN controller is also proved.

List of Symbols

V_d and V_q are the d and q axis stator voltages;
i_d and i_q are the d and q axis stator currents;
i_{od} and i_{oq} are the d and q axis air gap currents;
L_d and L_q are the d and. q axis inductances;
λ is the air-gap flux produced by the permanent magnet;
R_s is the stator resistance;
R_c is the equivalent iron loss resistance;

Manuscript received from Dr. Mona N. Eskander
Accepted on : 1 / 6 / 2002
Engineering Research Journal Vol 25,No 3, 2002 Minufiya University, Faculty Of Engineering , Shebien El-Kom , Egypt , ISSN 1110-1180

ω_s is the inverter frequency;
P is the number of pole pairs;
T_L is the load torque;
B is the damping coefficient;
ω_r is the rotor speed;
J is the moment of inertia.

I. Introduction

Permanent magnet synchronous motors (PMSM) are progressively replacing dc motors in applications that require variable speed drives. The PMSM offers several advantages, namely; a high torque–to-inertia ratio and an excellent power factor, since the copper losses are confined to the stator. In addition, for the same delivered mechanical power, a PMSM needs a smaller line current value, which is favorable for the design of the electronic power converter feeding this drive. These advantages make the PMSM attractive for industrial application, as well as in electric vehicles. However, the need to save energy still exists to develop an efficient drive. The main efforts for higher efficiency are focused on improvement of materials and optimization of design strategies [1]. However, efficiency can also be improved by intervening in the operational principle of motors. Such methods can be implemented on adjustable speed drives fed through an inverter. Several control methods have been proposed to minimize the losses of PMSM drives [2-5]. The proposed method to specify the loss minimization condition for surface and interior PMSM drives in Ref. [2] is complicated and its implementation based on the knowledge of machine parameters. In Ref. [4], loss optimization is achieved using a fuzzy table within a fuzzy controller. In Ref [5], air-gap flux weakening algorithm is proposed for loss optimization, but the stator resistance was neglected in the required optimum voltage to frequency ratio.
Increasing drive efficiency by maximizing the generated torque was investigated in Ref [6-7]. In Ref [6] an equation relating the optimum angle of advance of the PWM inverter feeding the drive was derived as a function in the speed only, i.e. load effect was not included. In Ref [7], the load was considered but without suggesting a method for implementation.
In the previously described work, no attempt was done to apply Neural Network (NN) controllers for maximum efficiency operation of PMSM drive. However NN was applied for position control of PM servo drives Ref [8], for tracking of PM synchronous generator parameters Ref [9], or for speed control of permanent magnet motors Ref [10].
In this paper, a loss minimization technique is developed to minimize copper and iron losses in both surface type permanent magnet synchronous machine (SPMSM) and interior type permanent magnet synchronous machine (IPMSM) drives. The proposed technique is based on the air-gap flux weakening, where the value of the d-axis stator current component that leads to minimum losses is first derived for IPMSM and SPMSM drives. To achieve fast response with minimum losses within wide speed range, flux weakening is implemented using neural networks (NN). The advantages of the NN lie in its learning character, as well as in its ability to deal with nonlinearities. A three-layer feed-forward NN is adopted to implement the loss minimization model for of the investigated drives. The accuracy and fast response of the proposed controller is tested by applying sudden changes in speed and torque, then examining the corresponding change in stator current.

Also, another scheme is proposed for deducing the efficiency of the PMSM drive, when setting the d-axis stator current component to zero, to prevent demagnetization of the permanent magnet, while varying the angle of advance "φ" of the PWM inverter supplying the PMSM drive. The value of φ that allows maximum efficiency is derived as function of speed and load, and a NN controller is designed and tested to implement this scheme. The accuracy and fast response of the proposed controller is tested by applying sudden changes in speed and torque, then examining the corresponding change in inverter angle.

II. Loss Minimization Model of Interior PMSM

The steady state model of the IPMSM is derived from the d and q-axes per-phase equivalent circuit shown in Fig.(1):

$$V_q = R_s\, i_q + \omega_s . L_d\, i_{od} + \omega_s\, \lambda \qquad (1)$$

$$V_d = R_s\, i_d - \omega_s\, L_q\, i_{oq} \qquad (2)$$

The electromagnetic torque is given by:

$$T_e = 1.5\, P\, [\lambda\, i_{oq} + (L_d - L_q) i_{od}\, i_{oq}] \qquad (3)$$

And the equation for motor dynamics is:

$$T_e = T_L + B\, .\omega_r + J.d\omega_r / dt \qquad (4)$$

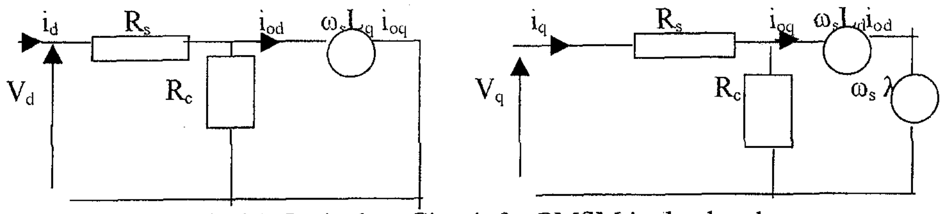


Fig.(1) Equivalent Circuit for PMSM in the d and q axes

The main losses of the PMSM are the copper and iron losses. Referring to the general equivalent circuit of the PMSM given in Fig.(1), the copper losses are given by:

$$P_{cu} = R_s . i^2_d + R_s\, i^2_q \qquad (5)$$

While the iron losses P_{fe} are given by:

$$P_{fe} = \omega^2_s * \lambda^2_o / R_c \qquad (6)$$

Where, λ_o is the air gap flux.

Equation (6) could be written as:

$$P_{fe} = \omega^2_s\, [(\lambda + L_d\, i_{od})^2 + (L_q\, i_{oq})^2] / R_c \qquad (7)$$

Neglecting harmonic losses, which are indirectly controlled by flux weakening, the total losses are P_{cu} and P_{fe} For a given torque, P_{cu} and P_{fe} are functions of i_{od} . Hence, adding (5) and (7) and differentiating with respect to i_{od} gives:

$$\partial P_L / \partial i_{od} = i_{od}\, [R_s + (\omega^2_s * L^2_d / R_c)]$$

From the electric torque equation (3), the current i_{oq} is given by:

$$i_{oq} = T_e /1.5*P\,[\lambda + (L_d - L_q)i_{od}] \qquad (9)$$

Hence $\partial i_{oq}/\partial i_{od}$ is derived as:

$$\partial i_{oq}/\partial i_{od} = -[(L_d - L_q)*T_e / 1.5*P\,[\lambda + (L_d - L_q)i_{od}]^2 \qquad (10)$$

Substituting eq.(10) into eq.(8) and equating the result to zero, gives the following expression for the optimum d-axis stator current i_{dop} that leads to minimum losses at a given steady state speed and torque:

$$i_{dop} = 1.5\, P*L*\{[(R_s*R_c) + (\omega_s^2 * L_q^2)] / [(R_s*R_c + \omega_s^2 L_d^2)]\}\, i_{oq}^3 - \{[\lambda * \omega_s^2 * L_d^2] / [R_s*R_c + \omega_s^2 L_d^2]\} \qquad (11)$$

Equation (11) gives the optimal d-axis component of stator current, which can be applied in current-controlled schemes. Loss minimization condition for voltage controlled schemes is obtained by substituting eq.(11) into equations (1) and (2) and using the supply voltage V_s as:

$$V_s = \sqrt{(V_d^2 + V_q^2)} \qquad (12)$$

To prove that the losses are minimized as speed and load varies, the total losses are plotted versus V_s at different speeds and constant torque as shown in Fig.(2), and at variable load torque and constant speed in Fig.(3). It is worth notice that the voltage value at which minimum losses occurs differs at different speeds, and is lower at lower values of load torque.

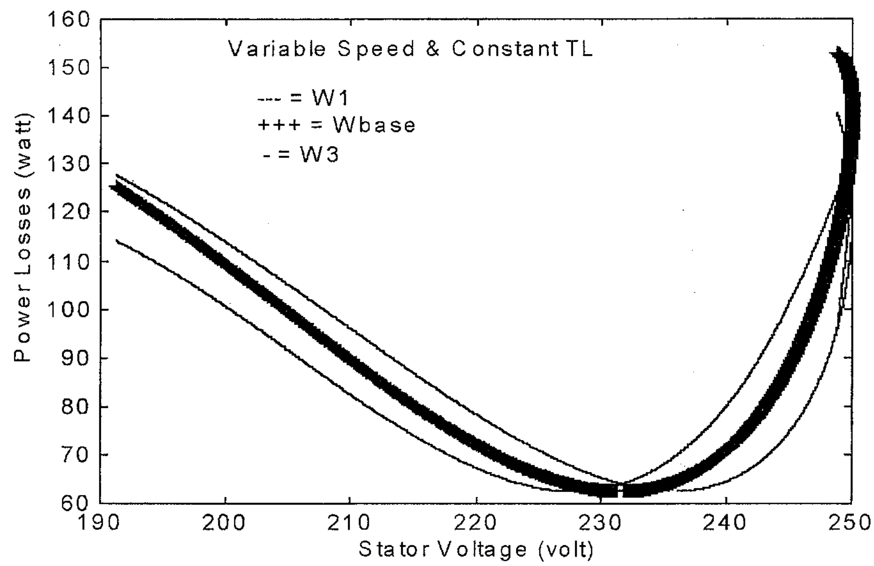


Fig.(2) Power Loss Versus Stator Voltage at Variable Speed and Constant Load

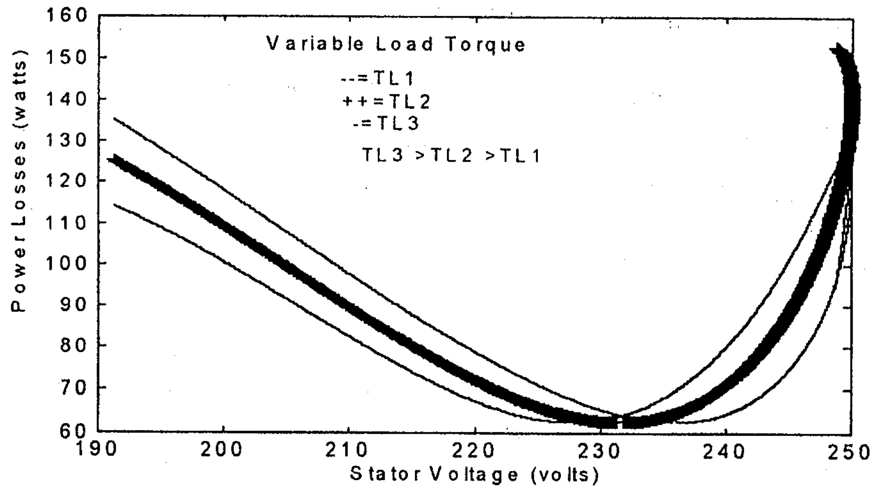


Fig.(3) Power Loss Versus Stator Voltage at Variable Load and Constant Speed

III. Network Controller for Loss-Minimization in IPMSM

(i) Control Scheme

Among the advantages of neural networks (NN) are the ability to learn nonlinear mapping, the rapidity of response, and robustness. The quick response time of the NN makes their computation time almost negligible. All these characteristics make the NN suitable for application in loss minimization strategy, especially in the case of the interior type PMSM due to the complexity of the derived loss model given by equation (11). The control scheme to implement loss minimization is shown in Fig. (4). In such scheme, a PI controller is used to calculate i^*_q from the difference between the torque command and the actual torque. The inputs to the proposed NN are i^*_q and the rotor speed ω_r. The output of the NN is i_{dop}, which is used with i^*_q to calculate the 3-phase currents, in current controlled schemes, or the 3-phase voltages in the voltage-controlled scheme.

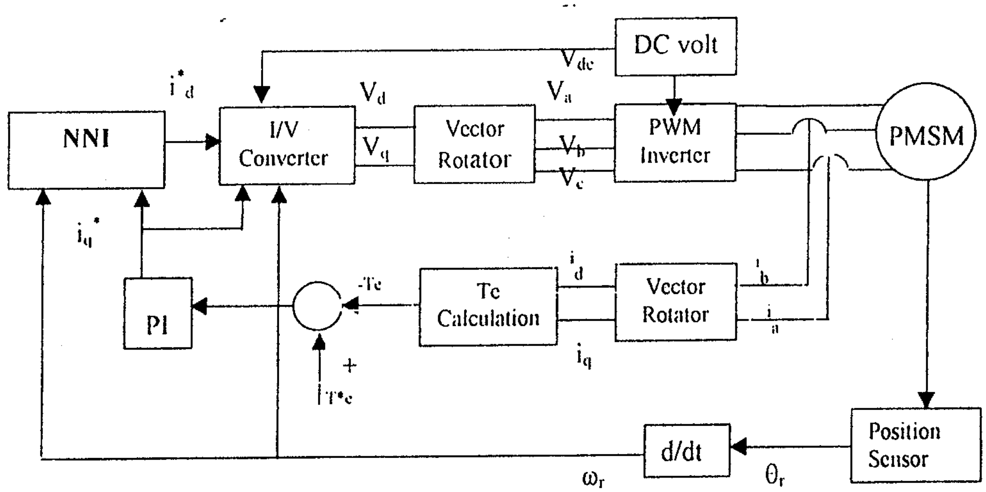


Fig.(4) Control System for Loss Minimization In IPMSM Drives

In order to establish the neural network model, the interconnected weights and biases are trained according to an existing input/output pattern. This pattern is obtained from the simulation results of the described loss minimization control strategy, i.e. off- line training. This training method has the merit of simplicity and fast training. After many trials, a 3-layer NN with two input neurons, 2- hidden layer neurons, and one output neuron gave the required error goal after few epochs. The sum squared error as function of training epochs is shown in Fig.(5). The trained output of NNI is compared with i_{dop} calculated from the condition of minimum losses, and the results given in Fig.(6) as function of rotor speed. The slight difference between the two values of current proves the accurate tracking of the current value required for loss minimization. The q-axis current component, as calculated from the PI controller, is shown in Fig.(7) versus rotor speed. The accuracy of NNI is further proved from Fig.(8) where the minimum power loss calculated from i_{dop} is compared with power loss resulting due to application of NNI As shown the error is less than 0.001%(0.1/118.9), i.e. application of NN leads to efficient operation.

In order to verify the fast response of the established NNI loss minimization controller, sudden step change in the drive speed is imposed at constant load torque, and the calculated power loss at this operating point is plotted versus time in Fig.(9a), while the existing power loss after applying NNI controller is plotted in Fig.(9b) for clarity. The corresponding fast change in the output of NNI as the speed changes proves the fast response of the neural network output, which assures that minimum losses are obtained at different operating conditions. This fact is further proved by applying a step change of load torque and plotting the expected power loss with that obtained after applying NNI. Results shown in Fig.(10) assures the fast response of the designed NNI.

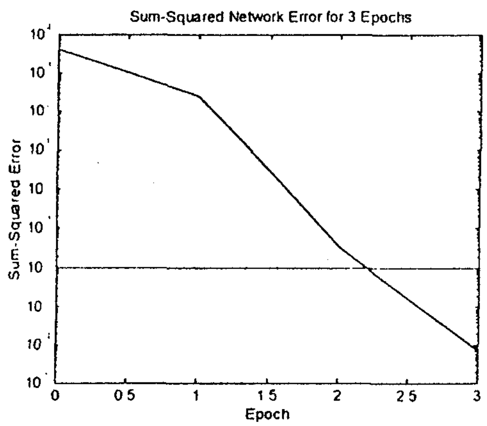


Fig.(5) Declination of Error for the NNI

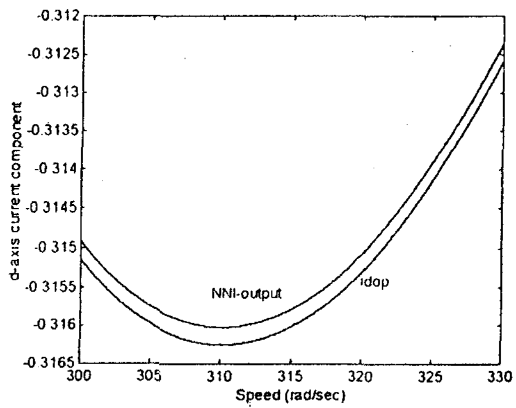


Fig.(6) Calculated & NNI i_{dop}

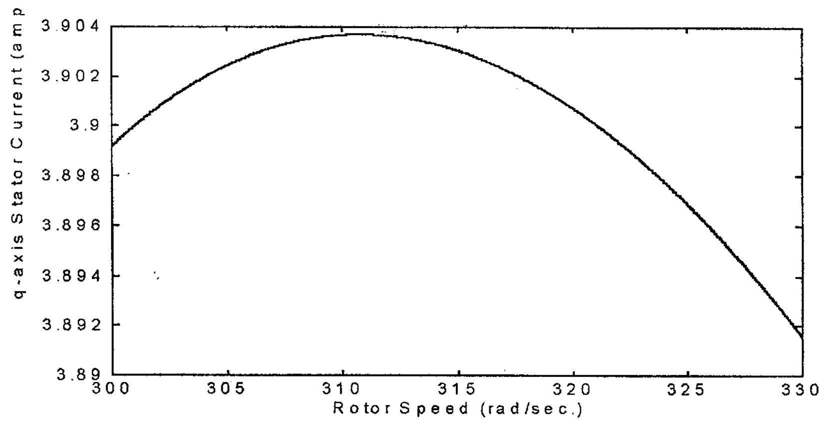


Fig.(7) Q-axis Current Component

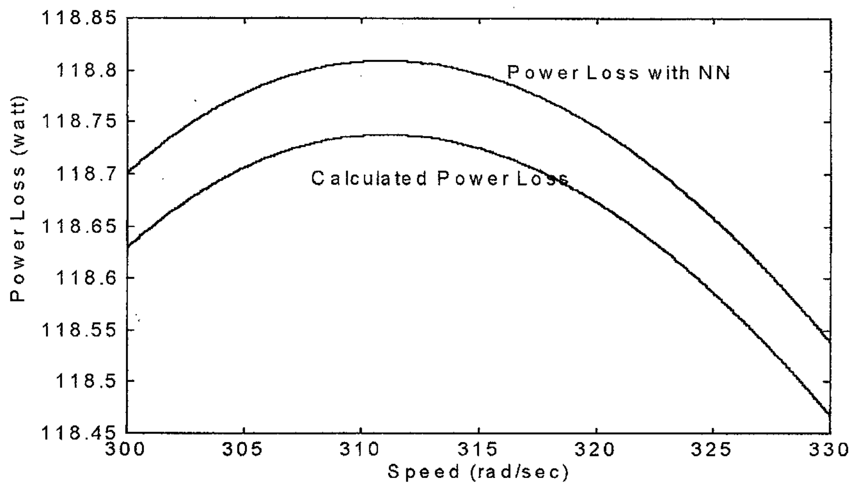
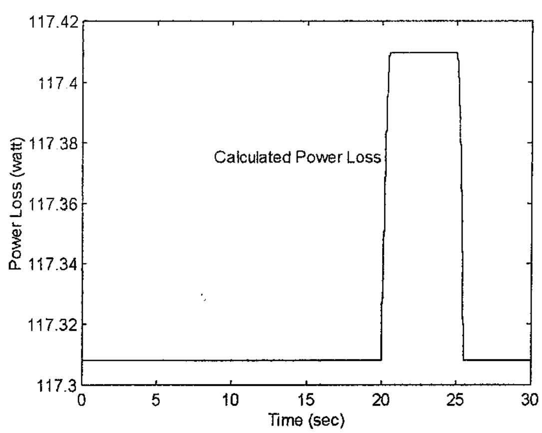


Fig.(8) Calculated and Actual Power Loss



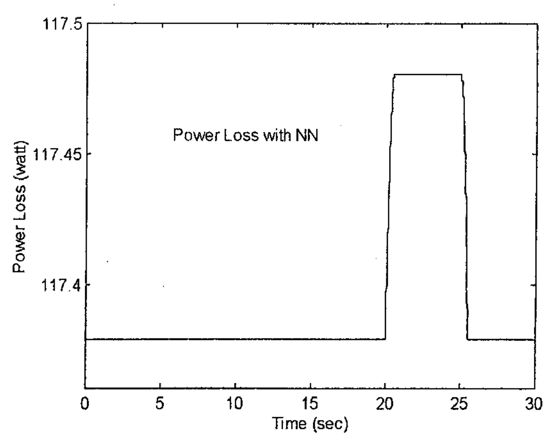


Fig.(9a) Calculated PL at Step Change in ω_r Fig.(9b) Actual PL at Step Change in ω_r

(PL=power losses)

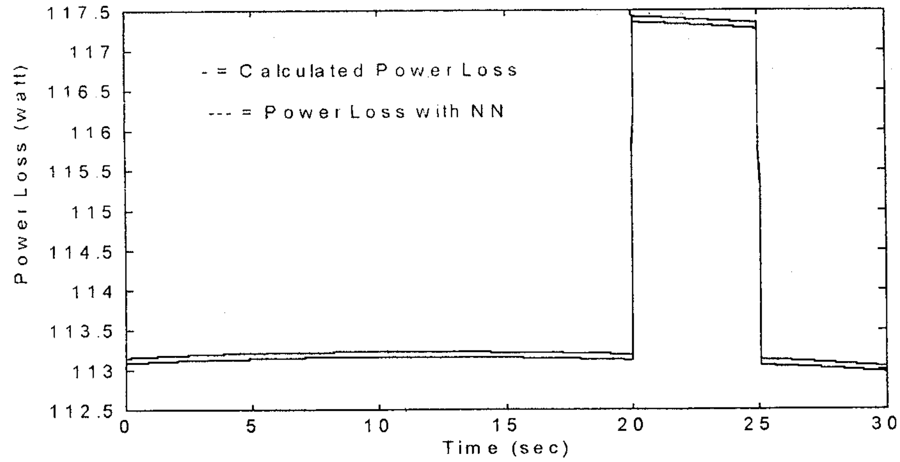


Fig.(10) Difference Between Calculated and Actual Power Loss when Applying NNI at a Step Change in Load Torque

IV. Loss Minimization Model of Surface SPMSM

In the case of SPMSM drive, $L_d = L_q = L_s$, where L_s is the stator inductance. Hence, the iron loss equation (7) reduces to

$$P_{fe} = \omega_s^2 * [(\lambda + L_s i_{od})^2 + (L_s i_{oq})^2] / R_c \quad (13)$$

and the electric torque reduces to:

$$T_e = 1.5P \lambda i_{oq} \quad (14)$$

Adding cupper and iron losses and differentiating with respect to i_{od} gives:

$$\partial P_L / \partial i_{od} = R_s.i_{od} + (L_s \omega_s^2 \lambda)/R_c + (\omega_s^2 L_s^2 i_{od})R_c \quad (15)$$

Equating (15) to zero leads to the following expression for the optimum d-axis current at a given speed and torque:

$$i_{dop} = (L_s \omega_s^2 \lambda)/(R_s.R_c + \omega_s^2 L_s^2) \quad (16)$$

V. Neural Network Controller for Loss-Minimization in SPMSM

(i) Control Scheme

Due to the simpler expression for optimal d-axis current given in (16), and the independency of i_{dop} on th q-axis current component, the PI controller used with IPMSM drive is canceled. Instead the q-axis current is directly calculated from the command torque, which is used as one of the inputs of the neural network controller for SPMSM drive (NNS). The simpler control scheme is shown in a block diagram in Fig. (11).

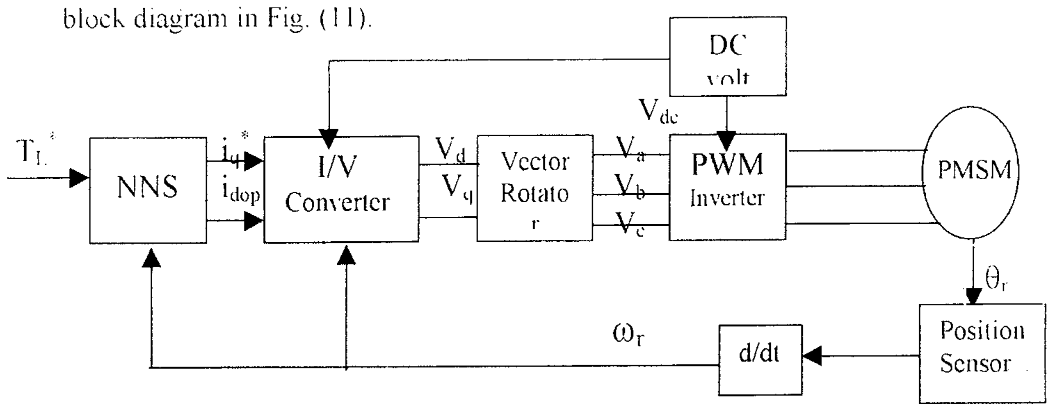


Fig.(11) Control Scheme for Loss Minimization In SPMSM Drives

(ii) Neural Network (NNS) Description

For fast and robust application of loss minimization technique at all operating speed range, an off line trained neural network NNS is designed for loss minimization in surface PMSM. The inputs to the NNS are the drive speed, and the load torque (which determines the q-axis component of the stator current). The output of the network is the optimal value of d-component of stator current i_{dop}. The input/output pattern used to train NNS is obtained from the simulation results of the described loss minimization control strategy. A 3-layer NN with two input neurons, 2- hidden layer neurons, and one output neuron gave the required error goal after few epochs. The sum squared error as function of training epochs is shown in Fig.(12). The trained output of NNS is compared with i_{dop} calculated from the condition of minimum losses, and the results given in Fig.(13) as function of rotor speed. The slight difference between the two values of current proves the accurate tracking of the current value required for loss minimization.

In order to verify the fast response of the established NNS loss minimization controller,. a step change of load torque is applied to the SPMSM, and NNS output current plotted in Fig.(14). Results proves the fast response of the designed NNS. This fact is further proved by applying a sudden step change of 30 rad/sec to the speed command at constant load torque, and NNS output plotted versus time in Fig.(15). The corresponding fast change in the output of NNS as the speed changes proves the fast response of the neural network output, which assures that minimum losses are obtained at different operating conditions.

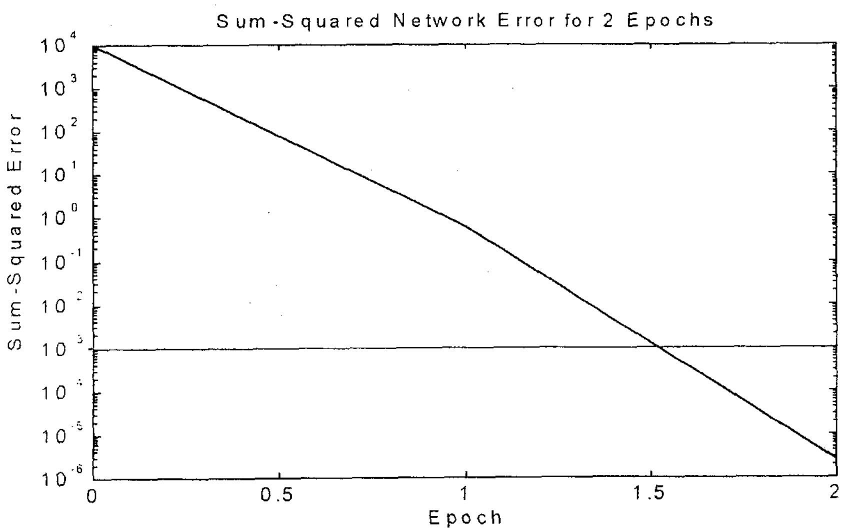


Fig.(12) Declination of Error for the NNS

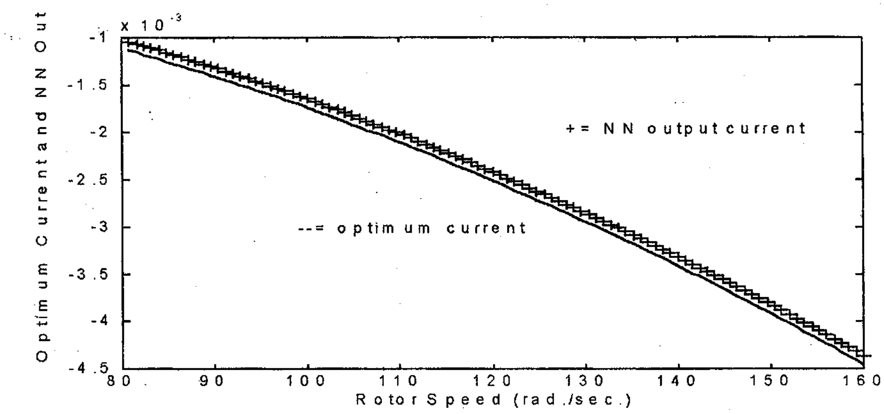


Fig.(13) NNS Output and i_{dop} versus Speed

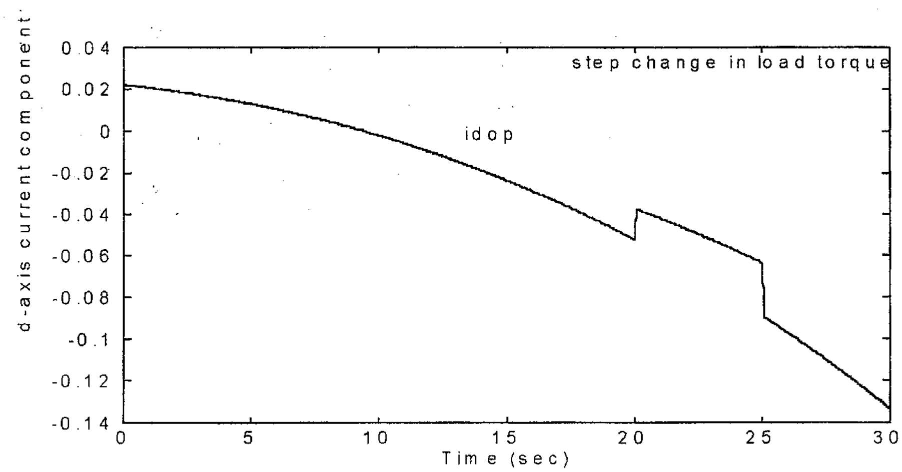


Fig.(14) NNS Output at Step Change in Load Torque

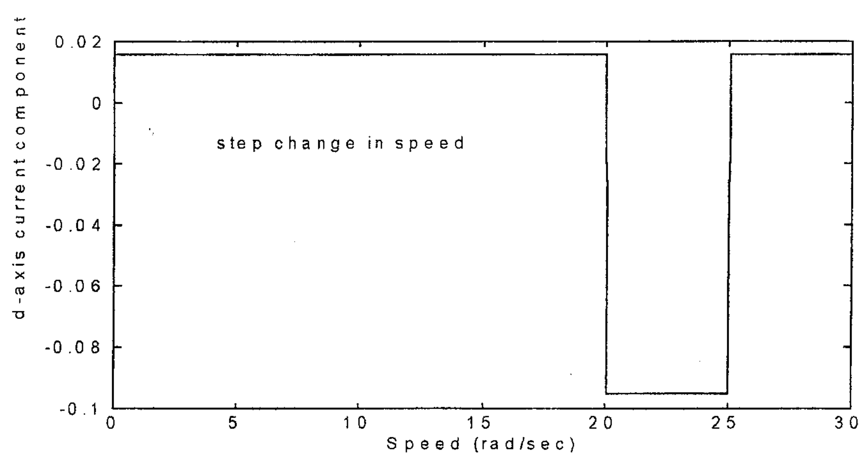


Fig.(15) NNS Output at Step Change in Speed

VI. Maximum Efficiency Operation At i_d=0

(i)Equation Derivation

To prevent the demagnetization of the permanent magnets, the d-component of the stator current is set to zero, and another approach is used to allow the PMSM to operate with minimum winding losses. This approach depends on variation of the inverter angle as the speed and load varies to achieve minimum losses [11]. To determine this optimum angle in an analytical manner, id is set to zero in equations (1)-(3) leading to the following voltage and torque equations:

$V_q = V_i \cos\varphi = R_s . i_{oq} + \omega_s \lambda$ (17)

$V_d = -V_i \sin\varphi = -\omega_s L i_{oq}$ (18)

The electromagnetic torque is given by:

$T_e = 1.5 P \lambda i_{oq}$ (19)

Where L = Lq for IPMSM drive, and L=Ls for SPMSM drive

It is clear that with this constraint and for steady state operation at a required load torque, the quadrature axis current can be calculated from eq.(19), and used to optimize the inverter angle. From eqns. (17) and (18) we can get;

$\varphi_{op} = \tan^{-1}[(\omega_s L i_{oq} / (R_s . i_{oq} + \omega_s \lambda)]$ (20)

To study the range of the optimum inverter angle φ_{op} as the rotor speed is varied, φ_{op} is plotted versus speed at different values of load torque in Fig.(16). It is clear that the optimum inverter angle is in the region of 0.5 to 2.5 degrees[6] within wide speed range.

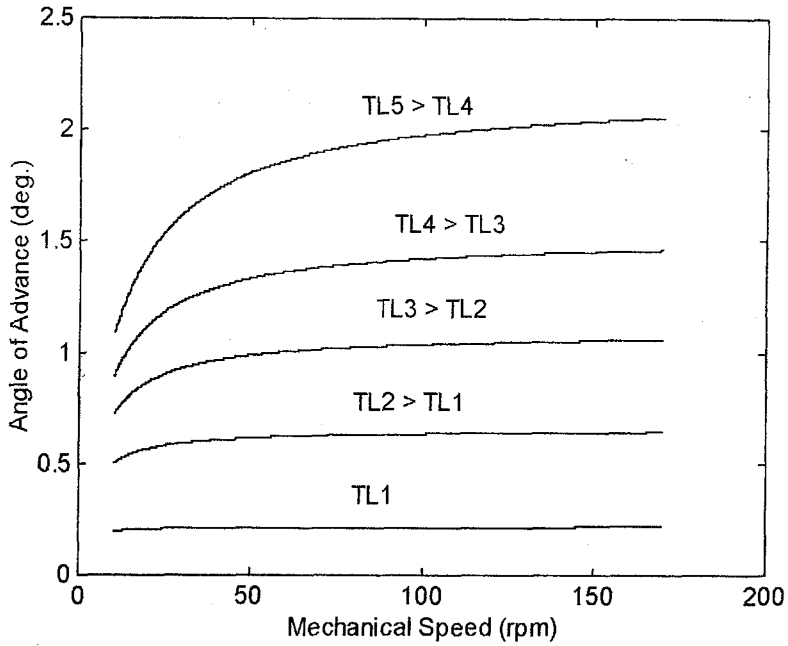


Fig.(16) Variation of Optimal Inverter Angle with Speed at Different Load Torque

To prove the effect of the inverter angle of advance on the drive efficiency, the efficiency and electromagnetic torque for φ= 0, and for $\varphi = \varphi_{op}$ are plotted versus speed in Fig.(17). Results show that a much higher torque and a higher efficiency are obtained when φ is varied with speed to follow the values of φ_{op} as given in eq.(20).

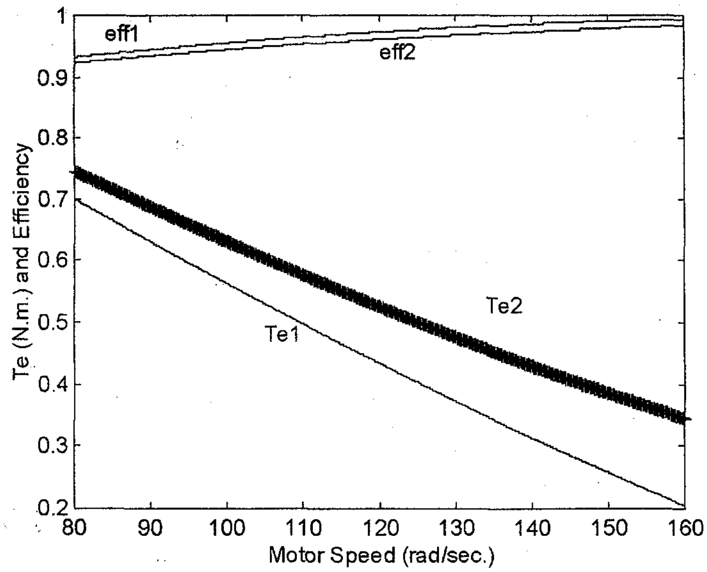


Figure (17) Torque and Efficiency at Zero Angle of Inverter Advance (Te1 and eff1), and Torque and Efficiency for Optimal Inverter Angle Operation (Te2 and eff2)

(ii).Comparison Between Maximum Efficiency Operation Schemes

A comparison is done between the values of efficiency obtained by flux weakening technique, and that obtained by varying the inverter angle of advance in SPMSM. Figure (18) shows the developed torque and efficiency with loss minimization scheme (Te1 and eff1), and de torque and efficiency for optimum inverter angle operation (Te2 and eff2). It is concluded that while the efficiencies are nearly equal, the developed torque is slightly higher for the case of optimum inverter angle operation. Therefore, since the two investigated techniques for maximum efficiency operation gave same results, setting the d-axis current component to zero while varying the optimum angle of advance might be more economic to implement, and more safe from the point of view of magnet demagnetization. Flux weakening is better used for high speed operation of PMSM drives.

(iii) Neural Network Implementation

For fast and robust application of optimum inverter angle at all operating speed range, an off line trained neural network NNA is designed, and is applicable for both SPMSM and IPMSM drives. The inputs to the NNA are the drive speed, and the load torque (which determines the q-axis component of the stator current). The output of the network is the optimal value of the inverter angle of advance φ_{dop}. The input/output pattern used to train NNA is obtained from the simulation results given in the previous section. A 3-layer NN with two input neurons, 2- hidden layer neurons, and one output neuron gave the required error goal after few epochs.

In order to verify the fast response of the established NNA maximum efficiency controller,. a step change of 0.2 N.m.in load torque is applied to the SPMSM, and

NNA output (optimum inverter angle), as well as the calculated inverter angle are plotted in Fig.(19). Results proves the fast response of the designed NNA.

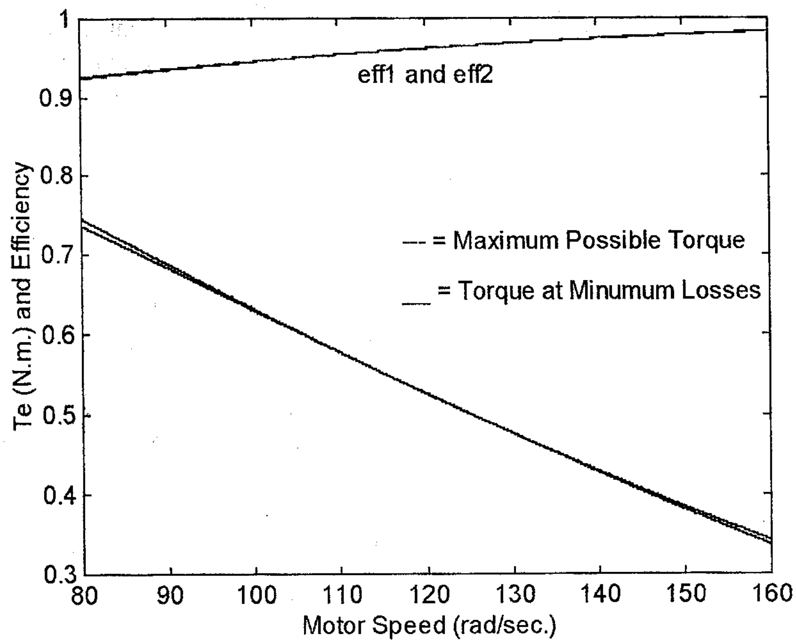


Fig. (18) Torque and Efficiency with Loss Minimization Technique (Te1 and eff1), and Torque and Efficiency for Optimal Inverter Angle Operation (Te2 and eff2)

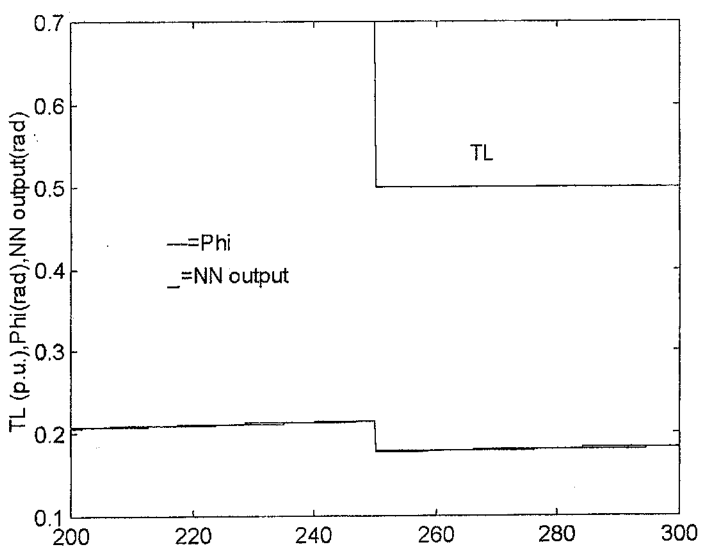


Fig.(19) Performance of NNA at Step Change in Load Torque

VII.Conclusion

In this paper, efficiency of two types of permanent magnet synchronous machine drives, namely; surface type permanent magnet synchronous machine (SPMSM) and interior type permanent magnet synchronous machine (IPMSM), are investigated is maximized by minimizing cupper and iron losses. Loss minimization is implemented using flux weakening. A neural network controller (NNC) is designed for each drive, to achieve loss minimization at different speed and load values. Data for training the NNC are obtained through off-line simulations of SPMSM and IPMSM at different operating conditions. The accuracy and fast response of each of the NNC is proved by applying sudden changes in speed and load and tracking the NNC output.

Also the PMSM drives efficiency is derived when setting the d-axis current component to zero, while varying the angle of advance "φ" of the PWM inverter supplying the PMSM drive. A neural network "NNA" is also designed, and trained to vary φ following the derived control law. The accuracy and fast response of NNA controller is also proved.

Comparison is done between the drive efficiency obtained with flux weakening, and the drive efficiency obtained with the conventional "$i_d=0$" control. Results proved that the two methods lead to equal efficiencies. This result are in favor of the "$i_d=0$" control, since less control circuits are needed for its implementation. Also it prevents magnet demagnetization that may occur due to any maloperation of the control system.

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Appendix

(i) IPMSM parameters:
900watt, 1800rpm at 60 Hz.,
L_d=0.027 H.
L_q=0.067 H.
R_s=4.3 ohm
V_{dc}=250 V.
2P=4 poles.
λ=0.232 web.

(ii) SPMSM parameters
400 watt, 1800rpm at 60 Hz,
R_s=3 ohm
L_s=0.0121 H.
λ=0.083 web
2P=4 poles
V_{dc}=100 V

استخدام الشبكات العصبية في الحصول على أقل فاقد في المحركات المتزامنة ذات المغناطيسية الدائمة

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تم فى هذة المقالة بحث تشغيل المحرك المتزامن ذو المغناطيسية الدائمة بنوعيه: الداخلى والسطحى-و بأعلى كفاءة ممكنةوذلك بتقليل الفاقد الناتج من مقاومة الأسلاك النحاسيةوأيضا الفاقد الناتج فى الجزء الحديدي من المحرك. ويتم تقليل الفاقد باستخدام طريقة اضعاف المجال المغناطيسى.
وقد تم فى البحث التحليل الرياضى لمعادلات كلا المحركين واستخلاص معادلة التيار اللازم لكل منهما لتحقيق طريقة اضعاف المجال المغناطيسى للحصول على أعلى كفاءة ممكنة بتقليل الفواقد
ثم تم فى البحث استخدام الشبكات العصبية كنوع جديد من أنواع التحكم لكل محرك على حده لتحقيق أعلى كفاءة للمحرك وقد تم تدريب الشبكات العصبية لكى تخرج التيار المستنتج من التحليل الرياضى باستخدام نتائج برامج المحاكاة الخاصه بكل محرك عند ظروف تشغيل مختلفه أى عند سرعات مختلفة ولأحمال متعددة القيمة..
وللتأكد من دقة وسرعة استجابة كلا من الشبكتين العصبيتين تم تتبع خرج الشبكتين العصبيتين عند احداث تغييرات مفاجئة فى السرعة والحمل. وقد أثبتت النتائج دقة تتبع خرج الشبكه العصبيه للتغيرات المفاجئه لكلا المحركين.
كما تم فى هذا البحث دراسة كفاءة المحركات بضبط تيار المحور المباشر عند قيمة صفرية مع تغيير زاوية التقديم للقلاب المغذى للمحرك (PWM Inverter) وتم استنتاج العلاقه بين زاوية التقديم للعاكس المغذى للمحرك وبين السرعه والحمل من أجل الحصول على أعلى كفاءه .

ثم تمت مقارنة كفاءة المحركات الناتجة من استخدام تقنية إضعاف المجال مع تلك الناتجة من ضبط تيار المحور المباشر عند قيمة صفرية مع تغيير زاوية التقديم للعاكس المغذى للمحرك (PWM Inverter) ووجد أن الكفاءات تتساوى عند قيم مختلفة لزاوية التقديم داله فى السرعة والحمل
كما. تم تصميم شبكة عصبية لتغيير قيمة زاوية التقديم تبعا للدالة السابق ايجادها وذلك عند قيم السرعة والحمل المختلفة ، وللتأكد من دقة وسرعة استجابة الشبكه العصبيه المقترحه تم تتبع خرج الشبكه العصبيه عند احداث تغييرات مفاجئة فى الحمل. وقد أثبتت النتائج دقة تتبع خرج الشبكه العصبيه للتغيرات المفاجئه