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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 motor drives, namely; surface type permanent magnet synchronous machine (SPMSM) and interior type permanent magnet synchronous motor (IPMSM), are investigated. The efficiency of both drives is maximized by minimizing copper 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 drives' 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.

Key words: Permanent magnet synchronous motor, Loss minimization, Neural network controller

1. 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 [2] is complicated and its implementation based on the knowledge of machine parameters. In [4], loss optimization is achieved using a fuzzy table within a fuzzy controller. In [5], air-gap flux weakening algorithm is

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proposed for loss optimization, but the stator resistance was neglected while deriving the optimum voltage to frequency ratio.

Increasing drive efficiency by maximizing the generated torque was investigated in [6-7]. In [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 [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[8], for tracking of PM synchronous generator parameters[9], or for speed control of permanent magnet motors[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 the operating 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 designed to implement the loss minimization model 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 maximizing 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.

2. 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, [1]:

$$V_q = R_s i_q + \omega_s L_d i_{od} + \omega_s \lambda \tag{1}$$

$$V_d = R_s i_d - \omega_s L_q i_{oq} \tag{2}$$

The electromagnetic torque is given by:

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

And the equation for motor dynamics is:

$$T_e = T_L + B.\omega_r + J.d\omega_r / dt \tag{4}$$

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:

$$P_{cu} = R_s.i_d^2 + R_s\, i_q^2 \tag{5}$$

While the iron losses Pfe are given by:

$$P_{fe} = \omega_s^2 \cdot \lambda_0^2 / R_c \tag{6}$$

where, λo is the air gap flux.

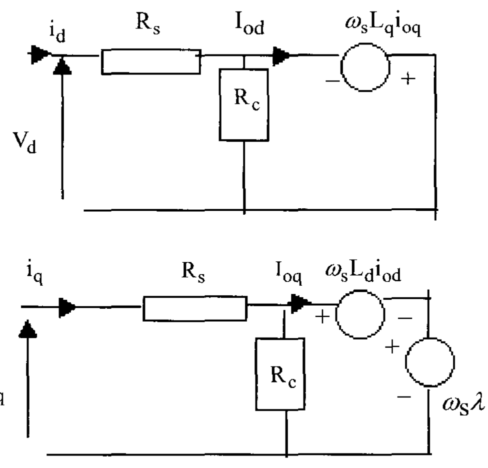

Fig. 1. Equivalent Circuit for PMSM in the d and q axes.

Equation (6) could be written as:

$$P_{fe} = \omega_s^2\left[(\lambda + L_d\, i_{od})^2 + (L_q\, i_{oq})^2\right]/R_c \tag{7}$$

Neglecting harmonic losses, which are indirectly controlled by flux weakening, the total losses are Pcu and Pfe. For a given torque, Pcu and Pfe are functions of i_{od}. Minimum losses satisfy $\partial(P_{cu}+P_{fe})/\partial i_{od} = \partial P_L/\partial i_{od} = 0$, Hence:

$$\partial P_L/\partial i_{od} = 2\begin{bmatrix} i_{od}\left[R_s + (\omega_s^2\, L_d^2/R_c)\right] + \\ i_{oq}\,\partial\, i_{oq}/\partial_{od}\left[R_s + (\omega_s^2\, L_q^2/R_c)\right] + (\omega_s^2\, \lambda\, L_d/R_c)\end{bmatrix} \tag{8}$$

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

$$i_{oq} = T_e/1.5\cdot P\left[\lambda + (L_d - L_q)\cdot i_{od}\right] \tag{9}$$

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

$$\partial i_{oq}/\partial i_{od} = -\left[\left(L_d - L_q\right)T_e/1.5\cdot P\left[\lambda + (L_d - L_q)i_{od}\right]\right]^2 \tag{10}$$

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

$$i_{dop} = 1.5P\cdot LT\cdot\left\{\begin{matrix}\left[\left(R_s\cdot R_c\right)+\left(\omega_s^2\cdot L_q^2\right)\right]/ \\ \left[\left(R_s\cdot R_c + \omega_s^2\cdot L_d^2\right)\right]\end{matrix}\right\} i_{oq}^3 - \left\{\left[\lambda\cdot\omega_s^2\cdot L_d^2\right]/\left[R_s\cdot R_c + \omega_s^2 L_d^2\right]\right\} \tag{11}$$

where, $LT = \left(L_d - L_q\right)/T_e$.

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 (11) into equations (1) and (2) and using the supply voltage V_s as:

$$V_s = \sqrt{V_d^2 + V_q^2} \tag{12}$$

To prove that the losses are minimized as speed and load varies, the total losses are plotted versus Vs 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.

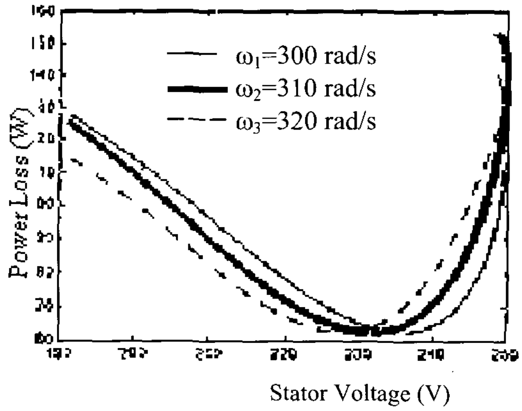

Fig. 2. Power Loss Versus Stator Voltage at Variable Speed and Constant.

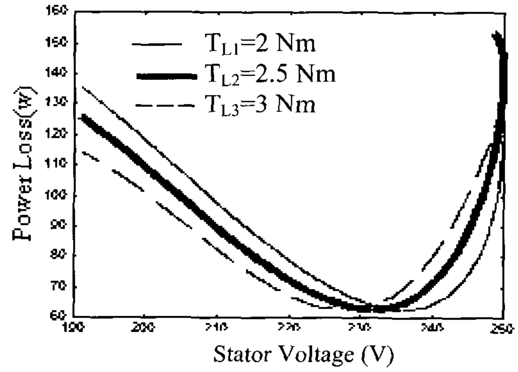

Fig. 3. Power Loss Versus Stator Voltage at Variable Load and Constant Speed.

3. Network Controller for Loss-Minimization in IPMSM

3.1 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

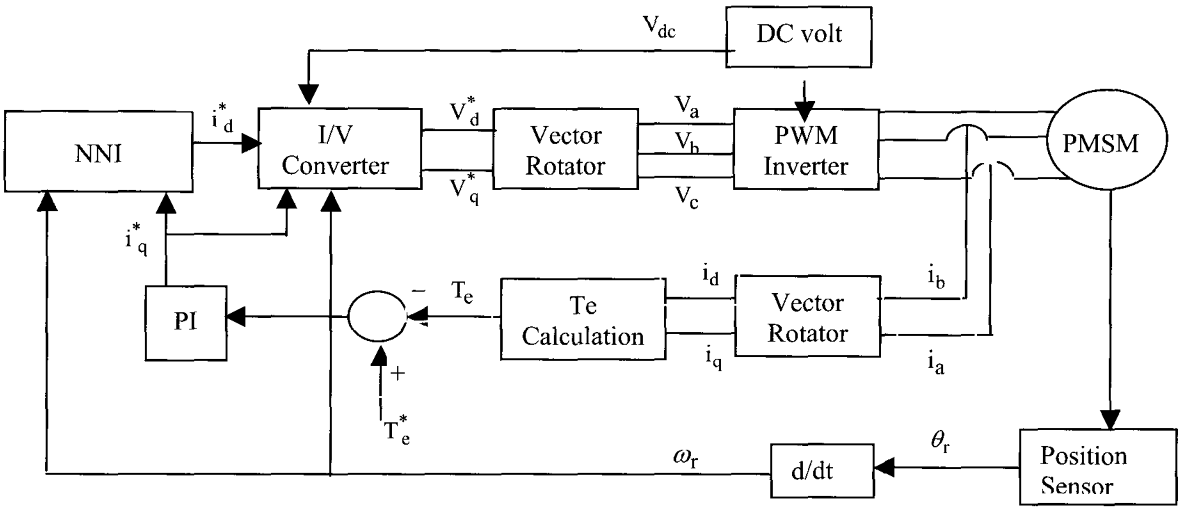

Fig. 4. Control System for Loss Minimization in IPMSM Drives

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 ωr. The output of the NN is id_{op}, 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.

3.2 Neural Network Controller for IPMSM

The type of neural network (NN) developed in this work is the multi-layer perceptron. The number of elements in the hidden layer is arbitrarily chosen depending on the complexity of the mapping being learnt. In order to introduce non-linearity into the network, a hyperbolic-tangent transfer function "tanh", is used in input and hidden layers' elements. All elements in the output layer have linear transformations. The Levenberg-Marquadet algorithm is used to train (adjust the weights and biases) of the NN such that the sum squared error between actual network outputs and corresponding desired outputs is minimized. Training is done 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 fast learning. Once the NN has been trained, the network output θi is computed from (nx1) input vector X according to [12]:

$$\theta_i = W2.\tanh(W1.X+B1)+B2$$

where, W2 denotes matrix of connecting weights from hidden to output layer, W2 denotes matrix of connecting weights from input to hidden layer. For a hidden layer with "m" elements, B2 and B1 denote the "1x1" and "mx1" bias vectors respectively. The task of training is to determine the matrices W1, W2 and bias vectors B1, B2. After many trials, a 3-layer feedforward 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 NN, defined as NN_I is compared with idop 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 NN_I is further proved in Fig. 8, where the minimum power loss calculated from id_{op} is compared with power loss resulting due to application of NN_I. As shown the error is less than 0.001% (0.1/118.9), i.e. application of NN leads to efficient operation.

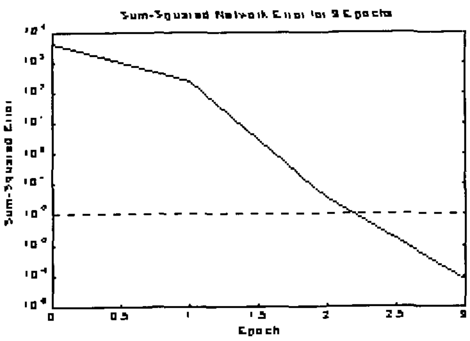

Fig. 5. Declination of Error for the NN_I.

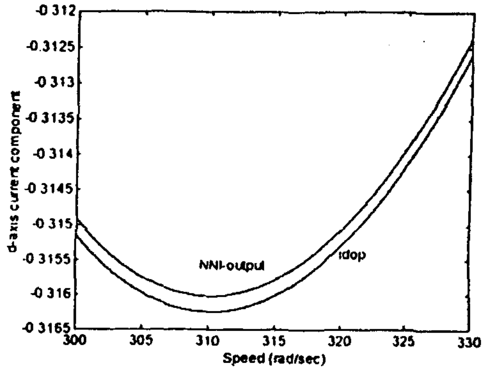

Fig. 6. Calculated i_{dop} & NN_I output.

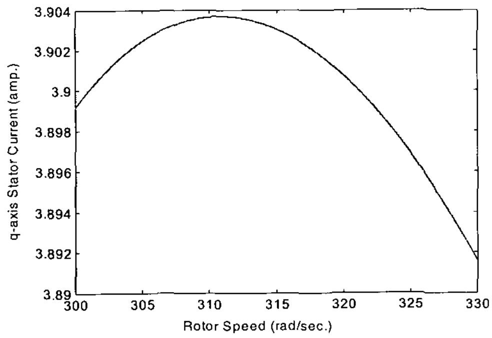

Fig. 7. Q-axis Current Component.

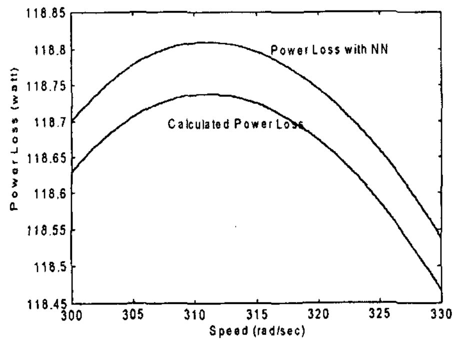

Fig. 8. Calculated and Actual Power Loss.

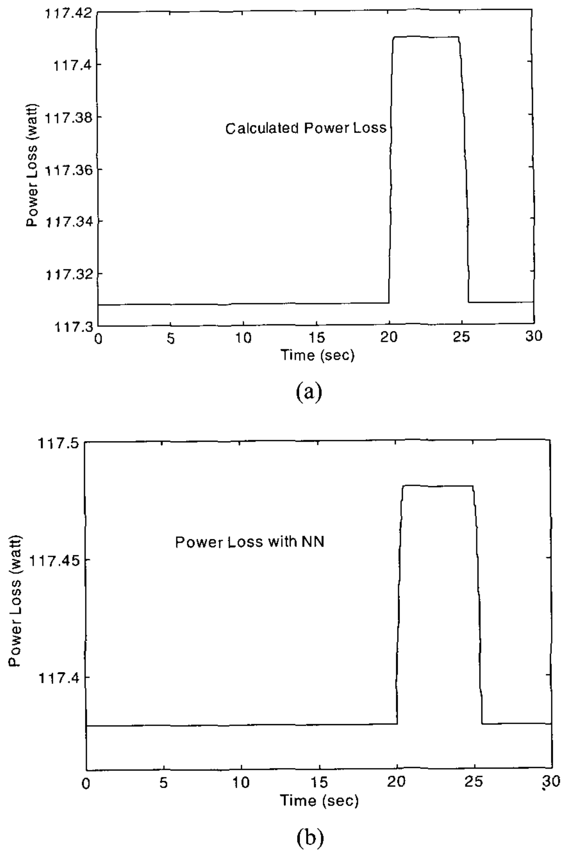

Fig. 9. (a) Calculated PL at Step Change in ωr, (b) Actual PL at Step Change in ωr (PL= power losses).

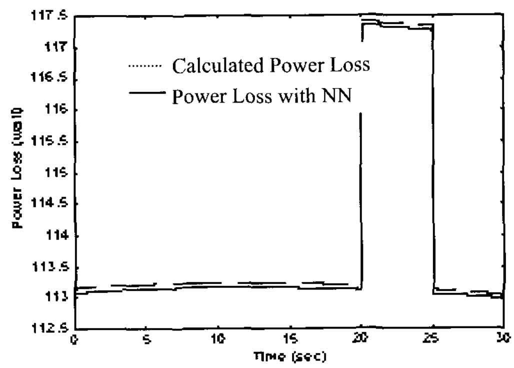

Fig. 10. Difference Between Calculated and Actual Power Loss when Applying NNI at a Step Change in Load Torque.

In order to verify the fast response of the established NN_I 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. 9(a), while the existing power loss after applying NN_I controller is plotted in Fig. 9(b) for clarity. The corresponding fast change in the output of NN_I 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 NN_I. Results shown in Fig. 10 assures the fast response of the designed NN_I.

4. Loss Minimization Model of Surface SPMSM

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

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

and the electric torque reduces to:

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

Adding copper and iron losses and differentiating with respect to iod gives:

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

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

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

5. Neural Network Controller for Loss-Minimization in SPMSM

5.1 Control Scheme

Due to the simpler expression for optimal d-axis current given in (16), and the independency of idop on the 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.

5.2 Neural Network Description

For fast and robust application of loss minimization technique within the operating speed range, an off line trained feed-forward neural network, defined as 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 outputs of the network are i^*_q and the optimal value of d-component of stator current idop. The input/output pattern used to train NN_S 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 two output neurons gave the required error goal after few epochs. The sum squared error as function of training epochs is shown in Fig. 12. The value of d- axis current output from NN_S is compared with id_{op} 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

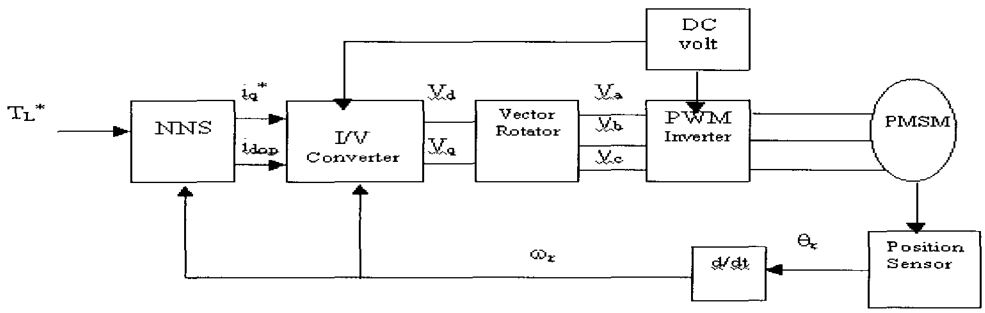

Fig. 11. Control Scheme for Loss Minimization in SPMSM Drives.

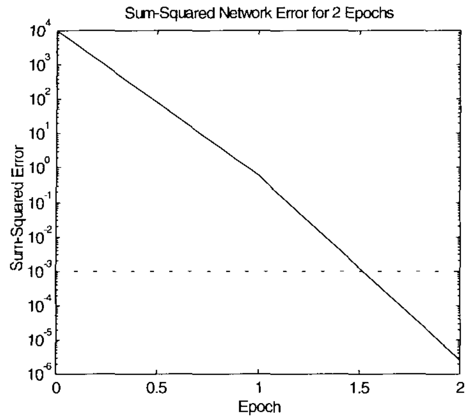

Fig. 12. Declination of Error for the NN_S.

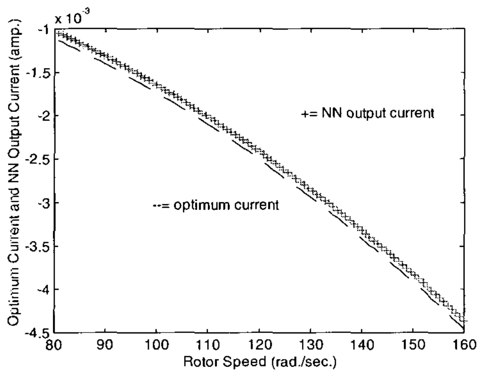

Fig. 13. NNS Output and idop versus Speed.

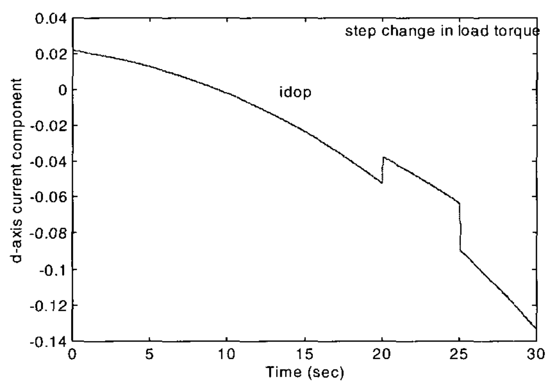

Fig. 14. NNS Output at Step Change in Load Torque.

for loss minimization.

In order to verify the fast response of the established NN_S loss minimization controller,. a step change of load torque is applied to the SPMSM, and NN_S output idop plotted in Fig. 14. Results proves the fast response of the designed NN_S. This fact is further proved by applying a sudden step change of 30 rad/sec to the speed command at

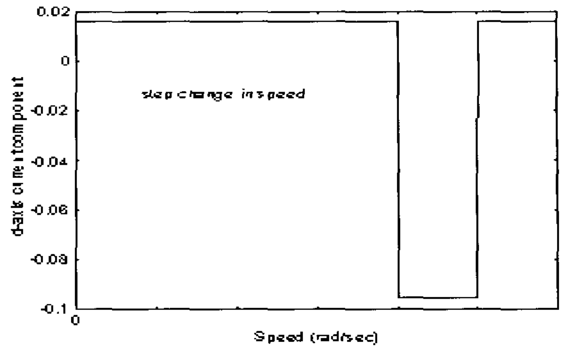

Fig. 15. NNS Output at Step Change in Speed.

constant load torque, and idop output plotted versus time in Fig. 15. The corresponding fast change in the output of NN_S as the speed changes proves the fast response of the neural network output, which assures that minimum losses are obtained at different operating conditions.

6. Maximum Efficiency Operation At id=0

6.1 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, i_d is set to zero in equations (1)-(3) leading to the following voltage and torque equations:

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

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

The electromagnetic torque is given by:

$$T_e = 1.5 \cdot P \cdot \lambda \cdot i_{oq} \tag{19}$$

where, $L = L_q$ for IPMSM drive, and $L = L_s$ for SPMSM drive.

It is clear that with this constraint, and for steady state operation at a given load torque, the quadrature axis current can be calculated from (19), and used to optimize the inverter angle. From (17) and (18) it is given by:

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

To study the range of the optimum inverter angle φop 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 the operating speed range.

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 (20).

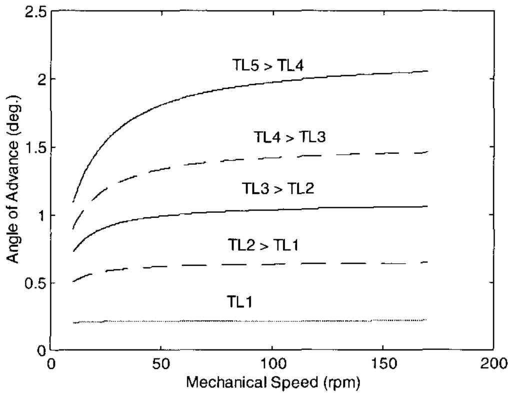

Fig. 16. Variation of Optimal Inverter Angle with Speed at Different Load Torque.

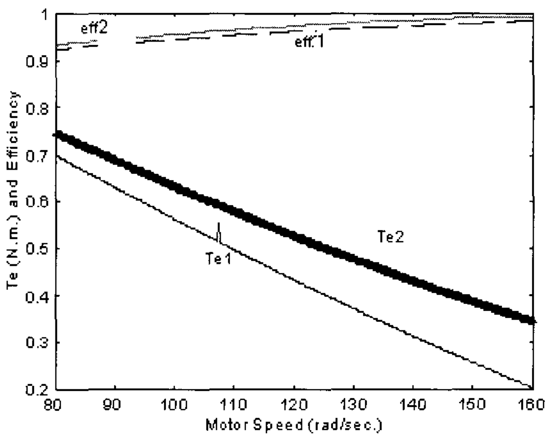

Fig. 17. Torque and Efficiency at Zero Angle of Inverter Advance (Te1 and eff1), and Torque and Efficiency for Optimal Inverter Angle Operation (Te2 and eff2).

6.2 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. Fig. 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.

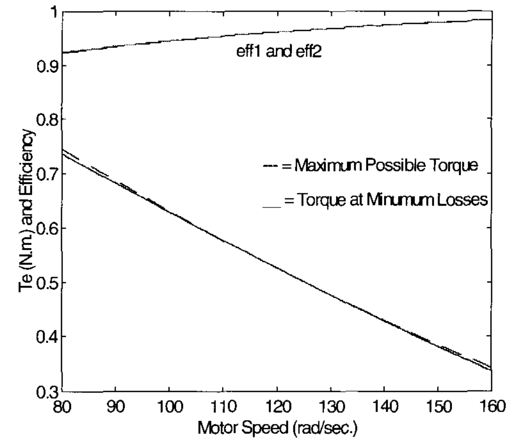

Fig. 18. Torque and Efficiency with Loss minimization Technique (Te1 and eff1), and Torque and Efficiency for Optimal Inverter Angle Operation (Te2 and eff2).

6.3 Neural Network Implementation

For fast and robust application of optimum inverter angle within the operating speed range, an off line trained neural network, defined as NN_A, is designed. The inputs to NN_A 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 φd_{op}. The input/output pattern used to train NN_A is obtained from the simulation results

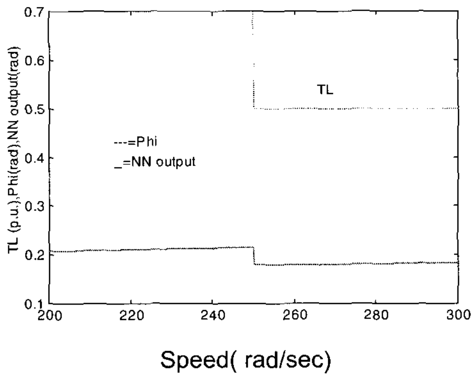

Fig. 19. Performance of NN_A at Step Change in Load Torque.

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 NN_A maximum efficiency controller, a step change of 0.2 N.m .in load torque is applied to the SPMSM, and NN_A output (optimum inverter angle), as well as the calculated inverter angle are plotted in Fig. 19. Results prove the fast response of the designed NN_A.

7.Conclusion

In this paper, loss minimization problem of interior-type permanent magnet synchronous motor (IPMSM) drive, and surface-type permanent magnet synchronous motor (SPMSM) drive has been investigated. The proposed method is based on flux weakening, where an expression is derived for the d-axis current component leading to minimum copper and iron losses for both drives. This is followed by designing a neural network controller (NNC) for each drive, to achieve loss minimization at different operating points. Data for training the NNC is obtained through off-line simulations of IPMSM and SPMSM at different operating conditions. The accuracy and fast response of each NNC is proved by applying sudden changes in speed and load and tracking the NNC output.

Also the PMSM drives efficiency has been investigated when setting the d-axis current component to zero, while varying the angle of advance " φ" of the PWM inverter supplying the drive. An expression giving the value of φ that results in maximum efficiency at different operating points is derived. This is followed by designing a neural network to vary φ following the derived control law. The accuracy and fast response of the NN controller is also proved.

Comparison is done between the drive efficiency obtained with flux weakening, and the drive efficiency obtained by setting "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 it prevents magnet demagnetization that may occur due to any maloperation of the control system.

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Appendix

IPMSM parameters

900watt, R_s=4.3 Ω, Ld=0.027 H, L_q=0.067 H., V_{dc}=250 V, 2P=8 poles, λ=0.232 web,

SPMSM parameters

400 watt, Rs=3 Ω, L_s=0.0121 H, V_{dc}=100 V, 2P=4 poles, λ=0.083 web.

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