Adaptive controller method for permanent magnet synchronous motor speed-regulation

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Abstract

Permanent Magnet Synchronous Motors (PMSM) have been used as variable speed drives, especially for speed control and position. This work present the performance of a B-Spline Neural Network (BSNN) scheme to adjusting the rotor speed of PMSG and estimation the load torque. The B-spline neural network is an efficient tool to implement the adaptive control speed and estimation of load torque, with the possibility of carrying out this task on-line, taking into account the systems non-linearities. One of the main tasks within is adjust the proportional-integral parameters for speed rotor controller. In this work, a neural network algorithm solves this. Results show that the proposed coordination scheme is comparable with an inner-loop sliding mode current control scheme, without requiring a strict model analysis. A nonlinear observer is designed for estimation of the rotor speed and load torque. To illustrate the performance of the proposed controller, the simulation studies are presented separately for the BSNN and sliding mode control. The results are compared with each other and discussed in detail.

1 Introduction

Nowadays PMSM has been receiving increased attention for a wide variety of industrial applications, due to its considerable advantages such as high efficiency, high power factor, superior power density, small size, simple mechanical construction, easy maintenance, good reliability large torque to inertia ratio and long life over other kinds of motors such as DC motors and induction motors [1,2]. However, one disadvantage of PMSM is the need for a more complex controller for high performance electric drive applications owing to its highly nonlinear characteristics. Conventional fixed gain PI, PID controllers are widely used for the reasons of simplicity and applicability in most industrial drive applications [1,3].

The control strategies based on recent modern control theories are put forward to meet high performance application requirements of industrial drive applications. Different authors present some control techniques such as nonlinear control [4,5], adaptive control [6,7], disturbance observer-based control [8], predictive control [9], sliding mode control [10,11], robust control [12,13], have been developed to overcome these problems for speed and position control of PMSM.

The standard controller for a PMSM is a vector-based cascade arrangement that uses Proportional plus Integral (PI) action. The inner-loop PI controllers are used to regulate the *d–q* axis current and the outer-loop PI speed controller produces the *q*-axis current command for the inner loop *q*-axis current controller. When a conventional PI control is used, the parameters have to be tuned, with a linear technique and the parameters are fixed. The performance of the system can only be assured around the operating point for which the parameters were adjusted. On the other hand, using the parameters from PI scheme like input for an adaptive technique, some author mixed neural networks and PID techniques to strengthen the linear controller. In [14] and [15] a back propagation neural networks was used to adjust coefficients K_P, K_I, and K_D of PID controllers attaining power regulation of wind turbines. Optimal PI coefficients are obtained using genetic algorithms [16]. In [17] a BSNN is used to estimate the best power system stabilizer's parameters and adjust the proportional-integral parameters for reactive power provision.

Conventional fixed gain PI, PID controllers are widely used for the reasons of simplicity and applicability in most industrial drive applications [18]. The objective is to adaptively adjust the gains in accordance to the external and internal disturbances. This is achieved by a strategy to update conventional PI's currently operating in specific plant parameter's that were tuned time ago. These work proposed a good adaptive technique based on BSNN to change the coefficients K_P, and K_I, of PI controllers from PMSM. The main idea is to re-tune basically the PIs gains through an online procedure, which involve a few measurements. To illustrate the performance of the proposed controller, the simulation studies are presented separately for the BSNN and sliding mode control.

The paper is organized as follows. The model of the permanent magnet synchronous motor is given in Section 2. Then, the control algorithms, which are used to control speed of the PMSM, are given in Section 3. The Section 4 comprises the simulations results and discussion about the results. The achievements obtained with the proposed controller are interpreted in the last section.

2 Mathematical model of PMSM

The mathematical model of a typical surface mounted PMSM can be described in the d–q frame as follows [19]:

$$L_d \frac{di_d}{dt} = -R_s i_d + PL_q i_q \omega + v_d \qquad (1)$$

$$L_q \frac{di_q}{dt} = -R_s i_q - P\left(L_d i_d + \psi\right)\omega + v_q \qquad (2)$$

where v_d, v_q, i_d and i_q are the *d-q* axis voltages and currents, respectively; R_s is the stator resistance; L_d and L_q are the *d-q* axis inductances; p is the number of pole pairs; ω is the generator rotational speed; ψ is the permanent magnetic flux. The electromagnetic torque is obtained as

$$T_e = \frac{3}{2} p\left[\psi_m i_q + \left(L_d - L_q\right) i_d i_q\right] \qquad (3)$$

When the permanent magnets are mounted on the rotor surface, then $L_d=L_q$, therefore the electromagnetic torque is, $T_e=pi_q\psi$. The complete mathematical description includes also the mechanical equation given by

$$\frac{d\omega}{dt} = \frac{P}{2}\frac{\left(T_e - T_l\right)}{J} \qquad (4)$$

where J is the moment of inertia and T_l is the load torque. From equations above, it is understood that PMSM is a highly nonlinear system owing to the cross-coupling between electrical current and speed state equations. It should be noted that all the parameters vary with operating conditions; primarily the applied load torque disturbance and temperature [1,10].

3 Design of the controller

Figure 1 shows a schematic diagram of a variable-frequency VSC system to control the PMSM. The control system consists by the following parts: a PMSM, a sinusoidal pulse width modulation (SPWM), torque controller in *dq* frame and voltage source inverter (VSI). The control goal is to design an asymptotically stable speed controller for PMSM to make the rotor speed track the reference trajectory correctly under different parameter perturbations and load torque disturbance variation. Hence, the main control error can be defined as

$$e = \omega_r - \omega \qquad (5)$$

where ω_r is the reference signal. Having two inputs v_d and v_q, we can choose other additional output to be controlled: the current i_d. Thus, we define the following auxiliary control error

$$e_d = i_{dr} - i_d \qquad (6)$$

where i_r is the reference constant signal for the current i_d. The absence of *d*-axis stator current there is no reluctance torque and only the *q*-axis reactance is involved in finding the terminal voltage, i.e. there is no direct magnetization or demagnetization of d-axis, only the field winding acts to produce flux in this direction, we chose the reference signal in (1) as i_{dr}=0. For this situation, the field current in the d-axis and the stator current in the q-axis are 90° apart as is the case in the dc machine.

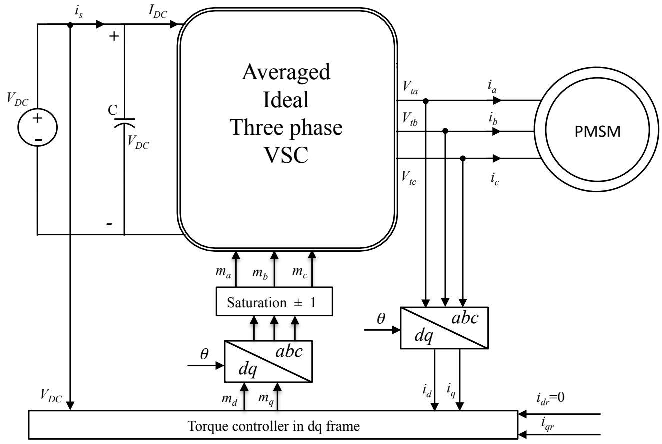

Figure 1: Block diagram of the control system for the PMSM.

Introducing the two new control variables as [20]

$$u_d = PL_q i_q \omega + v_d \qquad (7)$$

$$u_q = -P\left(L_d i_d + \psi\right)\omega + v_q \qquad (8)$$

we can simplify (1) and (2) as follows

$$L_d \frac{di_d}{dt} + R_s i_d = u_d \qquad (9)$$

$$L_q \frac{di_q}{dt} + R_s i_q = u_q \qquad (10)$$

We can see that (9) and (10) are two decoupled systems of first grade. Therefore, two independent feedback loops can be employed to control i_d and i_q, as shown in Figure 2. There are two PI controllers used in the strategy. The inner loops are constituted by two controllers, which regulate the d and q-axis of the stator currents. The electromagnetic torque may be controlled directly by the *q*-axis current component i_q, therefore the speed can be controlled by changing *q* axis current, and d-axis current component i_d is set to zero to minimize the current and resistive losses for a given torque. [21]. The outputs from the two current controllers are the *d* and *q*-axis stator voltage, which are sent to the sinusoidal pulse-width modulation (SPWM) block. The SPWM will generate the switching signals required by the IGBT elements of the VSI. This article proposes the use of adaptive PI controllers to regulate the speed rotor a desired value under load and parametric variations. This can be achieved adding a B-SNN to update K_P and K_I gains in the two PI controllers (Figure 2), where each PI transfer function is given by

$$\frac{U(s)}{E(s)} = \frac{K_I + sK_P}{s} \qquad (11)$$

Thus, K_P and K_I are updated from a B-SNN at every sampled time.

3.1 Reference current i_q

Differentiating (5) with respect to time, we have

$$\frac{de}{dt} = \frac{d\omega}{dt} - \frac{d\omega_r}{dt} = \frac{P}{2}\frac{3}{2}\frac{p\psi_m i_q}{J} - \frac{d\omega_r}{dt} \qquad (12)$$

To assign the desired dynamics for e as

$$\frac{de}{dt} = -c_1 e \qquad (13)$$

with c_1>1, we choose the fictitious control i_{qr} in the first as

$$i_{qr} = \frac{2}{P}\left(\frac{d\omega_r}{dt}\frac{J}{k_m} + \frac{Jc_1 e}{k_m}\right) + \frac{T_l}{k_m} \qquad (14)$$

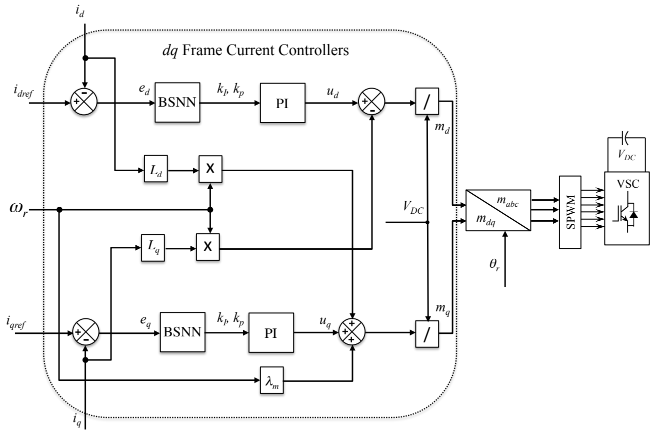

Figure 2: The closed loop speed control of PMSM with B-SNN.

3.2 B-spline neural network

The major advantages of the ANNs are the controller's design simplicity, their compromise between the complexity of a conventional non-linear controller, and its performance. The B-SNNs are a particular case of neural networks that allows the control and modelling of systems adaptively, with the option of carrying out such tasks on-line and taking into account the PMSM non-linearities.

B-spline NN belong to a class of networks known as lattice-based Associative Memory Networks (AMN), used generally for functional approximation tasks. The network has a fixed structure and a set of adaptive parameters that are iteratively trained in order to achieve the desired behavior, with the option of carrying out such tasks on-line, and taking into account the power grid non-linearities. The on-line B-spline associative memory network (AMN) adjusts its weights iteratively in an attempt to reproduce a particular function, whereas an off-line or batch B-spline algorithm typically generates the coefficients by matrix inversion or using conjugate gradient. B-spline AMNs adjust their (linear) weight vector, generally using instantaneous least mean square (LMS)-type algorithms, in order to realize a particular mapping, modifying the strength with which a particular basis function contributes to the network output. Through BSNN there is the possibility to bound the input space by the basis functions definition.

The BSNN's output can be described by [22],

$$y = \mathbf{a}^T\mathbf{w}$$
$$\mathbf{w} = \begin{bmatrix} w_1 & w_2 & \cdots & w_n \end{bmatrix}; \quad \mathbf{a} = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix}; \qquad (15)$$

where w_i and a_i are the i-th weight and the i-th BSNN basis function output, respectively; n is the number of weighting factors. i refers to sub-index that can take values from 1 to n (vector dimension); and n represents the number of weighting factors, it depends on a particular application. In this case, only two weight's factor was used to each ANN, Fig. 3. It allows diminish the computational effort with well system response. In this paper it is proposed that K_P and K_I be adapted through one BSNN, respectively, for each voltage source converter. The error signals are the same of PI controllers. Then the dynamic control parameters for the PMSM can be described as follows:

$$K_x = NN_m\left(e_x, w_i\right) \qquad (16)$$

where NN_m denotes the BSNN which is used to calculate K_P and K_I; w_i is the corresponding weighting factor; m=1,2,3 number of PI controllers. Fig. 3 depicts a scheme of the proposed BSNN.

The appropriate design requires the following a-priori information: the bounded values of e_x, the size, shape, and overlap definition of the basis function. Likewise, with this information the BSNN estimates the optimal weights' value. The neural network adaptive parameters, (15)-(16) are created by univariate basis functions of order 3, considering that e_x is bounded within [-1.5, 1.5].

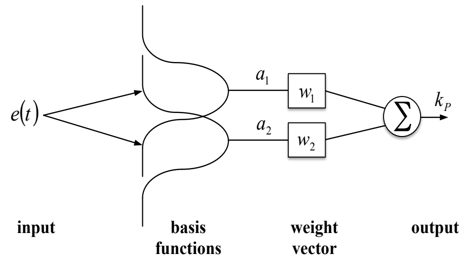

Figure 3: Proposed BSNN for adapting K_P and K_I control parameters.

3.3 B-spline learning

Many neural network-training rules are simply instantaneous algorithms (together with nonlinear variations) and in recent years there has been a growing interest in trying to understand what and how neural networks learn. The learning must be local, in that the parameters adapted should only affect the output of the network locally. Instantaneous learning rules are formulated by minimizing instantaneous estimates of a performance function, which is generally the Mean Square output Error (MSE), and the parameters are updated using gradient descent rules. The B-spline network depends linearly on a set of weights, and they are these parameters, which are updated using the basic learning rules.

On-line learning of continuous functions, mostly via gradient-based methods on a differentiable error measure is one of the most powerful and commonly used approaches to train large layered networks in general [23], and for nonstationary tasks in particular. In this application, the parameter's quick updating is looked for. While conventional adaptive techniques are suitable to represent objects with slowly changing parameters, they can hardly handle complex systems with multiple operating modes. The instantaneous training rules provide an alternative so that the weights are continually updated and reach the convergence to the optimal values. Also, conventional nets sometimes do not converge, or their training takes too much time [23].

In this paper, the BSNN is trained on-line using the following error correction instantaneous learning rule [22],

$$w_i = w_i(t-1) + \frac{\eta e_i(t)}{\|\mathbf{a}(t)\|_2^2} a_i(t) \qquad (17)$$

where η is the learning rate and $e_i(t)$ is the instantaneous output error.

Respect to the learning rate, it takes as initial value one point within the interval [0, 1] due to stability purposes. This value is adjusted by trial-and-error. If η is set close to 0, the training becomes slow. On the contrary, if it is large, oscillations may occur. In this application, it settles down in 0.071 for K_P 0.0019 for K_I. The BSNN training process is carried out continuously on-line, while the weights' values are updated. It is proposed that during the actualization procedure, a dead band is included to improve the learning rule convergence. The weighting factors are not updated if the error has a value below 0.1%,

$$w_i(t) = \begin{cases} w_i(t-1) + \dfrac{\eta e_i(t)}{\|\mathbf{a}(t)\|_2^2} a_i(t), & if\ |e_i| > 0.0001 \\ w_i(t-1), & otherwise \end{cases} \qquad (18)$$

This learning rule has been elected as an alternative to those that use, for instance, Newton's algorithms for updating the weights that require Hessian and Jacobian matrix evaluation. Regarding the weight's updating (18) should be applied for each input-output pair in each sample time; the updating occurs if the error is different from zero.

The parameters are chosen by trial-and-error, following the heuristic given in [22], which states that the simplest acceptable adaptive system produces the best results. The position of the knots is selected using a priori information about the system. The learning rate values are elected based on a compromise between fast learning and greater noise filtering.

3.4 Sliding Mode Control

The control strategy is to design a controller to track the desired signals that are normally provided by an outer-loop speed controller, as shown in the Fig. 4. If we are able to make the current component i_d=0, we have some benefits. Select the control voltages as [10]

$$u_d = u_{0d}\,sign(S_d) \qquad (19)$$

$$u_q = u_{0q}\,sign(S_q) \qquad (20)$$

where u_{0i} are the maximum values of control signals, $S_d = e_d$ and $S_q = i_{qr} - i_q$. As stated previously, we consider the stator currents are measured signals. Nevertheless, the rotor speed and load torque can be estimated by means of the nonlinear observer described by

$$\frac{d\hat{\omega}}{dt} = \frac{\tau_p i_q}{J} - \frac{\hat{T}_l}{J} - K_\omega e_\omega \qquad (21)$$

$$\frac{d\hat{T}_l}{dt} = k_l e_\omega \qquad (22)$$

where $e_\omega = \omega - \hat{\omega}$ and $\tau_p = 1.5P\psi_m$. Thus, the nonlinear observer (21-22) can be seen as a linear system with time varying parameters when the currents i_d and i_q are assumed to be known functions. The resulting estimates ω and T_l are employed in the control law (7-8) and (19-20).

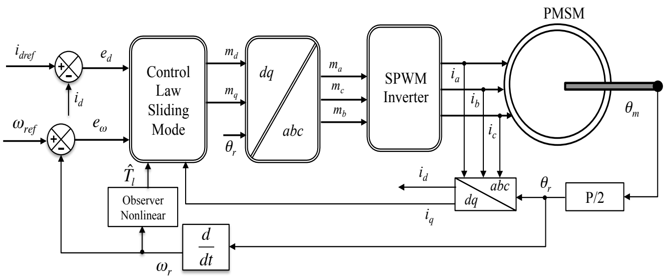

Figure 4: Block diagram of the speed control of a PMSM with Sliding Mode Technique

4 Simulation results

The simulations were performed in a personal computer to demonstrate the effectiveness of the proposed control algorithms. Throughout, the synchronous motor was modelled using (1-4) with parameters of the synchronous motor with a rated power of 1 Kw, that shows the table 1. The block diagram of the overall control system is depicted schematically in Fig. 1.

HSS inertia:	J=3.5x10^{-5} kg m^2
R_s is the stator resistance	2.6 Ohms
No. of poles	p=2
Stator inductance	L_d=L_q=6.73 mH
Magnet flux linkage	ψ_m=0.319 Wb
Rated Voltage	120 volts

Table 1: Parameters of the synchronous motor

The controller gain in (13) was adjusted to c_l=2900, and the no lineal observer gains in (24) were chosen as K_ω =850 y K_l =-7. All initial conditions of the motor and the observer are set to zero. In the simulation the speed of the loaded motor is required to reach first its rated value 150 rad/seg with a load torque of 0.5 N-m², at 0.4 seconds ω_r is subjected to a step change from 150 to 50 rad/seg, at 0.04 seconds ω_r is subjected to a step change from 150 to 50 rad/seg, at 0.11 seconds ω_r is subjected to another step change from 50 to -50 rad/seg, at 0.15 seconds ω_r is subjected to a step change from -50 to 20 rad/seg and finally 100 rad/seg after the 0.2 seconds, as show Fig. 5.

At 0.05 seconds the load torque is increased up to 1 N-m², which is 100% greater than the initial value, at 0.095 seconds T_l is subjected to a step change from 1 to 0.6 N-m², at 0.13 seconds T_l is subjected to another step change from 0.6 to 0.8 N-m² and finally 1.1 N-m² after the 0.23 seconds; as watch Fig. 6.

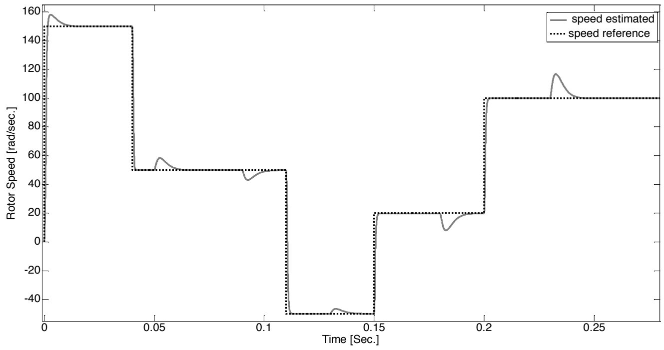

Figure 5: Motor speed reference (dotted line) and speed estimated (solid line).

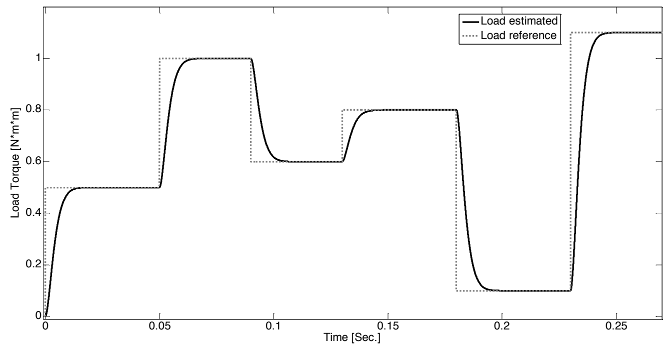

Figure 6: Motor speed reference (dotted line) and load estimated (solid line).

An important issue of the electrical drives is the capability to reject the effects of load disturbances. Figure 7-8 shows the responses when a step load torque T_l is suddenly applied after running up. With a maximum speed change of only 1 rad./sec. the speed velocity of rotor returns to desired value within 0.01 sec. as show in fig. 7. This reveals that the performance of the overall system is robust to the load disturbance.

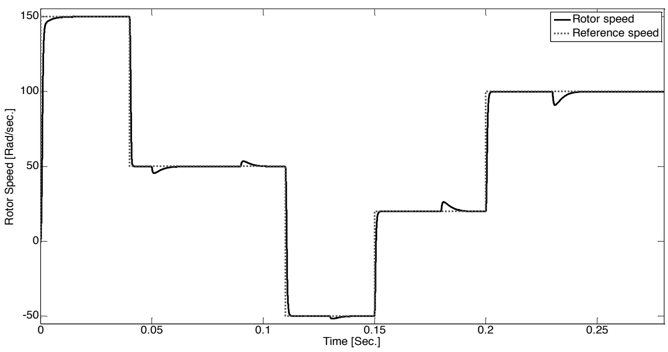

Figure 7: Speed tracking response under load torque disturbance variation.

5 Conclusions

A sliding mode controller is proposed exhibiting robust stability and performance when the plant experiences larges disturbances. An effectiveness robust nonlinear speed control scheme for a PMSM which guarantees the robustness in the presence of parameter variations. To show the validity of proposed control scheme experimental works have been carried out under various conditions. Compared with the conventional nonlinear control scheme, the proposed robust nonlinear control scheme provides good transient responses under the load torque and rotor speed desired variations. It is design is demonstrated through simulations.

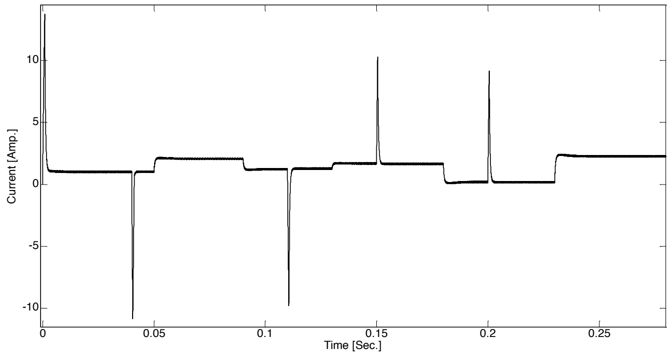

Figure 8: Dynamic performance of the current in q axis under different rotor speed and load torque disturbance variation.

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