Adaptive backstepping controller design based on neural network for PMSM speed control

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ABSTRACT

The aim of this research is the speed tracking of the permanent magnet synchronous motor (PMSM) using an intelligent Neural-Network based adapative backstepping control. First, the model of PMSM in the Park synchronous frame is derived. Then, the PMSM speed regulation is investigated using the classical method utilizing the field oriented control theory. Thereafter, a robust nonlinear controller employing an adaptive backstepping strategy is investigated in order to achieve a good performance tracking objective under motor parameters changing and external load torque application. In the final step, a neural network estimator is integrated with the adaptive controller to estimate the motor parameters values and the load disturbance value for enhancing the effectiveness of the adaptive backstepping controller. The robsutness of the presented control algorithm is demonstrated using simulation tests. The obtained results clearly demonstrate that the presented NN-adaptive control algorithm can provide good trackingperformances for the speed trackingin the presence of motor parameter variation and load application.

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1. INTRODUCTION

The permanent magnet synchronous motor (PMSM) is employed for a longue period in many industrial applications. It is characterised by numerous significant advantages such as: compact design, great efficiency, high ratios values between power/weight and torque/inertia. But, behind these advantages the PMSMs has most known advantages which are the high cost and time-varying magnetic characteristics [1]-[3]. Furthermore, their dynamic model presents a high nonlinearity in raison of the coupling between the motor torque and *d*-*q* axis currents. The parameters of PMSM, i.e. electrical/mechanics parameters, like stator resistance and friction coefficient are often not measured with accuracy. Of course, the external load torque value in the majority of cases is unknown and cannot be known precisely [1]-[2]. So, with these constraints the controllawscomputingbecame very difficult and may not be robust to PMSM speed control under severe operated conditions in some real industrial applications like high speed and precision requirement.

The fieldoriented control, known by vector control, is considered among the most important techniques used in closed loop control of alternative currentmachinesfor variable speed applications. It can suppress dynamic model nonlinearity especially the decoupling existing between torque and flux, so they can be regulated each one seperatly [1]-[5].

With this control strategy the PMSM can be shown like a separately excited direct currentmotorwhile it can maintain the AC motor advantages over DC motors [1], [2], [4], [5]. However, the vector control performances may be deteriorated due to mator parameters variation, in particular the stator resistance and winding inductances which increase with temperature increasing and the magnetizing saturation effect [2], [4]-[11]. Recently, great attraction has been shown to the identification of parameters variation of the PMSM during normal operationg drive. This refreshing an important scientific activity to devlop new nonlinear adaptive control strategies in order to enhance the drive performances achieving speed and flux tracking with accuracy [6], [7], [9]-[17].

Due the great evolution in nonlinear and adaptive control, several techniques have been successfully implemented for industrial applications in the past decades. Among these strategies that have been applied in electric drives systems, especially AC motors, is the backstepping method [9]-[16], [18]. It is an orderly and recursive design algorithm destined for nonlinear feedback control, convenable with a wide type of feedback nonlinear systems which can be linearised and feedback linearisable nonlinear systems presenting invariant uncertainty, and it ensures total regulation and tracking performances. This strategy may reduce some limitations existing in other nonlinear methods [9]-[13]. It provides the choice of procedure design to taking into account uncertainties and high nonlinearities and can avert inutilsconcellations. The basic procedure of backstepping control developpement depends on recursive selection of some adequate functions in terms of state variables like pseudo-control inputs for subsystems of the global system. In each step end of the backstepping, a new pseudo-control variable is obtained which is expressed as a function of the pseudo-control variables from the previous steps. At the end of the procedure, a feedback computing for the real control input is obtained and realizes the objective design using a global Lyapunov function wich is expressed as sum of Lyapunov functions of each step [9]-[16].

In the literature, several researches have showing the introduction of artificial intelligence (AI) techniques, especially neural networks, in various industry applications to improve the robustness of the nonlinear adaptive control techniques. Neural networks (NNs) have been employed like a function approximation to represent functions with weighted sums of nonlinear terms [19]-[21]. They have proven a good potentiality for complex systems modelling and as adaptive controller for nonlinear systems [19]-[28]. Exploiting their universal approximation potentienality, the intelligent controller associated with NNs may be constructed without knowledge requirement of the systems. A detailed state-of-art about the different applications of NNs and their employement in the power electronics devices and variable speed applications has been presented in [24]. The authors of [19] have been proposed an intelligent adaptive-backstepping controller design using a hidden-layer RNN for the mover position control of linear induction motor, in which the method of gradient-descent is utiliszed to determine the NN parameter-training algorithms. F. J. Lin*et al.*, [22], a PI-NNs controller with single NN is introduced for Maglev position control, where a single neuron network unit is integrated in the vector control closed-loop for LIM servo-drive.

In this paper, the developpement of nonlinear adaptive backstepping controller exploiting the vector control using neural network for estimation of electrical parameters for PMSM speed control is proposed. The presented controller is developed to construct the control scheme, which is unsensitive to changing of the parameters and load variations. The rest of this paper is organized as follows. Section 2 describes the motor dynamic model and the application of the vector control for permanent magnet synchronous motor. Section 3 reviews different step designs of the adaptive backstepping controller for PMSM speed control. The principle of the neural network estimator of electrical parameters associated to the nonlinear adaptive backstepping is detailled in section 4. Section 5 gives different simulation tests and results. Finally, some conclusions are given in section 6.

2. MATHEMATICAL MODEL OF THE PMSM

The model of a non sailentPMSM can be expressed in the synchronous (*d–q*) frame through the Park transformation as: [1], [2], [5], [29]-[32]:

$$\begin{aligned} v_d &= R_s i_d + p\phi_d - \omega\phi_q \\ v_q &= R_s i_q + p\phi_q + \omega\phi_d \end{aligned} \tag{1}$$

Where

$$\phi_d = L_d i_d \tag{2}$$

$$\phi_q = L_q i_q + \phi_f \tag{3}$$

ϕ_f is the magnet flux linkage,

Thus, the dynamic model of a non sailent PMSM can be described as [29]-[32]:

$$\begin{aligned}
\frac{di_d}{dt} &= -\frac{R_s}{L_d} i_d + \frac{P\omega L_q}{L_d} i_q + \frac{1}{L_d} v_d \\
\frac{di_q}{dt} &= -\frac{R_s}{L_q} i_q + \frac{P\omega L_d}{L_q} i_d - \frac{P\phi_f}{L_q}\omega + \frac{1}{L_q} v_q \\
\frac{d\omega}{dt} &= \frac{3P\phi_f}{2J} i_q + \frac{3P}{2J}\left(L_d - L_q\right) i_d i_q - \frac{B}{J}\omega - \frac{T_l}{J}
\end{aligned} \tag{4}$$

Where i_d and i_q denote the *d–q* axis currents, v_d and v_q represent the *d–q* axis voltages, R_s is the stator resistance, L_d, L_q denoted*d*- and *q*- axes stator inductances, P represents the pole pairs, J denotesthemoment of inertia, B is the coefficient of friction, T_l is the load torque, ω is the mechanical angular speed, ϕ_f is the permanent magnetic flux linking the stator.

According to the model given in (4), it can be observer that the control of the rotor speed can be done by regulating the *q*-axisvoltage v_q [1], [2]. When the *d*-axis current i_d is keeped equal to zero, then the PMSM dynamic model can be shown as [1], [2], [29]-[35]

$$\begin{aligned}
\frac{di_q}{dt} &= -\frac{R_s}{L_q} i_q - \frac{P\phi_f}{L_q}\omega + \frac{1}{L_q} v_q \\
v_d &= -P\omega L_q i_q \\
T_{em} &= \frac{3P\phi_f}{2J} i_q
\end{aligned} \tag{5}$$

3. NONLINEAR ADAPTIVE BACKSTEPPING CONTROLLER FOR PMSM SPEED CONTROL

The backstepping technique is a methodical approach to build Lyapunov equation and unsensitive controller, so that the system is evenly asymptotic stable [9]-[16]. In the design, constructing suitable function enables system design to achieve expected purpose. The main objective of designing this controller is to compute the input control voltages of the PMSM to attend precisely speed tracking performance. Utiliszing stability theory according to Lyapunov and adaptive backstepping strategy, with the appropriate Lyapunov function, we can obtain a specific controller. As there are various disturbed parameters in different combinations according to various situations, and then the adaptive update law can be designed correspondingly [11]-[16]. In order to track the speed of PMSM, the development of the adaptive nonlinear controller involves the following steps.

Step 1:

In this first step, a speed tracking error can be defined as

$$e_1 = \omega^* - \omega \tag{6}$$

Where ω^* is the desired reference trajectory of the rotor speed, and the speed error dynamic is given by (7).

$$\begin{aligned}
\dot{e}_1 &= \dot{\omega}^* - \dot{\omega} \\
&= \dot{\omega}^* - \left(\frac{3P\phi_f}{2J} i_q + \frac{3P}{2J}\left(L_d - L_q\right) i_d i_q - \frac{B}{J}\omega - \frac{T_L}{J}\right)
\end{aligned} \tag{7}$$

As the speed error needs to be reduced to zero, the q-axe current component i_q is identified as the first virtual control element to stabilize the motor speed. To determine the stabilizing function, the following Lyapunov function is shoosenas

$$V = \frac{1}{2} e_1^2 \tag{8}$$

We differentiate (8) to get

$$\begin{aligned} \dot{V}_1 &= e_1 \dot{e}_1 \\ &= e_1 \left(\dot{\omega}^* - \left(\frac{3P\phi_f}{2J} i_q + \frac{3P}{2J} \left(L_d - L_q\right) i_d i_q + \frac{B}{J} \omega + \frac{T_l}{J} \right) \right) \\ &= -k_1 e_1^2 + e_1 \cdot \left(k_1 e_1 + \dot{\omega}^* - \frac{3P\phi_f}{2J} i_q - \frac{B}{J} \omega - \frac{T_l}{J} \right) - \frac{3P}{2J} \left(L_d - L_q\right) i_d i_q e_1 \end{aligned} \tag{9}$$

Where, k_1 is positive gain. The tracking speed objectives are achieved if a stabilizing function is defined as

$$i_q^* = \frac{2J}{3P\phi_f} \left(k_1 e_1 + \dot{\omega}^* - \frac{B}{J} \omega - \frac{T_l}{J} \right) \tag{10}$$

$$i_d^* = 0 \tag{11}$$

i_d^* and i_q^* are the references currents. By substituting (10) and (11) into (9) yields

$$\dot{V}_1 = -k_1 e_1^2 \tag{12}$$

Thus, the virtual control is asymptotically stable. Since the load torque T_l is unknown we must use its estimate value $\hat{T}_l$ in (10). Thus, let us define

$$\hat{i}_q^* = \frac{2J}{3P\phi_f} \left(k_1 e_1 + \dot{\omega}^* - \frac{B}{J} \omega - \frac{\hat{T}_l}{J} \right) \tag{13}$$

Step 2: Now we go to next step and try to make the signals i_d^* and i_q^* behave as desired. So, we define the following error signals involving the desired variables

$$\begin{aligned} e_2 &= \hat{i}_q^* - i_q \\ &= \frac{2\hat{J}}{3P\phi_f} \left(k_1 e_1 + \dot{\omega}^* - \hat{F}\omega - \hat{\Gamma} \right) - i_q \end{aligned} \tag{14}$$

$$\begin{aligned} e_3 &= i_d^* - i_d \\ &= -i_d \end{aligned} \tag{15}$$

Then the error (7) can be written as

$$\dot{e}_1 = \frac{1}{J} \left[-\tilde{T}_l + \frac{3P}{2} \phi_f e_2 - k_1 e_1 J + \frac{3P}{2} \left(L_d - L_q\right) e_1 i_q \right] \tag{16}$$

Where $\tilde{T}_l = \hat{T}_l - T_l$ is the estimation error.

To stabilize the current components i_d and i_q, we define now the current error dynamics as

$$\begin{aligned}\dot{e}_2 &= \dot{\hat{i}}_q^* - \dot{i}_q = \frac{2}{3P\phi_f}\left(B\dot{\omega} + k_1 J\dot{e}\right) - \dot{i}_q \\ &= \frac{2}{3P\phi_f}\left(B - k_1 J\right)\dot{\omega} - \left(-\frac{R_s}{L_q}i_q - \frac{P\omega L_d}{L_q}i_d - \frac{P\omega\phi_f}{L_q} + \frac{1}{L_q}v_q\right) \\ &= \frac{2\left(B - k_1 J\right)}{3P\phi_f J}\left[\frac{3P}{2}\left(\phi_f i_q + \left(L_d - L_q\right)i_d i_q\right) - B\omega - T_l\right] + \frac{R_s}{L_q}i_q \\ &\quad + \frac{P\omega L_d}{L_q}i_d + \frac{P\omega\phi_f}{Lq} - \frac{v_q}{L_q}\end{aligned} \tag{17}$$

$$\dot{e}_3 = -\dot{i}_d = \frac{R_s}{L_d}i_d - \frac{P\omega L_q}{L_d}i_q - \frac{1}{L_d}v_d \tag{18}$$

Now, since the actual control inputs v_d and v_q have appeared in the above equations, we can go to the final step where both control and parameter updating laws are determined. In the most practical cases, it's very known that the PMSM inductances L_d and L_q frequently vary with the saturation effect in the stator and rotor cores, so it is very necessary to identify their values using an adaptive method to update the applied control laws.

Step 3: To develop the control and parameter updating laws, we define a new Lyapunov candidate function which include the current error variables e_2, e_3 and the parameter estimation errors $\tilde{L}_d$, $\tilde{L}_q$ and $\tilde{T}_l$ as:

$$V_2 = \frac{1}{2}\left(e_1^2 + e_2^2 + e_3^2 + \frac{1}{\gamma_1}\tilde{L}_d^2 + \frac{1}{\gamma_2}\tilde{L}_q^2 + \frac{1}{\gamma_3}\tilde{T}_l^2\right) \tag{19}$$

Where γ_1, γ_2 and γ_3 denote adaptive positive constants, and $\tilde{L}_d = \hat{L}_d - L_d$, $\tilde{L}_q = \hat{L}_q - L_q$ and $\tilde{T}_l = \hat{T}_l - T_l$ are the errors on the estimated inductances.We differentiate the Lyapunov function V_2 in (19) and substitute all error dynamics to get.

$$\dot{V}_2 = \dot{e}_1 e_1 + \dot{e}_2 e_2 + \dot{e}_3 e_3 + \frac{1}{\gamma_1}\tilde{L}_d\dot{\tilde{L}}_d + \frac{1}{\gamma_2}\tilde{L}_q\dot{\tilde{L}}_q + \frac{1}{\gamma_3}\tilde{T}_l\dot{\tilde{T}}_l \tag{20}$$

$$\begin{aligned}\dot{V}_2 &= -k_1 e_1^2 - k_2 e_2^2 - k_3 e_3^2 + \frac{e_1}{J}\left[-\tilde{T}_l + \frac{3P}{2}\phi_f e_2 - k_1 e_1 J + \frac{3P}{2}\left(L_d - L_q\right)e_2 i_q\right] \\ &\quad + e_3\left(\frac{R_s}{L_d}i_d + \frac{P\omega L_d}{L_d}i_d + k_3 e_3 - \frac{1}{L_d}v_d\right) + \\ &\quad e_2\left\{\begin{aligned}&\frac{2\left(B - k_1 J\right)}{3P\phi_f J}\left(\frac{3P}{2}\left(\phi_f i_q + \left(L_d - L_q\right)i_d i_q\right)\right. \\ &\left. - B\omega - T_l\right) + \frac{R_s}{L_q}i_q + \frac{P\omega L_d}{L_q}i_d \\ &+ k_2 e_2 - \frac{1}{L_q}v_q\end{aligned}\right\} + \frac{1}{\gamma_1}\tilde{L}_d\dot{\tilde{L}}_d + \frac{1}{\gamma_2}\tilde{L}_q\dot{\tilde{L}}_q + \frac{1}{\gamma_3}\tilde{T}_l\dot{\tilde{T}}_l\end{aligned} \tag{21}$$

If the *d-q* axes control voltages are selected as:

$$v_d = R_s i_d - P\omega \hat{L}_q i_q + k_1 e_2 \hat{L}_d + \frac{3P}{2J} \hat{L}_d \left(\hat{L}_d - \hat{L}_q\right) i_q e_1 \tag{22}$$

$$\begin{aligned} v_q = {} & \frac{2L_q (B - k_1 J)}{3P\phi_f J} \left(\frac{3P}{2} \left[\phi_f i_q + \left(\hat{L}_d - \hat{L}_q\right) i_d i_q\right] \right. \\ & \left. + -B\omega - \hat{T}_l \right) + R_s i_q + P\omega \hat{L}_d i_d + P\omega\phi_f \\ & + k_2 e_2 \hat{L}_q + \frac{3P}{2J} \phi_f e_1 \hat{L}_q \end{aligned} \tag{23}$$

Then, the (21) can be simplified to:

$$\begin{aligned} \dot{V}_2 = {} & \frac{e_1}{J}\left[\tilde{T}_l + \frac{3P}{2}\phi_f e_2 - k_1 e_1 J + \frac{3P}{2}\left(L_d - L_q\right) e_2 i_q\right] \\ & + \frac{e_3}{\hat{L}_d}\left(- P\omega\left(L_q - \hat{L}_q\right) i_q - k_3 e_3 \hat{L}_d - \frac{3P}{2J}\left(\hat{L}_d - \hat{L}_q\right)\hat{L}_d e_1 i_q\right) \\ & + \frac{e_2}{\hat{L}_q}\left\{ \begin{array}{l} \frac{\hat{L}_q (B - k_1 J)}{\phi_f J}\left(L_d - \hat{L}_d - L_q + \hat{L}_q\right) i_d i_q \\ - \frac{2L_q (B - k_1 J)}{3P\phi_f J}\left(T_l - \hat{T}_l\right) + P\omega\left(L_d - \hat{L}_d\right) i_d \\ - k_2 e_2 \hat{L}_q - \frac{3P}{2J}\phi_f e_1 \hat{L}_q \end{array} \right\} \\ & + \frac{1}{\gamma_1}\tilde{L}_d \dot{\tilde{L}}_d + \frac{1}{\gamma_2}\tilde{L}_q \dot{\tilde{L}}_q + \frac{1}{\gamma_3}\tilde{T}_l \dot{\tilde{T}}_l \end{aligned} \tag{24}$$

So, we can get the following expression:

$$\begin{aligned} \dot{V}_2 = {} & -k_1 e_1^2 - k_2 e_2^2 - k_3 e_3^3 + \tilde{T}_l\left(\frac{e_1}{J} + \frac{2e_2 (B - k_1 J)}{3P\phi_f J} + \frac{1}{\gamma_3}\dot{\tilde{T}}_l\right) \\ & + \tilde{L}_d\left(- \frac{3Pe_1 e_3 i_q}{2J} - \frac{e_2 (B - k_1 J) i_d e_2}{\phi_f J} - \frac{e_q P\omega i_d}{L_q} + \frac{1}{\gamma_3}\dot{\tilde{L}}_d\right) \\ & + \tilde{L}_d\left(\frac{3Pe_1 e_3 i_q}{2J} + \frac{e_2 (B - k_1 J) i_d i_q}{\phi_f J} + \frac{e_d P\omega i_d}{L_q} + \frac{1}{\gamma_2}\dot{\tilde{L}}_q\right) \end{aligned} \tag{25}$$

From (26), the following update laws can be given as:

$$\dot{\tilde{T}}_l = -\gamma_1\left[\frac{e_1}{J} + \frac{2e_2 (B - k_1 J)}{3P\phi_f J}\right] \tag{26}$$

$$\dot{\tilde{L}}_d = -\gamma_3\left(- \frac{3Pe_1 e_3 i_q}{2J} - \frac{e_2 (B - k_1 J) i_d e_2}{\phi_f J} - \frac{e_q P\omega i_d}{L_q}\right) \tag{27}$$

$$\dot{\tilde{L}}_q = -\gamma_2\left(\frac{3Pe_1 e_3 i_q}{2J} + \frac{e_2 (B - k_1 J) i_d i_q}{\phi_f J} + \frac{e_3 P\omega i_d}{L_q}\right) \tag{28}$$

Therefore, the derivative of Lyapunov function (25) became as:

$$\dot{V}_2 = -k_1 e_1^2 - k_2 e_2^2 - k_3 e_3^2 \leq 0 \tag{29}$$

For sufficiently positive k_1, k_2 and k_3, then proved that (27) guarantees asymptotic stability in the complete system.

4. ADAPTIVE BACKSTEPPING WITH NEURAL NETWORKS ESTIMATOR DESIGN FOR PMSM SPEED CONTROL

The great progress shown in adaptive nonlinear control is followed with a remarkable increasing of the introduction of the neural networks in complex systems identification [20]. With the assistance of neural networks, the linearity-in-the-parameter assumption of nonlinear function and the determination of regression matrices can be avoided. As a consequent of this association that in the last decade, a several scheme based on backstepping design schemes which combine between the backstepping technique and adaptive NNs are proposed [19], [20], [21], [24]-[28]. In this section, a neural network for parameter estimation of the adaptive nonlinear backstepping controller is investigated. This approach consists to employ the recurrent neural networks to improve the parameters adaptation of the nonlinear adaptive backstepping. The principle of this approach is based on the controller proposed in the above section where the updating laws of the motor parameters and load disturbance (L_d , L_q and T_l) is replaced by a neural networks estimator. The new estimator has the same input variables as shown in (27), (28) and (29) which have been undergone to a learning phase in order to get an intelligent estimator. The Figure 1 illustrates the principle scheme of the adaptive backstepping controller based on the neural networks estimator for PMSM speed control. A three-layer recurrentneuralnetwork as shown in Figure 2 which is comprised of an input layer, a hidden layer, and an output layer, is used to estimate the PMSM inductances L_d , L_q and the load torque T_l . The NN weights are adjusted adaptively by using the stable on-line learning algorithm derived from Lyapunov theory and the sigmoid activation function $\sigma(\cdot)$ is defined as:

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{30}$$

To design the neural networks estimator, the NN function is adopted in order to approximate the continuous function $F(x): \Re^n \rightarrow \Re$ over a compact set:

$$F(x,W) = W^T \Psi(x) \tag{31}$$

Where $x \in \Omega \subset \Re^n$ is neural networks input, $W = [w_1, \ldots, w_i]^T \in \Re^i$ is weight vector, $\Psi(x) = [\psi_1(x), \ldots, \psi_i(x)]^T$ is node vector, and element $\psi_i(x)$ is a Gaussian function.

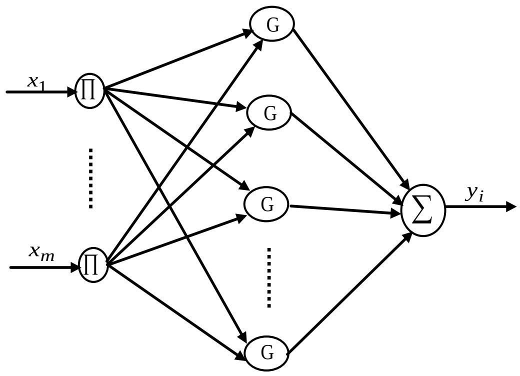


Figure 1. Structure of the neural network estimator

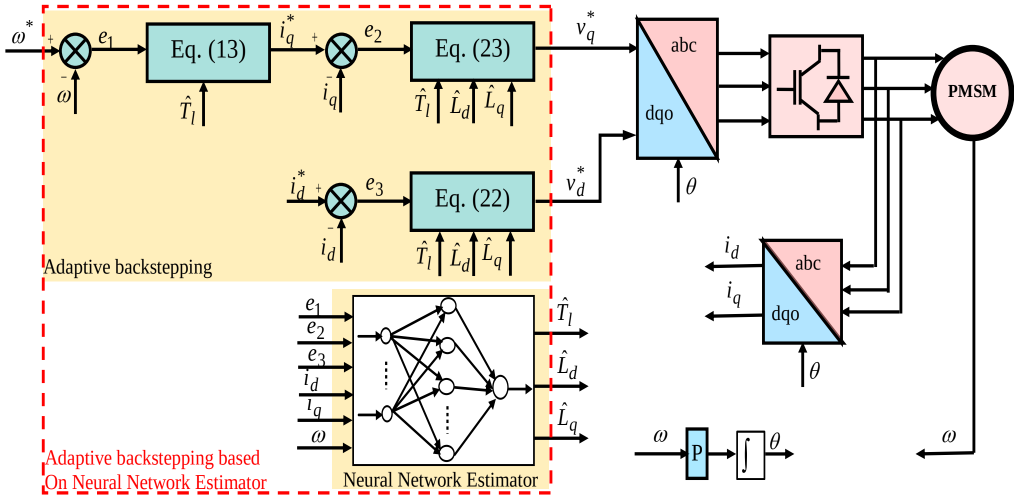


Figure 2. Block diagram of the adaptive backstepping based on NNs for PMSM control

5. SIMULATION RESULTS

To demonstrate the effectiveness and the robustness of the PMSM speed control using the described intelligent adaptive control scheme, some simulations tests have been carried out using MATLAB/Simulink software. Numerous simulations were performed, and sample results are shown here. The machine parameters are given in Table I in the Appendix. The configuration of the adopted control scheme is drawn in Figure 2. The parameter used in simulation are chosen as $k_1 = 200$, $k_2 = 300$, $k_3 = 300$.Twodifferent operating conditions for the permanent magnet synchronous motor are simulated to illustrate the operation of the proposed adaptive backstepping with neural network estimator, and the influence of the parameters uncertainties into PMSM drive system.

Test 1: In this test, the effectiveness of the adaptive nonlinear controller with NN estimator has been tested under reversing speed operation mode. This first test consists of step change on speed reference from 100rd/s to -100rd/s where the change is made at 5sec. The PMSM drive system is started with a constant load torque set at 1.2N.m then an additive load torque of 2.4N.m has been applied at $t = 1\text{sec}$ and it has taken off at $t = 2\text{sec}$. The performance of PMS motor drive using adaptive backstepping-NN estimator scheme under this operating condition test is depicted in Figures 3 (a)-(d). The rotor speed and the *d*-*q*axes motor current (i_d and i_q) are depicted in Figure 3 (a) and Figure 3(b), respectively. The Figures 3 (a)-(b) clearly shows that, the proposed adaptive backstepping based on NNs estimator scheme can achieve good tracking performance even in relation to load torque and electric parameters uncertainties. In Figure 3 (a), the speed response of the intelligent adaptive controller is observed that an accurate tracking performance and more robustness are obtained against speed reference reversals (minimal rising time, small undershoot against load torque application, with negligible overshoot and zero steady-state error). It could be noted that, with the presentedadaptivecontrolalgorithm, the current level in*d*-axis is kept to zero which proves a proper cross-coupling and an unperturbed field orientation ($i_d = 0$). The *q*-axis stator current swiftly reaches to its new value regarding to load torque values. This shows the capability of the adaptive controller in terms of disturbance rejection. Figure 3 (c) and Figure 3 (d) show the electromagnetic torque of the motor. It is observer that the electromagnetic torque T_{em} increases when the load disturbance is applied and it takes the form of the *q*-axis stator current i_q . Furthermore, Figures 4 (a)-(c) show the estimated values of the electrical parameters and load disturbance ($\hat{L}_d$, $\hat{L}_q$ and $\hat{T}_l$) and their real values. It is clearly shown that the estimated values of these parameters follow properly the measured values (real L_d , L_q and T_l) with a minimal error (error converges to zero), during different drive conditions.

***Test 2*:** Now, the proposed adaptive backstepping with neural network parameter adaptation has been tested under motoring mode at constant speed operating point. In this test, the PMSM control drive is subjected to a fixed desired speed equal to 100rd/s and load torque which is increased from 1.2N.m to 3.6N.m at 1sec and its return to its initial value at 2sec. An increasing in the *d*-axis and *q*-axis inductance has been applied from L_{dqN} to 150% of its nominal value. The performance of proposed adaptive control motor drive using the NN estimator under this operating test is depicted in Figures5 (a)-(c). The rotor speed and *d*-*q*axes motor current (i_d and i_q) are shown in Figure 5 (a) and Figure 5 (b). Figure 5 (c) show the electromagnetic torque of the motor. From the different simulation results, we can observe that the proposed adaptive control scheme can achieve favourable tracking performances even in relation to parameters variation and load uncertainties. It can be shown, that when parameters variation occur, the control performances didn't degenerated. Figures 6 (a)-(c) show the estimated values of the motor parameters and load disturbance ($\hat{L}_d$, $\hat{L}_q$ and $\hat{T}_l$) and their real values. It is clearly shown that the estimated values of these parameters perfectly follow the real values of L_d , L_q and T_l during different operation conditions.

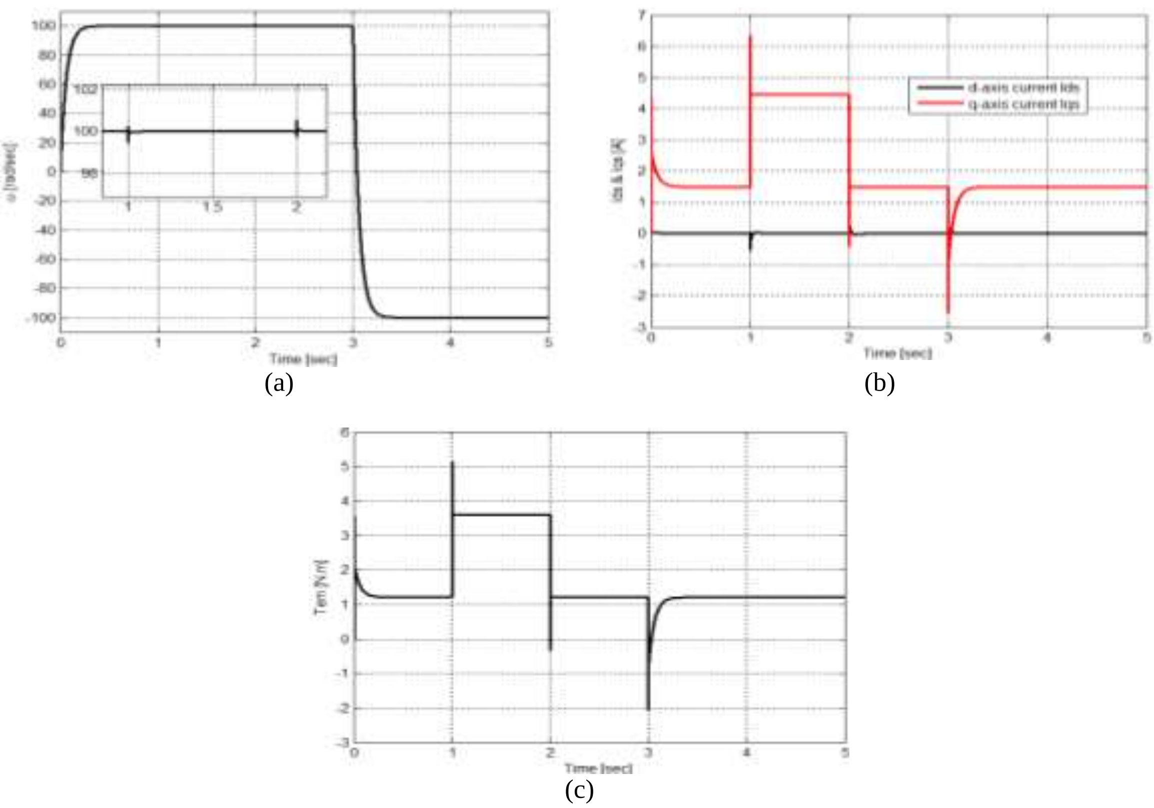
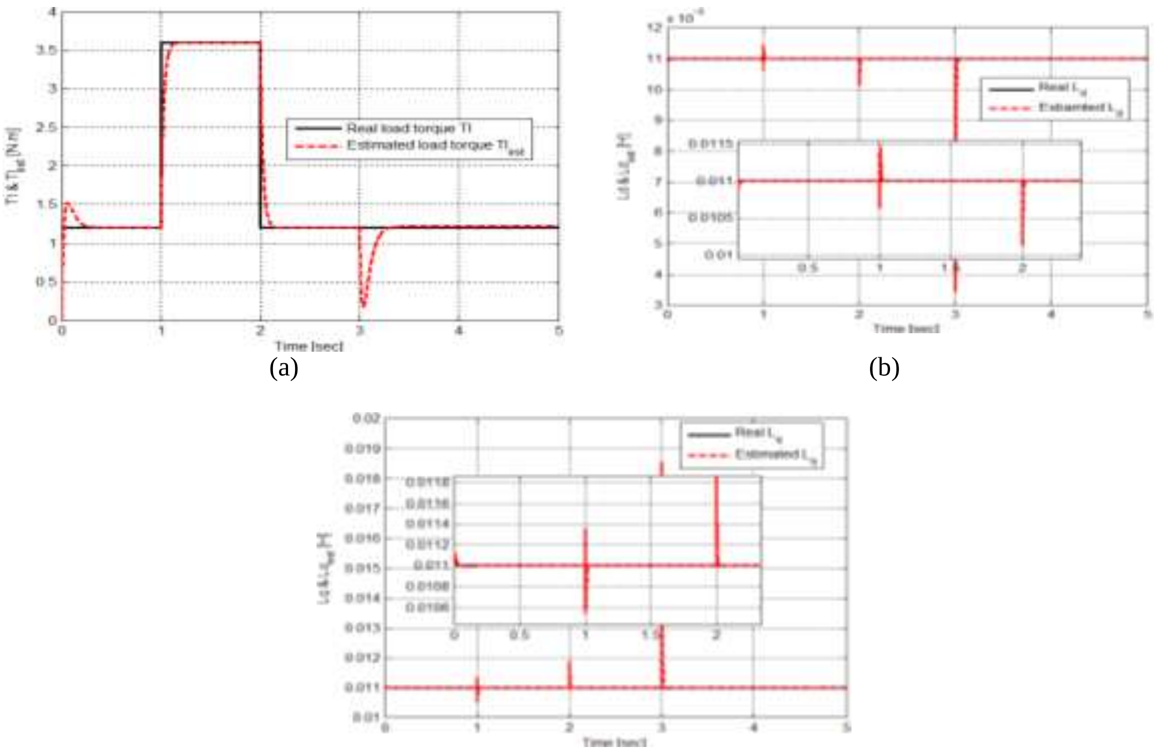


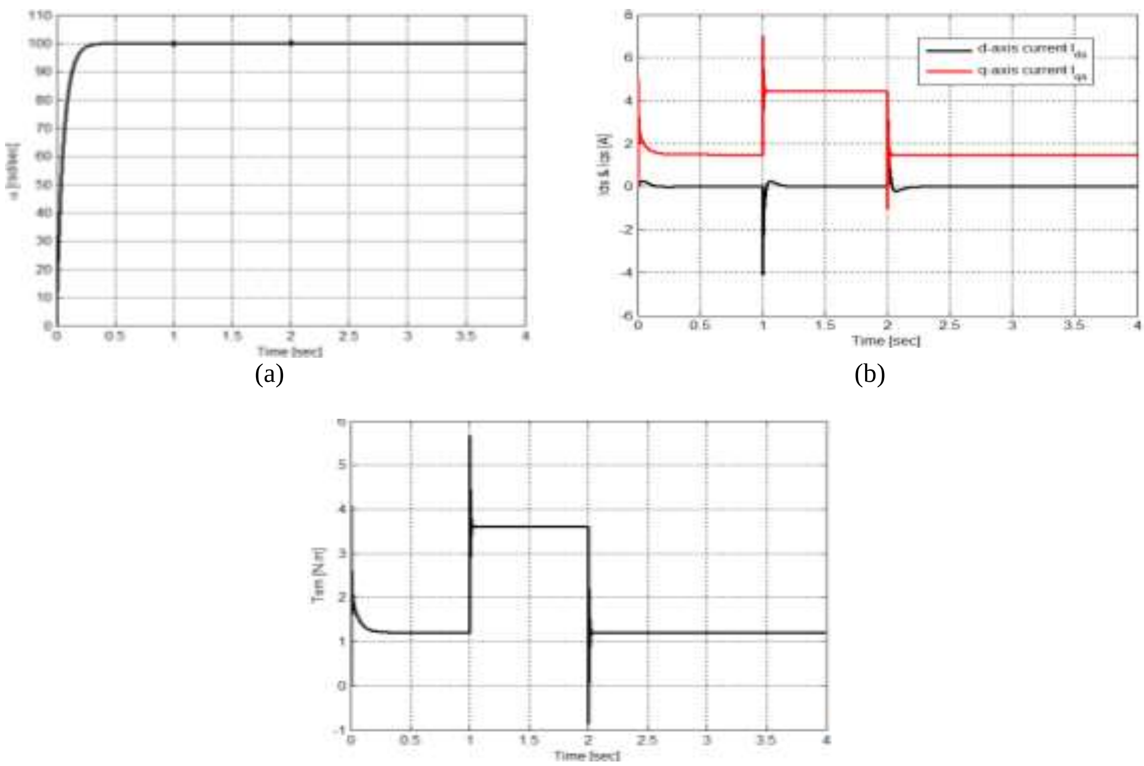
Figure 3. Simulation results of proposed AB-NNs estimator for the 1st test (a) speed, (b) d- & q-axis currents, (c) electromagnetic torque



(a) (b)

(c)

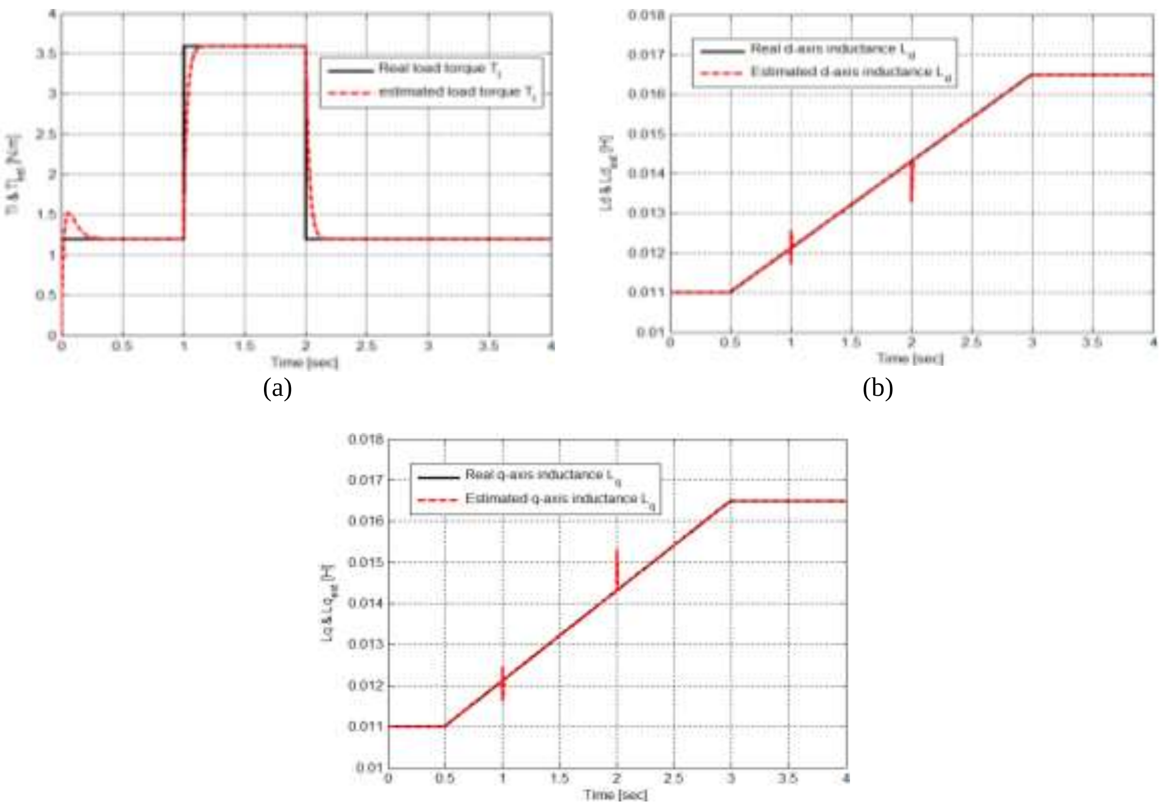
Figure 4. Simulation results of proposed AB-NNs estimator for the 1st test (a) T_l and $\hat{T}_l$, (b) L_d and $\hat{L}_d$ (c) L_q and $\hat{L}_q$



(a) (b)

(c)

Figure 5. Simulation results of proposed AB-NNs estimator for the 2nd test (a) speed, (b) *d*- &*q*-axis currents (c) electromagnetic torque



(a) (b)

(c)

Figure 6. Simulation results of proposed AB-NNs estimator for the 2nd test (a) T_l and $\hat{T}_l$, (b) L_d and $\hat{L}_d$ (c) L_q and $\hat{L}_q$

6. CONCLUSION

In this presented study, we have presented an adaptive nonlinear controller using backstepping technique with a neural networks parameter estimator in order to offer a choice of design to compensate parameters uncertainties and load disturbance estimation. This study has successfully demonstrated the application of the nonlinear adaptive backstepping control for the speed regulation of a permanent magnet synchronous motor based on field orientation control. The control laws were derived using the motor model incorporating the parameters variation and the external disturbances. By recursive procedure, pseudo-control states of the PMSM drive have been determined and stabilizing laws are calculated using the theory of Lyapunov stability. Variations of the electrical parameters and load torque have been estimated using a neural network employing the equation quantities developed by adaptive backstepping. The performance of the studied nonlinear adaptive control associated to neural network has been investigated in simulation using Matlab/Simulink software. The simulation results show its effectiveness and robustness at tracking a reference speed under electric parameters uncertainties and load torque disturbance.

APPENDIX

Table 1. PMSM parameters

Rated voltage	208V
Rated current	3A
Rated frequency	50Hz
Pole pair number P	3
d-axis inductance, L_d	11.00 mH
q-axis inductance, L_q	11.00 mH
Stator resistance, R_s	1.2Ω
Motor inertia, J	0.006 kgm^2
Friction coefficient, B	0.0001$Nm/rad/s$
Magnetic flux constant, ϕ_f	0.18 Wb

REFERENCES

[1] B. K. Bose, *Modern power electronics and AC drives*, Condra Chair of Excellence in Power Electronics the University of Tennesse, 2002.

[2] P. Vas, *Sensorless vector and direct torque control*, Oxford University Press, 1998.

[3] A. Khlaief, M. Boussak, and A. Châari, "A MRAS-based stator resistance and speed estimation for sensorlessvector controlled IPMSM drive," *Electric Power Systems Research*, vol. 108, pp. 1-15, 2014, doi: 10.1016/j.epsr.2013.09.018.

[4] A. Ghamri, R. Boumaaraf, M.T. Benchouia, H. Mesloub, A. Goléa, and N. Goléa, "Comparative study of ANN DTC and conventional DTC controlled PMSM motor," *Mathematics and Computers in Simulation*, vol. 167, pp. 219-230, 2020, doi: 10.1016/j.matcom.2019.09.006.

[5] L. M'hamed, A. Roufaida, A. A. N. Nawa, "Sensorless control of PMSM with fuzzy model reference adaptive system," *International Journal of Power Electronics and Drive System (IJPEDS)*, vol. 10, no. 4, pp. 1772-1780, 2019, doi: 10.11591/ijpeds.v10.i4.1772-1780.

[6] P. Gao, G. Zhang, H. Ouyang, and L. Mei, "An adaptive super twisting nonlinear fractional order PID sliding mode control of permanent magnet synchronous motor speed regulation system based on extended state observer," *IEEE Access*, vol. 8, pp. 53498-53510, 2020, doi: 10.1109/ACCESS.2020.2980390.

[7] X. Zhao, C. Wang, W. Duan, and J. Jiang, "Research on sensorless control system of low speed and high power PMSM based on improved high frequency signal injection," *Energy Reports*, vol. 7, pp. 499-504, 2021, doi: 10.1016/j.egyr.2021.01.066.

[8] W. A. E. M. Ahmed, M. M. Adel, M. Taha, and M. A. Saleh, "PSO technique applied to sensorless field-oriented control PMSM drive with discretized RL-fractional integral," *Alexandria Engineering Journal*, vol. 60, no. 4, pp. 4029-4040, 2021, doi: 10.1016/j.aej.2021.02.049.

[9] J. Lau, "Adaptive backstepping based nonlinear control of interior permanent magnet synchronous motor drive," Master thesis, Lakehead University Thunder Bay, Ontario, 2005.

[10] M. N. Uddin, and J. Lau, "Adaptive-backstepping-based design of a nonlinear position controller for an IPMSM servo drive," *Canadian Journal of Electrical and Computer Engineering*, vol. 32, no. 2, pp. 97-102, Spring 2007, doi: 10.1109/CJECE.2007.365710.

[11] M. A. Rahman, D. M. Vilathgamuwa, M. N. Uddin, and King-Jet Tseng, "Nonlinear control of interior permanent-magnet synchronous motor," *IEEE Transactions on Industry Applications*, vol. 39, no. 2, pp. 408-416, March-April 2003, doi: 10.1109/TIA.2003.808932.

[12] J. Zhou, and Y. Wang, "Real-time nonlinear adaptive backstepping speed control for a PM synchronous motor," *Control Engineering Practice*, vol. 13, no. 10, pp. 1259-1269, 2005, doi: 10.1016/j.conengprac.2004.11.007.

[13] J. Zhou, and Y. Wang, "Adaptive backstepping speed controller design for a permanent magnet synchronous motor," *IEEE Proceedings Electric Power Application*, vol. 149, no. 2, pp. 165-172, 2002, doi: 10.1049/ip-epa:20020187.

[14] F. J. Lin, and C. C. Lee, "Adaptive backstepping control for linear induction motor drive to track period references," *IEEE Proceedings Electric Power Application*, vol. 147, no. 6, pp. 449-458, 2000, doi: 10.1049/ip-epa:20000647.

[15] M. Kurabacak, and H. I. Eskikurt, "Design, modeling and simulation of a new nonlinear and full adaptive backstepping speed tracking controller for uncertain PMSM," *Applied Mathematical Modelling*, vol. 36, no. 11, pp. 5199-5213, 2012, doi: 10.1016/j.apm.2011.12.048.

[16] M. Karakacak, H. I. Eskikurt, "Speed and current regulation of a permanent magnet synchronous motor via nonlinear and adaptive backstepping control," *Mathematical and Computer Modelling*, vol. 53, no. 9-10, pp. 2015-2030, 2011, doi: 10.1016/j.mcm.2011.01.039.

[17] E. Lu, W. Li, S. Wang, W. Zhang, and C. Luo, "Disturbance rejection control for PMSM using integral sliding mode based composite nonlinear feedback control with load observer," *ISA Transactions*, 2021, doi: 10.1016/j.isatra.2021.01.008.

[18] M. Krstic, I. Kanellakopoulos, and P. V. Kokotovic, "Nonlinear design of adaptive controllers for linear systems," *IEEE Transactions on Automatic Control*, vol. 39, no. 4, pp. 738-752, April 1994, doi: 10.1109/9.286250.

[19] C. L. Lin, and C. F. Hsu, "Recurrent-neural-network-based adaptive-backstepping control for induction servomotors," *IEEE Transactions on Industrial Electronics*, vol. 52, no. 6, pp. 1677-1684, Dec. 2005, doi: 10.1109/TIE.2005.858704.

[20] W. Chen, S. S. Ge, J. Wu, and M. Gong, "Globally stable adaptive backstepping neural network control for uncertain strict-feedback systems with tracking accuracy known a priori," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 26, no. 9, pp. 1842-1854, Sept. 2015, doi: 10.1109/TNNLS.2014.2357451.

[21] S. H. Sadati, M. S. Parvar, M.B. Menhaj, and M. Bahrami, "Backstepping controller design using neural networks for a fighter aircraft," *European Journal of Control*, vol. 13, no. 5, pp. 516-526, 2007, doi: 10.3166/ejc.13.516-526.

[22] F. You-tong, and F. Cheng-zhi, "Single neuron network PI control of high reliability linear induction motor for Maglev," *Journal of Zhejiang University SCIENCE A*, vol. 8, no. 3, pp. 408-411, 2007.

[23] B. K. Bose, "Neural network applications in power electronics and motor drives—an introduction and perspective," *IEEE Transactions on Industrial Electronics*, vol. 54, no. 1, pp. 14-33, Feb. 2007, doi: 10.1109/TIE.2006.888683.

[24] R. Luo, Y. Deng, and Y. Xie, "Neural network backstepping controller design for uncertain permanent magnet synchronous motor drive chaotic systems via command filter," *Frontiers in Physics*, vol. 8, pp. 1-8, 2020, doi: 10.3389/fphy.2020.00182.

[25] S. Cheng, J. Yu, C. Lin, L. Zhao, and Y. Ma, "Neuroadaptive finite-time output feedback control for PMSM stochastic nonlinear systems with iron losses via dynamic surface technique," *Neurocomputing*, vol. 402, pp. 162-170, 2020, doi: 10.1016/j.neucom.2020.02.063.

[26] J. Zhang, S. Wang, P. Zhou, L. Zhao, and S. Li, "Novel prescribed performance-tangent barrier Lyapunov function for neural adaptive control of the chaotic PMSM system by backstepping," *International Journal of Electrical Power & Energy Systems*, vol. 121, p. 105991, 2020, doi: 10.1016/j.ijepes.2020.10599.

[27] F. F. M. El-Sousy, M. F. El-Naggar, M. Amin, A. Abu-Siada, and K. A. Abuhasel, "Robust adaptive neural-network backstepping control design for high-speed permanent-magnet synchronous motor drives: theory and experiments," *IEEE Access*, vol. 7, pp. 99327-99348, 2019, doi: 10.1109/ACCESS.2019.2930237.

[28] C.-H. Lin, "Integral backstepping control with RRFNN and MPSO of LPMSM drive system," *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, vol. 234, no. 7, pp. 834-848, 2020.

[29] Y. Guo, Z. Xi, and D. Cheng, "Speed regulation of permanent magnet synchronous motor via feedback dissipative Hamiltonian realization," *IET Control Theory Application*, vol. 1, no. 1, pp. 281-290, 2007, doi: 10.1049/iet-cta:20050307.

[30] M Lyu, G. Wu, Z. Rao, J. Zheng, C. Zhang, S. Huang, and Q. Wu, "Predictive cascaded speed and torque control for a novel three-modular three-phase PMSM," *International Journal of Electrical Power & Energy Systems*, vol. 129, p. 106798, 2021, doi: 10.1016/j.ijepes.2021.106798.

[31] H. Aschemann, B. Hau, and P. Mercorelli, "Second-order SMC with disturbance compensation for robust tracking control in PMSM applications," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 6225-6231, 2020, doi: 10.1016/j.ifacol.2020.12.1721.

[32] E. Delaleau, and A. M. Stankovic, "Flatness-based hierarchical control of the PM synchronous motor," *Proceedings of the 2004 American Control Conference*, 2004, pp. 65-70 vol.1, doi: 10.23919/ACC.2004.1383580.

[33] C. M. Verrelli, and P. Tomei, "Global stability for the inner and outer PI control actions in non-salient-pole PMSMs," *Automatica*, vol. 117, 108988, 2020, doi: 10.1016/j.automatica.2020.108988.

[34] Y. Deng, J. Wang, H. Li, J. Liu, and D. Tian, "Adaptive sliding mode current control with sliding mode disturbance observer for PMSM drives," *ISA Transactions*, vol. 88, pp. 113-126, 2019, doi: 10.1016/j.isatra.2018.11.039.

[35] A. M. Osama, W. Said, B. Mohammed, and Y. Amir, "Grey wolf optimizer algorithm based real time implementation of PIDDTC and FDTC of PMSM," *International Journal of Power Electronics and Drive System (IJPEDS)*, vol. 11, no. 3, pp. 1640-1652, 2020, doi: 10.11591/ijpeds.v11.i3.pp1640-1652.