ROBUST ADAPTIVE CONTROL OF TRANSVERSE FLUX PERMANENT MAGNET MACHINES USING NEURAL NETWORKS

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Abstract: This paper deals with modelling and adaptive output tracking of a Transverse Flux Permanent Magnet Machine (TFPM) as a non-linear system with unknown nonlinearities by utilizing High Gain Observer (HGO) and Radial Basis Function (RBF) networks. The technique of feedback linearization and H_∞ control are used to design an adaptive control law for compensating the unknown nonlinearity parts, such the effect of cogging torque, as a disturbance is decreased onto the rotor angle and angular velocity tracking performances. Finally, the capability of the proposed method is shown in the simulation results.

Keywords: High gain observer, transverse flux permanent magnet machine, H_∞ control, RBF neural network, output tracking.

1. INTRODUCTION

Adaptive control of electrical machines, especially with nonlinear and complicated dynamics, may have many advantages in industrial applications such as drive and manipulating systems, see (Melkote and Khorrami, 1999; Milman; Melkote, et al., 1999; Bartoff et al. 1998). In spite of many advantages over other conventional machines, TFPMs have not been used widely in industrial applications. Nonlinear dynamics with unknown nonlinearities, which makes some problems in control design, is one of the main reasons. Therefore, applying the new control methods can increase the performance of these machines. In other words, using new ways to handle nonlinearities can improve the position of TFPMs as high performance machines in industrial applications; see (Babazadeh and Parspour, 2004; Beyer, 1997).

TFPMs using high power permanent magnets and a novel flux path can be designed to increase the torque density by a factor of three to five compared to conventional machines. Moreover, producing high torque at low speeds and having high efficiency are the other advantages of these machines. There are two main reasons for high efficiency operation: the first is reduced copper losses, due to the absence of end-turns in stator winding, and the second is separation between magnetic circuit and electrical circuit which allows a high number of poles. Due to these advantages over other machines, TFPMs are well suited for direct drive applications such as robots, electrical vehicles and manipulating systems, see (Parspour and Babazadeh, 2004; Beyer, 1997). The concept of TFPMs was developed at the turn of the 20th century. But due to lack of appropriate electronic devices and converters, the practical use of these machines started many decades later. In the 80's, Weh developed new types of machines based on the transverse flux principle, see (Weh and May, 1986; Weh, et al., 1988).

There are two general concepts for TFPMs: passive rotor machine with permanent magnets on the stators and active rotor machine with permanent magnet on the rotor. Regarding the direction of permanent magnets, two different types of active rotor TFPM can be designed: flux concentrating TFPM (FCTFPM) - or buried permanent magnet machine- and surface mounted TFPM (SMTFPM). Here, the focus is on the FCTFPMs which are an important class of TFPMs, see (Beyer, 1997).

Due to the unknown nonlinearity parts in the dynamics of TFPMs, the approximation by basis functions can be very useful for system modelling and identification. In recent years, the analytical study of adaptive nonlinear control systems using universal function approximators has received much attention. Typically, these methods use neural networks or wavelet networks as approximation models for the unknown system nonlinearities; see (Cheng, et al., 1998; Polycarpou and Ioannou, 1992). Recently, Wavelet based neural networks to compensate for the plant nonlinearities and application of wavelet networks in identification and control design for a class of nonlinear dynamical systems has been considered in (Cheng, et al., 1998; Karimi, et al., 2004).

In this paper, the focus is on the application of RBF networks to compensate for the plant nonlinearities and control design for FCTFPM. The developed model for the FCTFPM includes two nonlinear parts. The first part, which depends on the rotor angle and input current, includes the magnetic and reluctance torque. The second part, which is modelled as a bounded disturbance, is the cogging torque. Combination of the feedback linearization technique and H_∞ control is used to design an adaptive control law for control of the machine. Then, using a Lyapunov-based design, the parameters of the neural networks are adapted. In order to have a sensoreless approach, the states of the machine including rotor angle and velocity are estimated by HGO.

The rest of this paper is organized as fallows. Section 2 considers the machine structure and operation principles. Section 3 presents the analytical model and dynamic equations. In section 4, the control design using HGO and RBF neural networks is proposed. In section 5, simulation results are presented and finally the conclusion is discussed.

2. MACHINE STRUCTURE AND OPERATION PRINCIPLES

TFPMs can be designed either rotational or linear, although the operation principles are relatively similar. Fig.1 shows one phase of a typical FCTFPM (These machines can be used with two or more phases as well). The stator is composed of several C-shape cores, which are connected together; see (Weh, 1995). The number of poles is equal to number of stator teeth; so one pole pitch (2τ) is the distance between two successive stator teeth along θ - axis. The stator coil lies transverse to the axial length in parallel with rotor, whereas in the conventional machines the coils lie in the longitudinal plane.

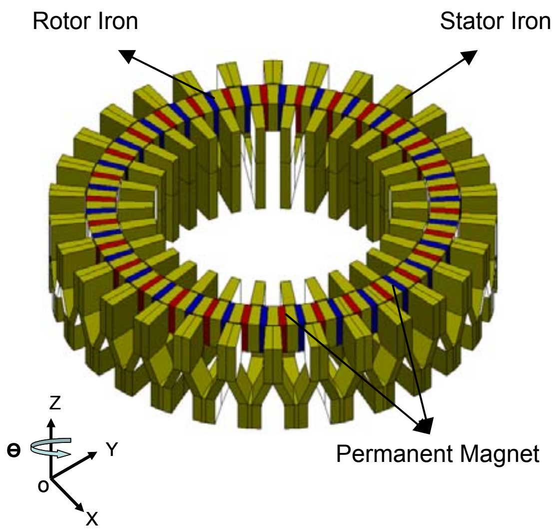

Fig. 1. One phase of a FCTFPM with thirty poles

The rotor is composed of several blades and permanent magnets with opposite polarity in direction of the θ - axis (Fig.1). The number of rotor blades is two times the number of poles. The interaction between exciting current and permanent magnet flux produces a magnetic torque, the dominant torque, and causes the rotor to move.

3. ANALYTICAL MODEL AND DYNAMIC EQUATIONS

The first step in modelling of TFPMs is to study the flux distribution produced by exciting coil in the air gap. The permeance of the air gap can be calculated by quasi-flux tubes with boundaries determined by straight lines and semicircular segments drawn to minimize the tubes length. Ultimately, the inductance of the machine can be computed in 5 steps, see (Babazadeh and Parspour, (2004); Pengtao and Zhu, 1999). The phase terminal voltage equation is

$$v = R_s.i + \frac{d\psi}{dt} = R_s.i + \frac{d}{dt}(Li + \psi_m) \tag{1}$$

where R_s, I and ψ_m are the resistance of the winding, the input phase current and the magnet flux linkage, respectively. So the input power can be expressed as

$$P_e := v.i = R_s.i^2 + iL\frac{di}{dt} + i^2\frac{dL}{dt} + i\frac{d\psi_m}{dt} \tag{2}$$

$$= R_s.i^2 + \frac{d}{dt}(\tfrac{1}{2}L.i^2) + (\frac{1}{2}i^2\frac{dL}{d\theta} + i\frac{\partial\psi_m}{\partial\theta})\omega_r \qquad (3)$$

where $R_s.i^2$ is the winding copper loss, $\frac{1}{2}Li^2$ the energy stored in the magnetic field, and $\omega_r = \frac{d\theta}{dt}$ the angular velocity of the rotor. Therefore, the output-produced torque can be determined by

$$T := T_r + T_m = \tfrac{1}{2}i^2\frac{dL}{d\theta} + i\frac{\partial\psi_m}{\partial\theta}. \qquad (4)$$

Another type of torque, which called cogging torque, is produced in the FCTFPMs as well. The cogging torque is generated under the non-excited condition and does not contribute to the average output torque. The stored magnetic energy in the air gap under non excited condition can be written as

$$W_m = \frac{\phi^2{}_g}{2P_g} \qquad (5)$$

where P_g is air gap permeance and ϕ_g is the flux due to the permanent magnets in the air gap. The cogging torque can be calculated by

$$T_{cog} = \frac{\partial W_m}{\partial\theta}. \qquad (6)$$

Consequently, the overall torque can be written by

$$T_{total} := T_m + T_r + T_{cog} = B_m(\theta).i + B_r(\theta).i^2 + B_{cog}(\theta) \qquad (7)$$

where $B_m(\theta)$, $B_r(\theta)$ and $B_{cog}(\theta)$ are non-linear and periodic functions with period of $2\tau, \tau$ and τ respectively, see (Babazadeh and Parspour, 2004). Therefore, the dynamic equation can be express as

$$J\ddot{\theta} + f\dot{\theta} = T_{total} = B_m(\theta).i + B_r(\theta)i^2 + B_{cog}(\theta) \qquad (8)$$

where J is the rotor inertia and f is friction coefficient.

Let's assume that $x_1 = \theta$, $x_2 = \dot{\theta}$ and $u = i$, so the extended system model in the state-space form can be described as

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -\alpha x_2 + G\ (x_1,u).u + \omega \\ y = x_1 \end{cases} \qquad (9)$$

where $G = (B_m + B_r.u)/J$, $\alpha = f/J$ and $\omega = B_{cog}/J$. The function $G(.)$ is smooth and bounded function of y and u. That is, we have to make the following assumption.

Assumption 1. There exist functions $G^u(x_1,u)$ and $G_l(x_1,u)$ such that $G_l(x_1,u) \le |G(x_1,u)| \le G^u(x_1,u)$, where $G^u(x_1,u) < \infty$ and $G_l(x_1,u) > 0$ for all $x_1 \in U_{x_1}$.

4. CONTROL DESIGN USING RBF NEURAL NETWORKS

In this section, we present the problem of identifying and H_∞ tracking control problem using HGO and RBF for the single-input-single-output non-linear system of (9). First, all the elements of the state vector $\underline{x}(t) = [x_1(t) \quad x_2(t)]^T$ are assumed to be available and the disturbance ω is assumed to be bounded but unknown or uncertain.

Assumption 2. There exists a finite constant $B_\omega > 0$, such that $\int_0^T \omega(t)^2 dt \le B_\omega$.

The objective is to combine the characteristics of radial basis functions, adaptive control scheme and H_∞ control which guarantee that the output $y(t)$ and its derivative track a given reference signal $y_r(t)$ and its corresponding derivative, which are assumed the derivative of the signal $y_r(t)$ to be bounded.
To begin with, the reference signal vector $y_r(t)$ and the tracking error vector $\underline{e}(t)$ will be defined as

$$\underline{y}_r = [y_r, \dot{y}_r]^T \qquad (10)$$

$$\underline{e} = \underline{x} - \underline{y}_r = [e, \dot{e}]^T. \qquad (11)$$

If the function $G(.)$ is known and the system is free of disturbance ω, then by employing the technique of feedback linearization we can choose the controller to cancel the nonlinearity and achieve the tracking control goal. Specially, let $\underline{k} = [k_1, k_2]$ to be chosen such that all roots of the polynomial $p(s) = s^2 + k_2 s + k_1$ are in the open left half-plane, then the final control law is obtained as

$$u = \frac{1}{G(x_1,u)}\left[v^a + \alpha x_2 + \ddot{y}_r - \underline{k}\,\underline{e}\right] \qquad (12)$$

where v^a is an auxiliary control yet to be specified and the main objective of v^a is to attenuate the effect of disturbance on the tracking error vector.

Substituting (12) into (9) and using (10-11), we obtain the closed-loop system governed by

$$\ddot{e} + k_2\dot{e} + k_1 e = v^a. \qquad (13)$$

Note that the control signal (12) is useful only if the function $G(.)$ is known exactly. If $G(.)$ is unknown, then adaptive strategies must be employed. We employ one RBF neural network as

$$\hat{G}(x_1,u,\underline{\theta}_g)=\underline{\theta}_g^T\,\underline{\psi}_g(x_1,u) \qquad (14)$$

to approximate the non-linear function $G(.)$ of the system. The optimal weight vector $\underline{\theta}_g^*$ is the quantity required only for analytical purposes. Typically $\underline{\theta}_g^*$ is chosen as

$$\underline{\theta}_g^*=\arg\min_{\underline{\theta}_g}\{\max_{x_1}\left|G(x_1,u)-\underline{\theta}_g^T\,\underline{\psi}_g(x_1,u)\right|\} \qquad (15)$$

for all $x_1\in U_{x_1}$, which $U_{x_1}\in\Re^2$ is the compact set of x_1, have the following representation

$$\begin{aligned}G(x_1,u)&=\hat{G}(x_1,u,\underline{\theta}_g^*)+\Xi_g(x_1,u)\\&=\underline{\theta}_g^{*T}\,\underline{\psi}_g(x_1,u)+\Xi_g(x_1,u).\end{aligned} \qquad (16)$$

where $\Xi_g(x_1,u)$ is called *network reconstruction error,* see (Seshagiri and Khalil, 2000).

By using the definition of (10-11) and (16), we rewrite (9) as

$$\begin{aligned}\dot{\underline{e}}=A_m\underline{e}+\underline{b}\{&-\alpha\,x_2+\underline{\theta}_g^{*T}\,\underline{\psi}_g(x_1,u)u+\underline{k}\,\underline{e}-\ddot{y}_r\\&+\Xi_g(x_1,u)u+\omega\}\end{aligned} \qquad (17)$$

where $A=\begin{bmatrix}0&1\\0&0\end{bmatrix}$, $\underline{b}=\begin{bmatrix}0&1\end{bmatrix}^T$. It is clear from polynomial $p(s)$ that $A_m=A-\underline{b}\,\underline{k}$ is Hurwitz. In order to derive the control law, we need the following assumption hold for all $x_1\in U_{x_1}$ and $\underline{\theta}_g\in\Omega_b$, where the constraint set Ω_b is defined as $\Omega_b=\left\{\underline{\theta}_g\;\middle|\;\left\|\underline{\theta}_g\right\|_2\le \mathrm{M}_g\right\}$.

Remark 1 (Cheng, et al., 1998). The effect of ω, denoting the external disturbance, will be attenuated by the control signal v^a, such that the H_∞ control design efficiently deals with the attenuation of ω in the error dynamic system (17). Then, the problem under consideration becomes that of finding an adaptive scheme for v^a and $\underline{\theta}_g$ to achieve the following H_∞ tracking performance:

$$\int_0^T\underline{e}^TQ\,\underline{e}\,dt\;\le\;\underline{e}^T(0)P\underline{e}(0)+tr(\underline{\tilde{\theta}}_g(0)\underline{\tilde{\theta}}_g^T(0))+\gamma^2\int_0^T\omega^T\omega\,dt\quad\forall\,0\le T<\infty$$

where γ is a prescribed attenuation level, and P,Q are positive definite weighting matrixes.

The solution of the adaptive control to achieve H_∞ tracking performance is stated in the following theorem.

Theorem 1. Consider the non-linear system in (9) with unknown or uncertain function $G(.)$, according to Assumption 1. The H_∞ tracking performance in Remark 1 is achieved for a prescribed attenuation level γ if the following adaptive control law is adopted:

$$u=\frac{1}{\hat{G}(x_1,u,\underline{\theta}_g)}\left[v^a+\alpha\,x_2+\ddot{y}_r-\underline{k}\,\underline{e}\right]:=\phi\,(\underline{e},y_r,\underline{\theta}_g) \qquad (18)$$

with

$$v^a=\frac{-1}{\beta^2}\underline{b}^TP\underline{e} \qquad (19)$$

and

$$\dot{\underline{\theta}}_g=\mathrm{Pr}\,oj\,(\underline{\theta}_g,\underline{\Pi}_g)=\underline{\Pi}_g, \qquad (20)$$

where β is an arbitrary parameter and $\underline{\Pi}_g=2\underline{e}^TP\underline{b}\underline{\psi}_g(\underline{e}+\underline{y}_r,u)u$ and the positive-definite matrix P is the solution of the following equation

$$P\,A_m+A_m^TP+P\underline{b}(\frac{1}{\gamma^2}-\frac{2}{\beta^2})\underline{b}^TP+Q=0\,. \qquad (21)$$

According to (Khalil, 1996) by utilizing a high gain observer (HGO), we implement the controller (18) as an output feedback control such the states $\underline{e}(t)$ can be replaced by their estimates $\hat{\underline{e}}(t)$.

By defining the saturated function $\phi^s(.)$ as

$$\phi^s(\underline{e},y_r,\underline{\theta}_g)=S\;sat\left(\frac{\phi\,(\underline{e},y_r,\underline{\theta}_g)}{S}\right) \qquad (22)$$

where $sat\,(.)$ is the saturated function and $S\ge\max\left|\phi\,(\underline{e},y_r,\underline{\theta}_g)\right|$, then the output feedback controller will be as follows:

$$v=\phi^s\;(\hat{\underline{e}},y_r,\underline{\theta}_g)\;. \qquad (23)$$

The HGO used to estimate the states is the same one used in (Khalil, 1996) and is described as

$$\dot{\hat{e}}_1(t)=\hat{e}_2(t)+\frac{\alpha_1}{\varepsilon}(e_1(t)-\hat{e}_1(t)) \qquad (24)$$

$$\dot{\hat{e}}_2(t)=\frac{\alpha_2}{\varepsilon^2}(e_1(t)-\hat{e}_1(t)) \qquad (25)$$

where ε is a design parameter and positive constants α_1 and α_2 are chosen such that the roots of $s^2+\alpha_1\,s+\alpha_2=0$ have negative real parts.

Adaptive output feedback control that uses parameter projection. High gain and control saturation has also been considered in a similar way by (Jankovic, 1996;

Seshagiri and Khalil, 2000) and they showed that the tracking error can be made as small as desired by increasing the observer and parameter adaptation gains.

5. SIMULATION RESULTS

In this section, we illustrate the methodology proposed on a FCTFPM, which has the following characteristics:

Number of phases: 1, Number of stator poles: 30

Nominal power: $500\,W$, Nominal speed: $60\frac{rad}{s}$.

A RBF neural network is used to construct the function $G(x_1, u)$ such that the Gaussian RBFs are chosen as the activation functions. Fig. 2 and Fig. 3 show the time behaviours of the angle and the angular velocity to track the reference signal and its derivative without the term of H_∞ control in (18), respectively. And the tracking errors are depicted in Fig. 4. Also, by utilizing the H_∞ control in (18), attenuation of the effect of the cogging torque as a disturbance onto the angle and angular velocity tracking is shown in Fig. 5, Fig. 6 and Fig. 7 as well. It is clear that in the presence of modelling errors the stability of the overall identification scheme is guaranteed. Finally, it is seen that the technique of feedback linearization to design an adaptive control law and the parameter adaptive laws of the neural network can be used to identify the unknown non-linear terms well.

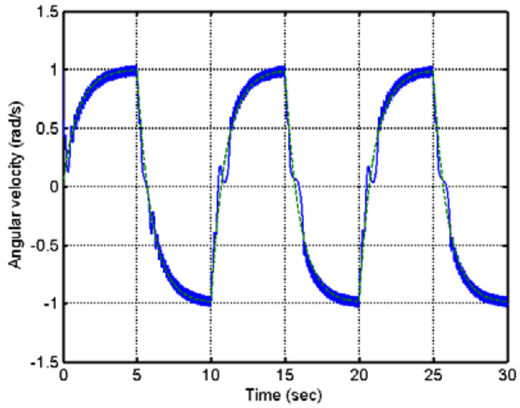

Fig. 3. Time behaviour of the angular velocity (solid) and the derivative of reference signal (dashed).

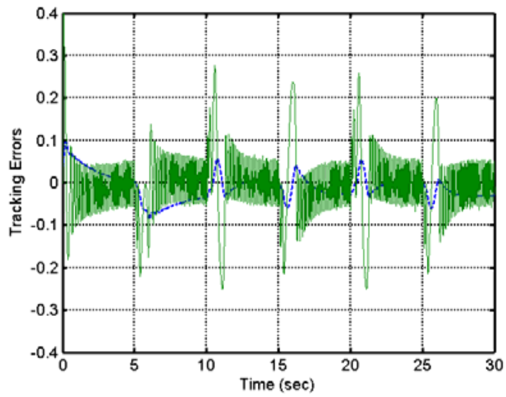

Fig. 4. The angle tracking error (dashed) and the angular velocity error (solid).

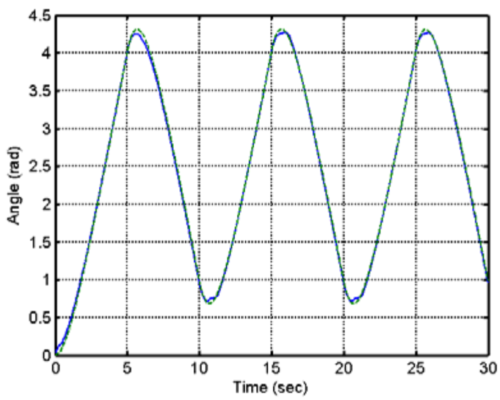

Fig. 2. Plot of the angle (solid) and the reference signal (dashed) without H_∞ control.

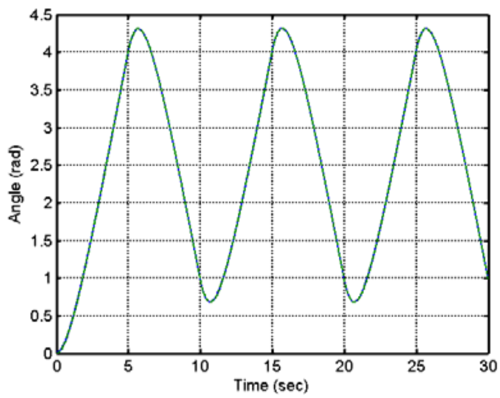

Fig. 5. Time behaviour of the angle (solid) and the reference signal (dashed) with H_∞ control.

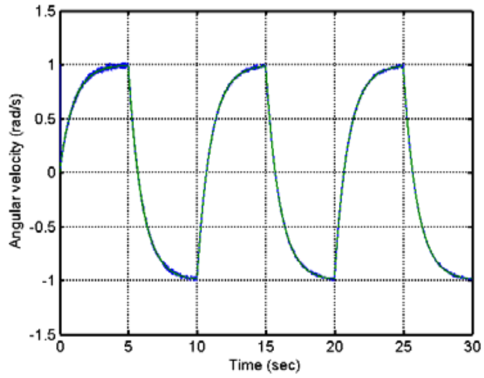

Fig. 6. Plot of the angular velocity (solid) and the derivative of reference signal (dashed).

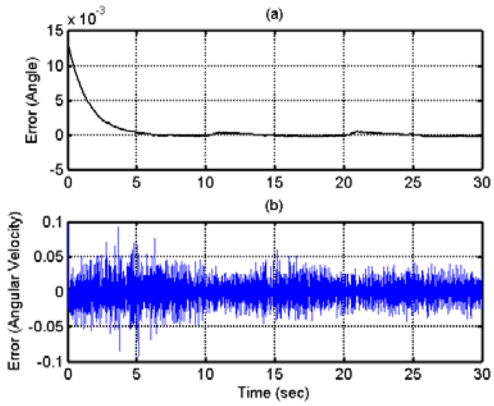

Fig. 7. Tracking errors using high gain observer: (a) $\hat{e}_1(t)$ and (b) $\hat{e}_2(t)$.

6. CONCLUSION

This paper considered modelling and adaptive output tracking of a FCTFPM as a non-linear system with unknown nonlinearities by utilizing HGO and RBF neural networks. The technique of feedback linearization and H_∞ control were used to design an adaptive control law for compensating the unknown nonlinearity parts, such the effect of cogging torque, as a disturbance has been decreased onto the angle and angular velocity tracking performances. Finally, the capability of the proposed method was shown in the simulation results.

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