An Adaptive Neural-Network Model-Following Speed Control of PMSM Drives for Electric Vehicle Applications

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Abstract:- A robust speed control technique for permanent-magnet synchronous motor (PMSM) drives is proposed in this paper for electric vehicle applications. The robust controller consists of a neural-network controller (NNC) in the speed feed-back loop in addition to an on-line trained neural-network model-following controller (NNMFC) combines the merits of the feed-back NNC and the feed-forward NNMFC for PMSM drive. The weights of the NNMFC are trained on-line according to the model-following error between the outputs of the reference model and the PMSM drive system to realize high dynamic performance in disturbance rejection and tracking characteristics. The NNMFC generates an adaptive control signal which is added to the feed-back neural-network speed controller output to attain robust model-following characteristics under different operating conditions regardless of parameter uncertainties and load disturbances. A computer simulation is developed to demonstrate the effectiveness of the proposed robust ANNMFC. The results confirm that the proposed robust speed controller grants robust performance and precise tracking response to the reference model regardless of load disturbances and PMSM parameter uncertainties using the adaptive neural-network model-following control.

Key-Words: PMSM, Vector Control, Neural Network (NN), Model Following Controller (MFC).

1 Introduction

In recent years, advancements in magnetic materials, semiconductor power devices and control theories have made the permanent-magnet synchronous motor (PMSM) drives play a vitally important role in motion-control applications. PMSMs are widely used in high-performance applications such as industrial robots and machine tools because of its compact size, high-power density, high air-gap flux density, hightorque/inertia ratio, high torque capability, high efficiency and free maintenance. Utilizing the vector control technique and by keeping *d*-axis current, $i_{ds}^{r} = 0$, the PMSM torque may vary linearly with the q-axis current component, i_{qs}^r , and the maximum torque per ampere is achieved which is similar to the control of separately excited DC motor [1-3]. Several control techniques in many researches have been developed to improve the performance of the PMSM drives and to deal with the nonlinearities and uncertainties of the dynamic model of the PMSM using fuzzy logic, neural network and/or the hybrid of fuzzy logic and neural network [4-6].

In the previous work [3], the vector control transfer functions of the PMSM and the d-q axes

synchronous PI current controllers has been designed to achieve the time domain specifications of the current control loops.

In this paper, a robust speed control strategy of a PMSM drive using an adaptive neural-network model-following speed controller (ANNMFC) is proposed. The robust speed controller consists of a feed-back neural-network controller (NNC) in addition to an on-line trained neural-network modelfollowing controller (NNMFC) to improve the dynamic performance of the drive system. The output of the NNMFC is added to the neural-network speed controller output to compensate the error between the reference model and the PMSM drive system output under load disturbances and parameter uncertainties. The dynamic performance of the PMSM drive system has been studied under load changes and parameter variations. The simulation results are given to demonstrate the effectiveness of the proposed controllers.

2 Mathematical Model of the PMSM

The mathematical modeling of the PMSM in the synchronously rotating rotor reference frames can be

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derived as follows [1,3]. The stator voltage equations in the d^r - q^r synchronously rotating rotor reference frame can be carried out as follows:

$$V_{qs}^{r} = R_{s}i_{qs}^{r} + L_{ss}\frac{d}{dt}i_{qs}^{r} + \omega_{r}L_{ss}i_{ds}^{r} + \omega_{r}\lambda_{m}^{'}$$

$$V_{ds}^{r} = R_{s}i_{ds}^{r} + L_{ss}\frac{d}{dt}i_{ds}^{r} - \omega_{r}L_{ss}i_{qs}^{r}$$
(1)

The electromagnetic torque can be expressed as:

$$T_e = \frac{3}{2} \cdot \frac{P}{2} \cdot \lambda_m i_{qs}^r$$

$$T_e = J_m \left(\frac{2}{P}\right) \frac{d}{dt} \omega_r + \beta_m \left(\frac{2}{P}\right) \omega_r + T_L$$
(2)
(3)

where V_{qs} , V_{ds} , i_{qs} and i_{ds} are the stator voltages and currents respectively. R_s and L_{ss} are the resistance and self inductance of the stator. ω_r , J_m , β_m and P are the rotor position, electrical rotor speed, effective inertia, friction coefficient and the number of poles. T_e , T_L , and λ_m are the electromagnetic torque, the load torque and the flux linkage of the motor respectively. The PMSM parameters are: three-phase, 1 hp, 4 poles, 208 V, 60 Hz, 1800 rpm, voltage constant: 0.314 v.s/rad, $R_s=1.5 \Omega$, $L_{ss}=0.05$ H, $J_m=0.003$ kg.m², and $\beta_m=0.0009$ N.m/rad/sec.

3 Problem Formulations

The system configuration of the proposed speed control for a FOC PMSM drive system is illustrated in Fig. 1. It basically consists of a PI current controllers in *d-q*-axes, a feed-back neural-network controller and a neural-network model-following controller. A reference model is derived from the closed loop transfer function of the PMSM drive system [3]. Although the desired tracking and regulation speed control can be obtained using the feed-back neural-network controller with the nominal PMSM parameters, the performance of the drive system still sensitive to parameter variations. To solve this problem, a robust adaptive speed controller combining the neural-network speed controller (NNC) and the on-line trained neuralnetwork model-following controller (NNMFC) is proposed. The control law is designed as:

$$i_{qs}^{rc} = i_{qs}^{r^*} + \delta i_{qs}^{r^*}$$
(4)

where i_{qs}^{r*} the *q*-axis current command generated from the proposed neural-network speed controller and δi_{qs}^{r*} is the adaptive control signal generated by the proposed NNMFC to automatically compensate the performance degradation. The inputs to feedback neural-network controller are the error signal, e_{ω}^{fb} , and the derivative of the rotor speed, ω_r . Similarly, the inputs to the NNMFC are the modelfollowing error signal, e_{ω}^{mf} , and the derivative of the rotor speed that are used to train the weights of neural-network controller on-line.

$$e_{\omega}^{fb} = (\omega_r^* - \omega_r) \tag{5}$$

$$\dot{\omega}_r^{fb} = k_{\omega}^{fb} d\omega_r / dt \tag{6}$$

$$e_{\omega}^{mf} = (\omega_r^{mf} - \omega_r) \tag{7}$$

$$r^{mf}_{r} = k_{\omega}^{mf} d\omega_{r} / dt \tag{8}$$

where e_{ω}^{fb} is the error speed between the reference and feed-back speed while ω_r^{mf} is the output of the reference model while ω_r is the rotor speed of the PMSM.

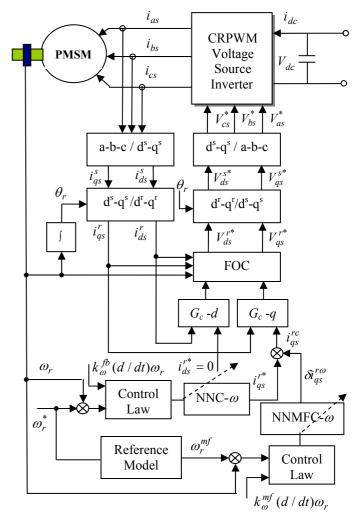


Fig. 1 The block schematic diagram of a field oriented PMSM drive system

4 Proposed Speed Control Strategy

The proposed robust speed controller consists of a feed-back neural-network controller (NNC) in addition to an on-line trained neural-network model-following controller (NNMFC) to improve the

(9)

dynamic performance of the drive system as shown in Fig. 1. The feed-back neural-network controller is designed for load regulation or disturbance rejection while the NNMFC to attain the desired tracking speed response.

4.1 Neural-Networks Signal Propagation

The neural-networks for both feed-back and modelfollowing speed controllers comprise a three layers neural-network as shown in Fig. 2. The input layer (i^{th}) , the hidden layer (j^{th}) and the output layer (k^{th}) . The signal propagation and activation functions for both controllers are introduced as follows.

A. Input Layer

 $nn_i = x_i$

For every node *i* in the input layer, the neuralnetwork input and output are expressed as:

$$y_i = f_i(nn_i)$$
 $i = 1,2$ (10)

$$x_1^{mf} = e_{\omega}^{mf}(t), \qquad x_2^{mf} = k_{\omega}^{mf} \frac{d}{dt} \omega_r$$
(11)

$$x_1^{fb} = e_{\omega}^{fb}(t), \qquad x_2^{fb} = k_{\omega}^{fb} \frac{d}{dt} \omega_r$$
 (12)

B. Hidden Layer

The input and output of the hidden layer to a node *j* are introduced, respectively, as follows.

$$nn_j = \sum_i (W_{ji}y_i) + \phi_j \tag{13}$$

$$y_j = f_j(nn_j)$$
 $j = 1,....m$ (14)

$$f_j(nn_j) = \frac{1}{1 + e^{-nn_j}}$$
(15)

C. Output Layer

The input of the output layer to a node k is given by: $nn_k = \sum_{i} (W_{kj}y_i) + \phi_k$ (16)

and the corresponding output is

$$y_k = f_k(nn_k) = \frac{1}{1 + e^{-nn_k}}$$
(17)

$$y_k^{fb} = i_{qs}^{r^*}, \qquad y_k^{mf} = \delta i_{qs}^{r^*}$$
 (18)

4.2 On-Line Training Algorithm

The back propagation training algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual output of a feed-forward net and the desired output. This technique uses a recursive algorithm starting at the output units and working back to the hidden layer to adjust the neural weights according to the following equations. Thus the energy error functions for both NNC and NNMFC are defined as follows:

$$E_{\omega}^{fb} = \frac{1}{2} \sum_{N} [\omega_r^*(N) - \omega_r(N)]^2 = \frac{1}{2} \sum_{N} e_{\omega}^{fb2}(N)$$
(19)

$$E_{\omega}^{mf} = \frac{1}{2} \sum_{N} [\omega_{r}^{mf}(N) - \omega_{r}(N)]^{2} = \frac{1}{2} \sum_{N} e_{\omega}^{mf2}(N)$$
(20)

where $\omega_r^{mf}(N)$ and $\omega_r(N)$ are the outputs of the reference model and PMSM drive system at the Nth-iteration. Within each interval from N-1 to N, the back propagation algorithm [3] is used to update the weights of the hidden and output layers in the NNMFC according to the following equations:

$$W_{ji}(N+1) = W_{ji}(N) - \varepsilon \left[\frac{\partial E_{\omega}}{\partial W_{ji}^{mf}(N)} + \gamma \Delta W_{ji}(N-1) \right]^{jo,mj}$$
(21)

$$W_{kj}(N+1) = W_{ki}(N) - \varepsilon \left[\frac{\partial E_{\omega}}{\partial W_{kj}^{mf}(N)} + \gamma \Delta W_{kj}(N-1) \right]^{fb,mf}$$
(22)

$$\Delta W_{kj}(N-1) = W_{kj}(N) - W_{kj}(N-1) \int_{0}^{t/b, mf}$$
(24)

The required gradients of E_{ω}^{fb} and E_{ω}^{mf} in (19-20) between the output and hidden layers is determined in [4]. To increases the on-line learning rate of the weights, a control laws are proposed as follows.

$$\left. \frac{\partial E_{\omega}}{\partial y_k} \right\}^{jb} = e_{\omega}^{fb} + k_{\omega}^{fb} \dot{\omega}_r$$
(25)

$$\left.\frac{\partial E_{\omega}}{\partial y_{k}}\right\}^{mf} = e_{\omega}^{mf} + k_{\omega}^{mf} \dot{\omega}_{r}$$
(26)

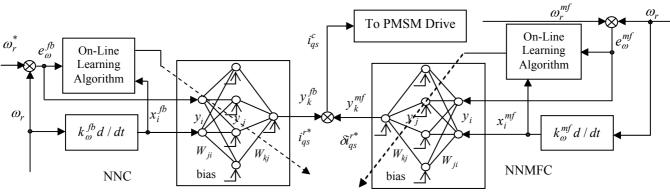


Fig. 2 The proposed robust speed controller (ANNMFC)

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5 Simulation Results

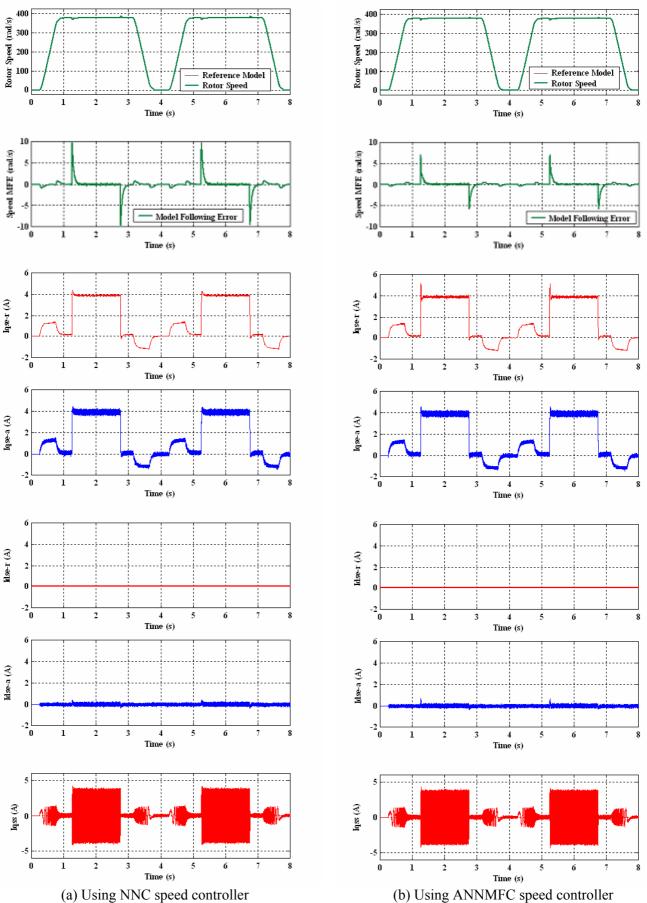
The simulations results of the PMSM drive systems are presented to verify the feasibility of the proposed control scheme under various operating conditions. The dynamic performance of the drive system due to speed command of 377 rad/sec under load of 3.6 N.m is predicted as illustrated in Fig. 3. The disturbance rejection capabilities have been checked when a load of 3.6 N.m is applied to the shaft at t =1.25 s and removed after a period of 1.5 s. The simulation results of the proposed NNC and ANNMFC speed controllers are shown in Fig. 3 that includes the command and actual responses for speed, *d-q* axes stator currents in the rotating and stationary reference frames for both speed controllers. These Figures clearly illustrate good dynamic performances load regulation and command tracking in performance are realized for both controllers. Improvement of the control performance by addition the proposed ANNMFC speed controller can be observed from the obtained results in command tracking and load regulation characteristics. The robustness of the proposed ANNMFC approach against large variations of PMSM parameters and external load disturbances has been simulated for demonstration. The speed response and the load regulation performance of the drive system with the NNC and ANNMFC speed controllers are shown in Figs. 4-6 under the three cases of PMSM parameter variations. The control performance by addition the proposed ANNMFC speed controller is robust in command tracking and load regulation characteristics as illustrated in Fig. 4-5. Also, the proposed ANNMFC speed controller attains a rapid and accurate response for the reference model and quickly returns the speed to the reference under full load with a maximum dip of 7 rad/sec and 0.25 s under parameter variations while the NNC provides a maximum dip of 11 rad/sec and 0.25 s. The results shown in Figs. 4-5 clearly indicate that as the variations of the PMSM parameters occurred, the responses deviate significantly from that nominal case with NNC speed controller but the ANNMFC speed controller confirms the correct operation and slightly influenced by parameter variations. It is evident that from Fig. 6 an obvious model-following error (MFE) due to the NNC speed controller reaches to ± 1.5 rad/sec while the MFE due to ANNMFC speed controller is about ± 0.5 rad/sec. Also, good model-following tracking responses at all cases of parameters variations are observed from these results, and the resulting regulation performances are also much better, in both speed dip and recovery time, than those obtained by the NNC speed controller.

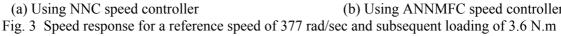
6 Conclusions

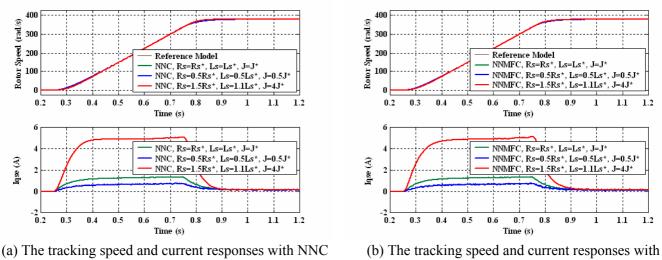
This paper proposes a robust speed controller for PMSM drive system under FOC which guarantees the robustness in the presence of parameter variations. The proposed robust speed controller (ANNMFC) consists of a feed-back neural-network controller (NNC) in addition to an on-line trained neural-network model-following speed controller (NNMFC). The design procedures for both speed controllers have been successfully designed according to the given command tracking and disturbance rejection specifications of the drive system. The NNMFC provides an adaptive feedback control signal based on the error between the reference model and the output speed of PMSM. This error was used to train the weights and biases of the NNMFC to provide a good model-following response. So, the rotor speed tracking response can be controlled to closely follow the response of the reference model under a wide range of operating conditions. Simulation results have shown that the proposed ANNMFC grant robust model-following tracking response and good regulation characteristics in the presence of PMSM parameter uncertainties and external load disturbance.

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ANNMFC

Fig. 4. The speed model following response of the drive system under parameter variations using NNC and ANNMFC speed controllers

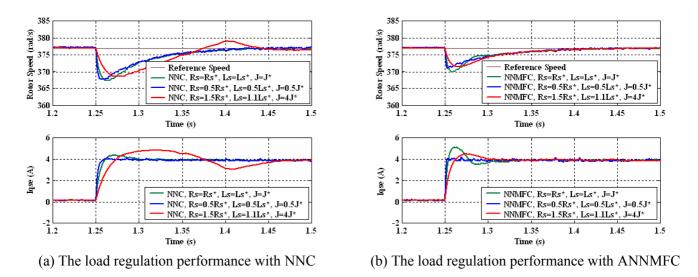


Fig.5. The load regulation performance of the drive system under parameter variations using NNC and ANNMFC speed controllers

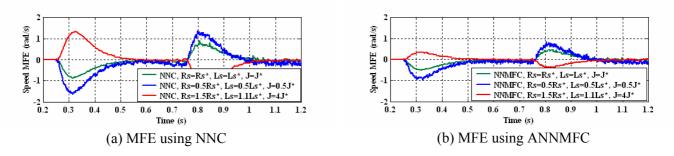


Fig. 6. The model-following errors (MFE) of speed response using NNC and ANNMFC speed controllers under parameter variations