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A Self-tuning Disturbance Observer Based Adaptive Speed Control for PMSM Servo System

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Abstract: A self-tuning disturbance observer based adaptive composite control method is proposed in this paper, to improve the disturbance rejection property for the Permanent-Magnet Synchronous Motor (PMSM) speed regulation problem. The composite controller is composed of an adaptive feedback control and a self-tuning disturbance observer (DOB) based feedforward compensator. Both the parameters of the feedback controller and the self-tuning DOB can be adaptively tuned online by using the parameters identified by the linear adaptive neural network (LANN). The self-tuning DOB is designed to estimate the lumped disturbances, including external disturbances and internal disturbances caused by parameter variations, and can also estimate the disturbances caused by wide range variation of parameters. The effectiveness and validity of the proposed control method are verified by simulation results.

Key Words: Self-tuning disturbance observer, Parameter identification, Linear adaptive neural network, Speed regulation

1 Introduction

In many industrial applications, different disturbances always exist in the PMSM servo system. These disturbances may arise internally, e.g. friction force and unmodeled dynamics, or externally, e.g. load disturbances, which will degrade the performance of the closed-loop system if the controller does not have enough ability to reject them. Disturbance observer (DOB) and extended state observer (ESO) techniques are successfully applied the disturbance compensation methods to motion control because of their simplicity and powerful ability to compensate disturbances [1-8].

It is well known that the DOB method can estimate the external and internal disturbances, then the observed lumped disturbances can be used to compensate the influence on output caused by disturbances. For traditional linear DOB (LDOB) design, the nominal model will be inaccurate when the parameters vary largely, so the LDOB-based controller can not obtain sufficient robustness in such cases [9-11].

The performance of systems may be diminished by the large parameter variations in some applications. For example, the inertia of the electric winding machine is increasing or decreasing with time. If the inertia of system increases to more than several times the original value, the dynamic response will be slowed and the control performance can not be guaranteed when the parameters of the controller and the disturbance compensator are fixed [1-3]. If the parameters of the controller and the disturbance compensator can be tuned automatically according to the inertia changes, then the control performance of the whole system will be improved greatly and the robustness and adaptability of the system also can be strengthened.

Ref. [1] proposes an adaptive controller combining the ESO scheme with an inertia identification technique to improve the adaptation of the closed-loop system against variations of inertia. Moreover a fuzzy inference based supervisor was designed to automatically tune the feed-forward compensation gain according to the identified inertia in Ref.[1]. Although this method can achieve a good speed response in the presence of inertia variations, it lacks an on-line adaptive mechanism and the speed command signal for inertia identification must be periodic signals [3]. Ref. [12] proposed an online gain tuning algorithm for a robust sliding mode speed controller of a PMSM. The proposed controller is constructed by a fuzzy neural network controller and a sliding mode controller. The fuzzy neural network controller is designed to approximate the nonlinear factors while the sliding mode controller is used to stabilize the system dynamics by employing an online tuning rule. The proposed control scheme does not require any knowledge of the system parameters. Although the simulation results show that the method is very robust to system parameter variations, this method may cause chattering problem and cannot achieve a good balance between the dynamic response and the disturbance rejection ability. Ref. [13] proposed an adaptive fuzzy speed controller by considering the existence of parameter variations and load disturbances in the PMSM servo system. The adaptive fuzzy logic system is used to approximate the non-linear parts of the servo system on-line.

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And the servo system parameters, such as stator resistance, stator inductance, flux, inertia, and load torque, are not necessarily known. The influence of parameter variations and load disturbances is effectively inhibited by this method.

A self-tuning disturbance observer based adaptive composite control method is proposed in this paper to improve the disturbance rejection property for the PMSM speed regulation problem. First, aiming to the parameter variations, a linear adaptive neural network (LANN) with two layers is used to identify the parameters on line. LANN has simple structure with only two layers including the input layer and the output layer, and the known parameters of the system can be reflected in the weights of LANN with a linear relationship [14]. Second, a self-tuning disturbance observer is designed based on the parameters of the identified system. The inverse of the nominal model can be changed along with the parameters changes. That is to say, the parameters of the self-tuning DOB can be tuned on-line according to the parameters identified by the LANN. So the disturbances, caused by parameter variations, unmodeled dynamics and external disturbances, can be estimated and compensated through a feed-forward compensation channel of the closed-loop system. Finally, the adaptive feedback control law can also be obtained according to the identified parameters. So the self-tuning DOB combining with the adaptive feedback controller can effectively suppress the disturbances of the closed-loop system.

In detail, the paper is organized as follows. In Section 2, the simplified mathematical model of PMSM is introduced. In Section 3, the proposed control scheme is demonstrated in detail. The validity of the adaptive composite control method is verified by some simulation results shown in Section 4. Finally, this paper is summarized in Section 5.

2 A Simplified Mathematical Model of PMSM

Suppose the model of a surface-mounted PMSM motor can be described as [15]

$$\begin{pmatrix} \dot{i}_d \\ \dot{i}_q \\ \dot{\omega} \end{pmatrix} = \begin{pmatrix} -\frac{R}{L} & n_p\omega & 0 \\ -n_p\omega & -\frac{R}{L} & -\frac{n_p\psi_f}{L} \\ 0 & \frac{K_t}{J} & -\frac{B}{J} \end{pmatrix} \begin{pmatrix} i_d \\ i_q \\ \omega \end{pmatrix} + \begin{pmatrix} \frac{u_d}{L} \\ \frac{u_q}{L} \\ -\frac{T_L}{J} \end{pmatrix} \tag{1}$$

where u_d, u_q are the stator voltages of the *d-q* axes, i_d, i_q are the stator currents of the *d-q* axes L, R are the stator inductance and resistance, n_p is the number of pole pairs, ω is the angular velocity, ψ_f, T_L, B and J are the rotor flux linkage, load torque, viscous friction coefficient, and the moment of inertia, respectively.

A well-known control framework for a PMSM is the field-oriented vector control scheme [16]. Under this scheme, the torque and flux producing components of the stator current are approximately decoupled so that the independent torque and flux controls are as possible as in the DC motors. Usually, the *d*-axis reference current i_d^* is set to zero to approximately eliminate the couplings between angular velocity and currents. In order to simplify the on-line implementation, the actual current component can be replaced by the reference one, i.e. $i_d \approx i_d^* = 0$ and $i_q \approx i_q^*$.

The PMSM dynamic equation from Eq. (1) can be rewritten as

$$\dot{\omega} = \frac{K_t i_q}{J} - \frac{B\omega}{J} - \frac{T_L}{J} = \frac{K_t i_q^*}{J} - \frac{B\omega}{J} - \frac{T_L}{J} \tag{2}$$

where $K_t = \frac{3}{2} n_p \psi_f$ is the torque constant. The discrete dynamic equation of a PMSM can be given by

$$\omega(k) = \alpha\omega(k-1) + \beta i_q^*(k-1) + \gamma T_L(k-1) \tag{3}$$

where $\alpha = e^{-\frac{BT_s}{J}}$, $\beta = \frac{K_t(1-\alpha)}{B}$, $\gamma = -\frac{\beta}{K_t}$, and T_s is the sample time.

As mentioned above, we know that the friction force, torque ripple and inertias may vary in a wide range or even be unknown, i.e., the parameters α, β, γ are time varying or sometimes unknown.

3 Design of the Control scheme

It is well known that the disturbance observer based control techniques are successfully applied for disturbance compensation in PMSM because of their simplicity and powerful ability to compensate the disturbances. In cases when the parameters change over a wide range, the fixed nominal model in the traditional DOB is always inaccurate and can not change with the parameter variations, so the traditional DOB may no longer be suitable. In this paper, a self-tuning disturbance observer based on the neural network parameter identification system is used to overcome the inertia variations as well as external load disturbances in the PMSM.

3.1 Parameter Identification Using a Linear Adaptive Neural Network

It is well known that the frequency of sampling is much faster than the frequency of load variations in PMSM servo system, so the load torque can be seen as a constant within a sampling period, i.e., $\dot{T}_L = 0$. A two layer linear adaptive neural network (LANN) is used to approximate the parameters (α and β) of the PMSM in the absence of load torque. LANN has a simple structure with two layers including the input layer and output layer, and its weights between the input and output layers can be considered as the parameters need to be identified. The block diagram of parameter identification system is shown in Fig. 1.

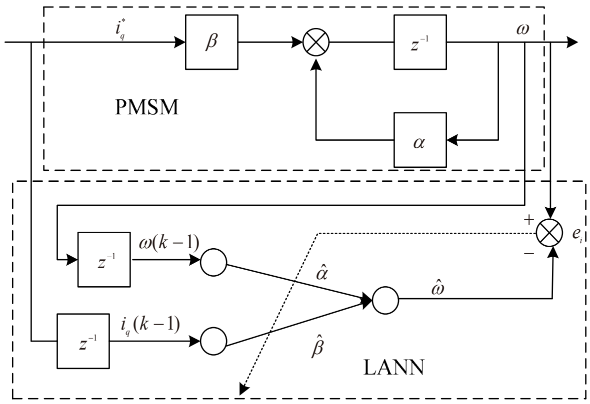

Fig. 1: The block diagram of parameters identification

The past input and output of PMSM, i.e., $\omega(k-1)$ and $i_q^*(k-1)$ can be used as the inputs of the LANN. And the weights of LANN between the input layer and output layer are the identified parameters $\hat{\alpha}$ and $\hat{\beta}$. According to the input and output data, the output of the neural network $\hat{\omega}(k)$ can be obtained

$$\hat{\omega} = \mathbf{\Phi}^T(k-1)\mathbf{W}(k) = \hat{\alpha}\omega(k-1) + \hat{\beta}i_q^*(k-1) \tag{4}$$

where $\mathbf{\Phi}(k-1) = [\omega(k-1), i_q^*(k-1)]^T$ is the input of the LANN, $W(k) = [\hat{\alpha}, \hat{\beta}]^T$ is the weight and also the estimated parameters of the PMSM. $\hat{\alpha} = \alpha, \hat{\beta} = \beta$ can be obtained when $\hat{\omega} = \omega$ via the on-line learning.

Define the identification error as follows,

$$e_i(k) = \omega(k) - \hat{\omega}(k) \tag{5}$$

And the performance index function can be defined as

$$E = \| \omega(k) - \hat{\omega}(k) \|_2 = \frac{1}{2}[\omega(k) - \hat{\omega}(k)]^2 = \frac{1}{2}e_i^2(k) \tag{6}$$

In order to get the precise parameters of the system, the least mean square (LMS) learning method can be used for the minimization of the performance index E .

$$\hat{\alpha}(k) = \hat{\alpha}(k-1) - \eta\frac{\partial E}{\partial \hat{\alpha}(k)} = \hat{\alpha}(k-1) + \eta e_i(k)\omega(k-1) \tag{7}$$

where $\eta = \frac{\xi(k)}{\| \theta(k-1) \|_2} = \frac{\xi(k)}{b + \omega^2(k-1) + i_q^{*2}(k-1)}$, and $\xi(k) = \xi_{\max} - k(\xi_{\max} - \xi_{\min})/k_{\max}$. ξ is the learning ratio and a constant between [0,1] which can make the algorithm convergent. $\xi_{\max}$ is the maximum learning ratio, $\xi_{\min}$ is the minimum learning ratio, k is the current iteration number, and $k_{\max}$ is the maximum iteration number. $b \neq 0$ is a constant which can make sure that the denominator is not zero to avoid divergence. Then

$$\hat{\alpha}(k) = \hat{\alpha}(k-1) + \frac{\xi(k)e_i(k)\omega(k-1)}{b + \omega^2(k-1) + i_q^{*2}(k-1)} \tag{8}$$

Similarly,

$$\hat{\beta}(k) = \hat{\beta}(k-1) + \frac{\xi(k)e_i(k)i_q^*(k-1)}{b + \omega^2(k-1) + i_q^{*2}(k-1)} \tag{9}$$

According to Eqs. (3), (8) and (9), the estimation parameters of PMSM can be obtained as follows

$$\hat{B} = \frac{K_t(1-\hat{\alpha})}{\hat{\beta}} \tag{10}$$

$$\hat{J} = -\frac{\hat{B}T_s}{\ln \hat{\alpha}} \tag{11}$$

3.2 A Self-tuning Disturbance Observer

The traditional disturbance observer usually relies on the choice of the nominal model, but if there are large parameter variations, the fixed nominal model is always inaccurate and can not change with the parameter variations. According to the identified parameters mentioned in Section 3.1, a self-tuning disturbance observer can be obtained in this section.

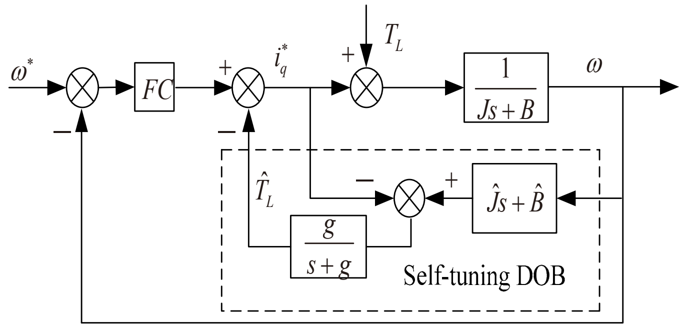

Fig. 2: The block diagram of self-tuning disturbance observer

In Fig.2, $\hat{J}$ and $\hat{B}$ are identified by LANN, which can be tuned on-line along with the real parameter variations. Eq. (2) can be rewritten as

$$(Js + B)\hat{\omega} = i_q^* + T_L \tag{12}$$

From Fig. 2, choose the low pass filter as $Q(s) = \frac{g}{s+g}$, the output of the self-tuning DOB is

$$\begin{aligned} \hat{T}_L &= (\omega G_n^{-1}(s) - i_q^*)\frac{g}{s+g} \\ &= ((\hat{J}s + \hat{B})\omega - i_q^*)\frac{g}{s+g} \end{aligned} \tag{13}$$

Compared with Eq. (12), if $\hat{J} \to J$, $\hat{B} \to B$, there will be $\hat{T}_L = T_L\frac{g}{s+g}$. Then if $g \to \infty$, there will be $\hat{T}_L \to T_L$. That is to say, the identification accuracy of the neural network determines the precision of DOB.

3.3 The LANN Parameter Identification and Self-tuning DOB Based Adaptive Speed Controller

Based on the parameters identified by LANN and the load torque observed by the self-tuning DOB, an adaptive on-line tuning composite speed controller can be obtained

$$i_q^*(k-1)=\frac{1}{\hat{\beta}}\omega^*(k)-\frac{\hat{\alpha}}{\hat{\beta}}\omega(k-1)-\frac{\hat{\gamma}}{\hat{\beta}}\hat{T}_L(k-1)+Ke(k) \tag{14}$$

where $\hat{\gamma}=-\frac{\hat{\beta}}{K_t}$, $e(k)=\omega(k)-\omega^*(k)$, ω^* is the reference speed, $Ke(k)$ can eliminate the speed fluctuation caused by the imprecise identification of LANN. K is the designed constant. Substituting Eq. (14) into Eq. (3) yields

$$\omega(k)=\alpha\omega(k-1)+\beta[\frac{1}{\hat{\beta}}\omega^*(k)-\frac{\hat{\alpha}}{\hat{\beta}}\omega(k-1)-\frac{\hat{\gamma}}{\hat{\beta}}\hat{T}_L(k-1)+Ke(k)] +\gamma T_L(k-1) \tag{15}$$

We can see that, if $\hat{\alpha}\to\alpha$, $\hat{\beta}\to\beta$ and $\hat{T}_L\to T_L$, there will be $\omega(k)\to\omega^*(k)$. That is to say, the accuracy of the LANN identification determines the performance of the self-tuning disturbance observer and also the adaptive composite speed controller.

The composite speed controller based on LANN parameter identification and self-tuning DOB of a PMSM servo system is shown in Figure 3.

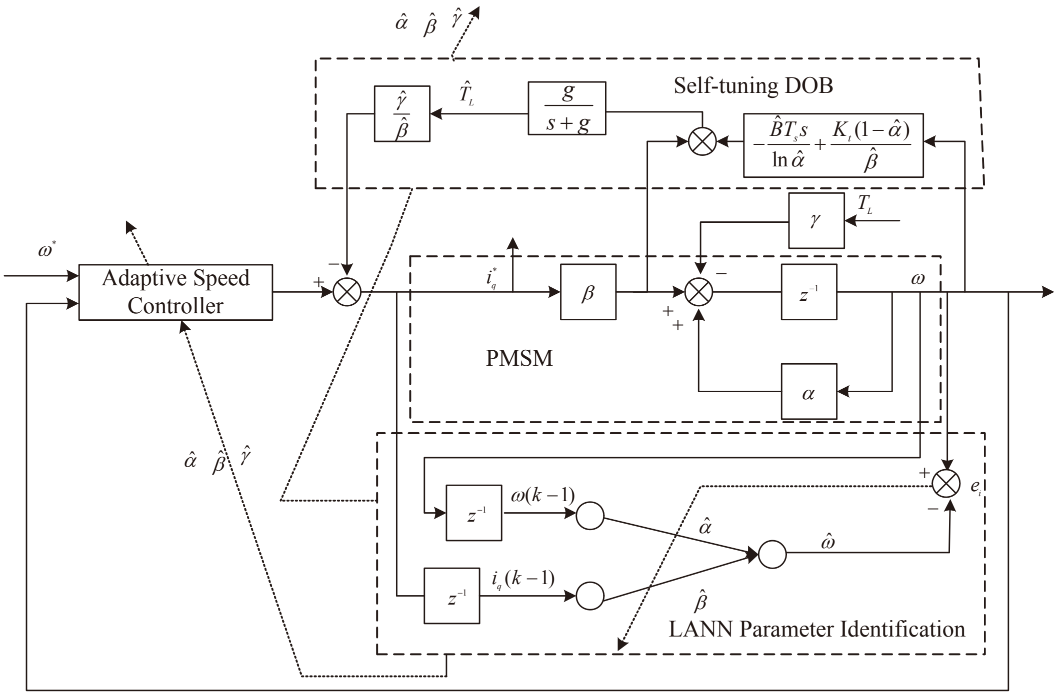

Fig. 3: The diagram of composite speed controller for PMSM servo system

4 Simulation Results

To evaluate the proposed adaptive composite control scheme, various digital simulations using MATLAB are undertaken. The specifications of the PMSM are $J_n=1.78\times10^{-4}kg.m^2$, ψ_f=0.402Wb, $n_p=4$, $B=7.4\times10^{-5}$Nms/rad, respectively. And assume $\omega^*(k)=500rad/s$. The sampling interval of the control processing in the simulations is set at 0.0001 s. And in the initial stage, the motor inertia is assumed to be $J=J_n$.

4.1 The Parameter Identification by LANN

In some application circumstances, PMSM systems driving different load devices have different inertias, such as the electric winding machine. Assume the inertia J is increased to 10 times of the original inertia, i.e., $J=10J_n$. Here the LANN is used to identify the changes of the inertia. In order to fully excite the system dynamic behavior in each frequency band, the pseudo-random sequence is used to identify the system, i.e., fourth-order M-sequence with cycle time Np = 15, as shown in Fig. 4. The output of the LANN can be seen in Fig. 5. And the parameters $\hat{\alpha}$ and $\hat{\beta}$ can be seen in Fig. 6. According to the identified $\hat{\alpha}$ and $\hat{\beta}$, the inertia variation can be seen in Fig. 7.

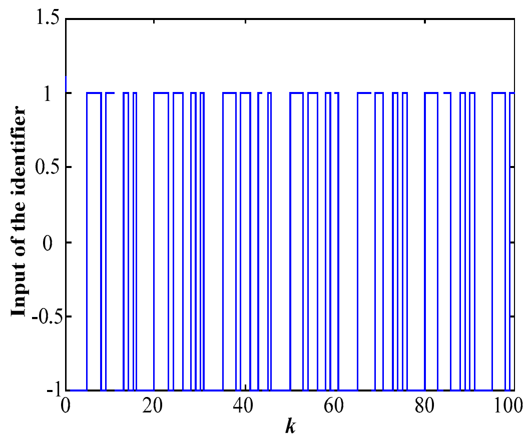

Fig. 4 The curve of the fourth-order M-sequence used for system identification

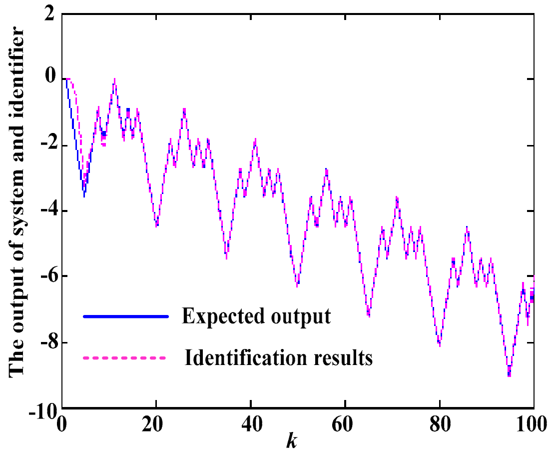

Fig. 5 The output curve of the LANN

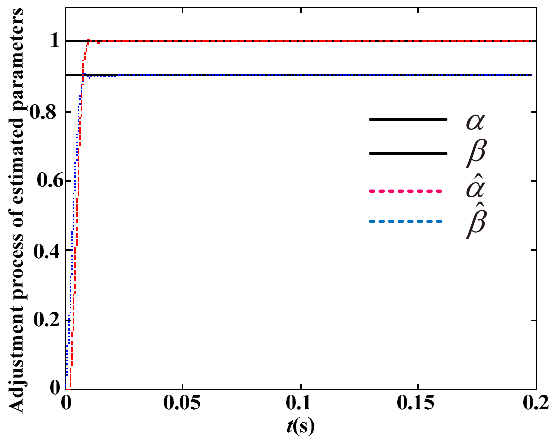

Fig. 6 The identified parameters by LANN

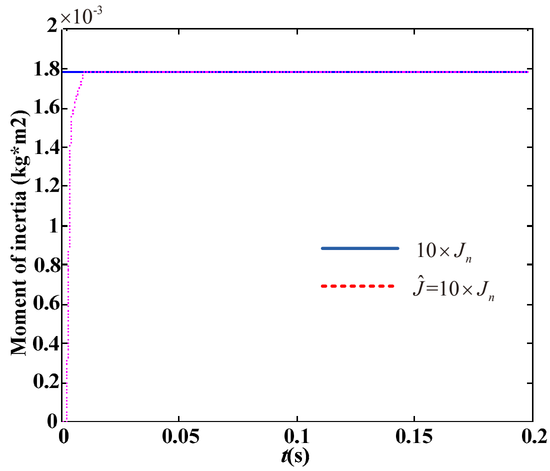

Fig. 7 The inertia curve identified by LANN

It can be seen from Fig. 5 that the identification accuracy of the LANN is very high. So from Fig. 6 and Fig. 7, the parameters variations of the system can be obtained precisely.

4.2 The Performance of the Self-tuning DOB

Assume the inertia J is changed into $10J_n$ and the 1Nm load torque is applied at the beginning, at t=0.07s the load torque is changed into 2Nm, and at t=0.1s is changed into 3Nm, then the load torque is removed at t=0.14s. The load torque observed by the self-tuning DOB is shown in Figure 8.

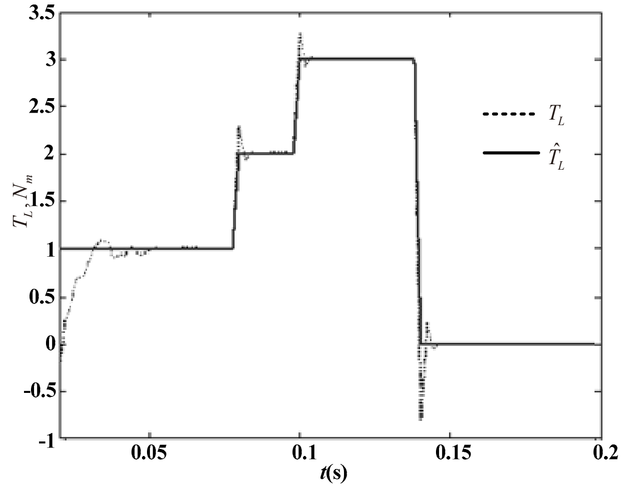

Fig. 8 The output of self-tuning DOB

As shown in Fig. 8, the curves of the observed and the real disturbances almost overlap, which means the self-tuning DOB can observe the disturbance effectively in the case of large parameter variations and external disturbance.

4.3 The Performance of composite speed controller

Fig. 9 shows the speed responses under the proposed composite speed controller in the same condition with inertia variations and load disturbances changes.

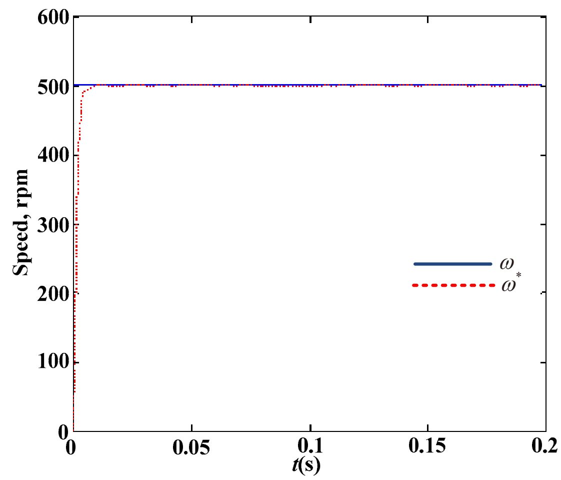

Fig. 9 Speed curve with inertia variations and load disturbances

It is evident that the speed response of the proposed control scheme shown in Fig. 9 is robust to the variations in inertia and the load disturbances.

5 Conclusions

In this paper, an adaptive composite speed control scheme for a PMSM servo system using an adaptive feedback controller and a self-tuning DOB based on linear neural network parameter identification has been proposed. A two layer linear neural network has been introduced to identify the parameters of the PMSM system on-line. Based on the identified parameters, a self-tuning DOB has been proposed to observe the disturbances including external disturbances and parameter variations of the system, especially for the case when the inertia varies over a large range. The estimated value is used in the feedforward compensation design, which enhances the disturbance rejection property of the closed-loop system. So internal disturbances caused by parameter variations, unmodeled dynamics and external disturbances can be compensated for by the self-tuning DOB through the feedforward channel. The simulation results show that the proposed method can achieve a robust control performance both in dynamic and static performance in the presence of inertia variations and load disturbances.

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