Adaptive dynamic neural network intelligent control of a nonlinear dc motor drive system

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Abstract: Nonlinear, parameter variations and external load disturbance are widespread in a DC motor drive system. The PID controller has poor self-regulation and adaptivity and robustness. In this paper, A model-following adaptive control approach based on the neural networks is proposed for the speed control of a nonlinear motor drive system with high stick slip and Coulomb friction and the compensation of the nonlinearities. Two neural networks formulate the identification and control approaches. A Wiener-type neural network (WNN) is proposed to identify the motor system, which formulates the Wiener model with a linear dynamic block in cascade with a nonlinear static gain. A feedforward neural network is proposed to formulate the PID controller, termed as PID-type neural network (PIDNN). In this way, the WNN is used as a motor system identifier to recognize the output of motor servo system and provide Jacobian identification information for PID controller in real-time, which realize self-adjusting and self-adaptive control of motor servo system. Based on MATLAB/Simulink simulation, Wiener-type dynamic neural network intelligent control strategy of motor servo system effectiveness is verified. The results obtained confirm the excellent disturbance rejection and tracking performance properties of the system.

Keywords: Nonlinear DC motor system; Dynamic neural networks; System identification; Intelligent control; friction compensation.

1. INTRODUCTION

DC motors are devices which can convert electrical energy into mechanical energy. It has been widely used in the engineering field. It has been widely used in the engineering field. High performance motor drive systems have become the preferred choice and there is a strong interest to develop new control tools to further enhance their performance and intelligence. Conventional control schemes (proportional-integral controller) have certain limitations and cannot achieve a good speed response when the system parameters vary. Many other difficulties could be also encountered when dealing with highly nonlinear plants. To overcome these drawbacks, the control scheme should include an additional compensation scheme to eliminate the variations in the system nonlinear friction and/or load disturbance. New control algorithms such as adaptive, variable structure, and robust controllers, are therefore introduced[1-3]. This however leads to an increasingly more complicated control algorithm requiring a complex design procedure and extensive computations for real-time implementation.

With the development of intelligent control technology and the deepening of advanced algorithm research, a variety of advanced algorithms are applied to PID controller. Among various intelligent technologies, neural network could approach any nonlinear function with arbitrary precision, and has the ability of adaptive self-learning, parallel processing and high robustness. It is widely used in the identification and control of motor dive system with good results[4]. In this paper, a new robust adaptive control scheme using two type neural networks are proposed for the identification and adaptive control of the speed tracking system of permanent magnet synchronous motor (PMSM). One is Wiener-type neural network (WNN), which formulates the Wiener model with a linear dynamic block in cascade with a nonlinear static gain. The other is PID type neural network (PIDNN), which formulates the new PID controller. The WNN is designed and trained first off-line to learn the DC motor system with nonlinear friction the input–output data. After the training process is completed, the proposed adaptive control structure is applied to control the speed and suppress the disturbances dues to nonlinearities and external

load in the system. In addition, the proposed approach is not designed for a special DC motor system and therefore, it can be used for any DC motor winding type. Furthermore, the approach can be used to identify and control other electrical or mechanical systems.

The different sections of this paper are organized as follows. In Section 2, dynamic model of the DC motor system with friction is described. In Section 3, the design of the WNN for identification and the training algorithm are given. In Section 4, overall adaptive control scheme PIDNN and its training algorithm are derived. The simulation results are given in Section 5 and Conclusion in Section 6.

2. DYNAMIC MODEL OF THE NONLINEAR PMSM DRIVE SYSTEM

The system considered for analysis is a dc motor drive system composed of a dc motor connected to a mechanical load through a harmonic driver. The complete system can be represented by the schematic diagram shown in Figure 1.

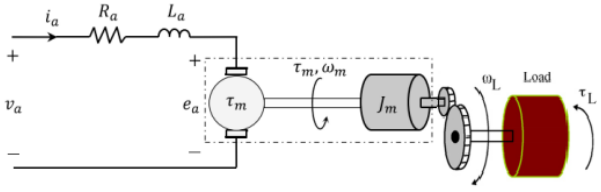


Fig. 1 dc motor drive system.

Based on the simplified permanent magnet synchronous motor model, in the synchronous rotating coordinate system, the constant amplitude transformation of the PMSM voltage equation is[5]

$$\begin{cases} u_d = Ri_d + L_d \dfrac{di_d}{dt} - \omega_e L_q i_q \\ u_q = Ri_q + L_q \dfrac{di_q}{dt} + \omega_e (L_d i_d + \psi_f) \end{cases} \tag{1}$$

Where, u_d and u_q are the stator direct axis voltage and quadrature axis voltage. R, L_d and L_q are stator resistance, direct axis equivalent inductance and quadrature axis equivalent inductance respectively. ω_e is the electrical angular speed of the motor. i_d and i_q are the stator direct axis current and quadrature axis current respectively. ψ_f is the flux linkage of rotor permanent magnet.

The permanent magnet synchronous motor electromagnetic torque equation equation is

$$T_e = \frac{3}{2} P_n i_q [i_d (L_d - L_q) + \psi_f] \tag{2}$$

The relationship between electromagnetic power and torque is

$$P_e = T_e \omega_m \tag{3}$$

The motor mechanical rotation equations is

$$J_m \frac{d\omega_m}{dt} = T_e - T_h - B_m \omega_m - T_f \tag{4}$$

Where T_e is the motor torque, P_e is the motor power, ω_m is the motor mechanical angular speed, B_m is the coefficient of motor viscous friction, and T_h is the harmonic torque, J_m is the motor inertia. T_f represents the nonlinear friction torque.

Friction is an inevitable characteristic of mechanical systems that is undesirable, and should be taken into consideration in the modeling and control design. The LuGre model including static, stick slip and Coulomb friction which could describe the friction characteristics more accurately is

$$\begin{cases} \dfrac{dz(t)}{dt} = v(t) - \dfrac{\sigma_0}{g(v)} z(t)|v(t)| \\ g(v) = F_c + (F_s - F_c) e^{-(v(t)/v_s)^2} \\ F_f(t) = \sigma_0 z(t) + \sigma_1 \dfrac{dz(t)}{dt} + \sigma_2 v(t) \end{cases} \tag{5}$$

Where $z(t)$ is the average elastic deformation of sideburns, $v(t)$ is the relative velocity between contact surfaces, v_s is Stribeck speed, F_c is Coulomb friction, F_s is the maximum Static friction, σ_0 is the stiffness coefficient, σ_1 is the damping coefficient, σ_2 is viscous coefficient. $g(v)$ is a function related to velocity. $F_f(t)$ is the friction force.

The mechanical load torque equations is

$$J_l \frac{d\omega_l}{dt} = T_h - B_l \omega_l - T_l \tag{6}$$

Where J_l is the load inertia, ω_l is the load angular speed, B_l is the load friction, and T_l is the load disturbance torque.

3. WIENER-TYPE NEURAL NETWORK FOR IDENTIFICATION

3.1. WNN topology model

A general Wiener model is closer to nonlinear dynamic system with a clear physical interpretation

which consists of a linear dynamic block and a nonlinear static block. Unlike the traditional black-box structure of neural network, Wiener model can describe a very wide range of nonlinear systems, which is closer to the actual controlled system[6,7]. Its structure is shown in Fig. 2. For the discrete-time Wiener model of single input and single output (SISO), the difference equation is described as follows.

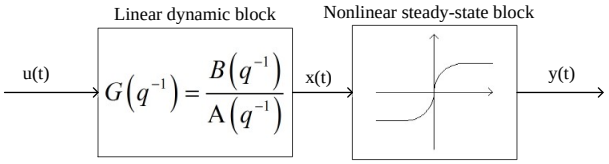


Fig. 2 Wiener model structure.

The linear dynamic block can be described as

$$x(k)=\boldsymbol{G}(q^{-1})\cdot u(k)=\frac{B(q^{-1})}{A(q^{-1})}u(k) \quad (7)$$

$$B(q^{-1})=b_0+b_1q^{-1}+\cdots+b_mq^{-m}$$

Which,

$$A(q^{-1})=1+a_1q^{-1}+\cdots+a_nq^{-n}$$

Where, $u(k)$ and $x(k)$ are the input of the WNN and the output from the hidden layer, respectively. $a_i=a_1,a_2,...,a_n$ and $b_i=b_0,b_1,...,b_m$ are the weights between the input and the hidden layer, which represent the parameters of the linear dynamic block. q^{-1} is the unit delay operator. m and n are the orders of linear dynamic block, usually $m\le n$. Rewriting the above formula:

$$\begin{aligned}x(k)=&-a_1x(k-1)-a_2x(k-2)-\cdots\\&-a_nx(k-n)+b_0u(k)+b_1u(k-1)\\&+\cdots+b_mu(k-m)\\=&-\sum_{i=1}^{n}a_ix(k-i)+\sum_{j=0}^{m}b_ju(k-j)\end{aligned} \quad (8)$$

The nonlinear static block is realized by dynamic recurrent neural network, and the relationship is:

$$y(k)=g(x(k)) \quad (9)$$

Static mapping g represents the nonlinear component of the Wiener model, realized by dynamic neural network with output feedback connection. In this paper, a two-layer dynamic neural network is adopted, in which the input of the static block is the intermediate variable $x(k)$ and the feedback is $x(k-1)$, and the feedback of the output layer is $y(k-i)$, which is expressed as:

$$rin(k)=\sum_{i=0}^{p}c_i\cdot x(k-i)+\sum_{i=1}^{q}d_i\cdot y(k-i) \quad (10)$$

The output of the neural network is:

$$y_m(k)=\varphi(rin(k)) \quad (11)$$

Where φ is a nonlinear mapping function $\varphi=\frac{e^x-e^{-x}}{e^x+e^{-x}}$. p and q are the orders of intermediate input layer and the output feedback layer. c_i and d_i represent the weights from the intermediate input layer to the output layer and the weight from the output feedback layer to the output layer respectively. The structure of the Wiener type dynamic neural network is shown in Figure 3.

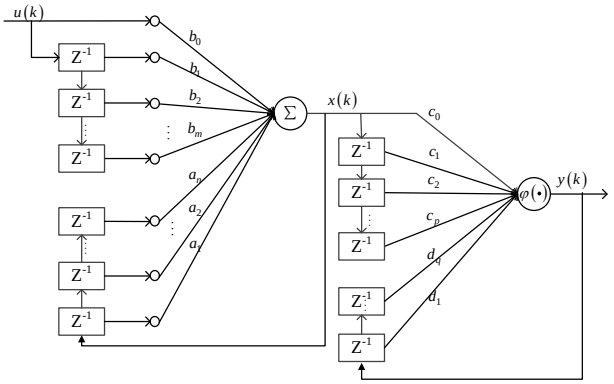


Fig. 3 The structure diagram of Wiener type dynamic neural network.

3.2. WNN training algorithm

The neural network could identify the nonlinear system model, The basic is that in the training strategy connection weights are updated according to the input and output data of the identified system. Wiener model is a parameter model, so a new weight parameter vector can be defined $\boldsymbol{W_I}=\left[a_1,...,a_n,b_0,...,b_m,c_0,...,c_p,d_1,...,d_q\right]$.In this paper, BP learning method is used to achieve the identification parameter optimization of Wiener type dynamic neural network through error back propagation algorithm and realize the neural network system model equivalent to nonlinear dynamic system.

For the input and output observation sequence of nonlinear system $\{u(t),y(t)\}_{t=1}^{N}$, if N it is the length of observation window, the objective evaluation function of Wiener model identification is:

$$\begin{aligned} \boldsymbol{J_I}(\boldsymbol{w_I},\boldsymbol{t}) &= \frac{1}{2N}\sum_{i=1}^{N}\left[y(k)-y_m(k)\right]^2 \\ &= \frac{1}{2N}\sum_{i=1}^{N} {e_m}^2(k) \end{aligned} \tag{12}$$

Where $y(k)$ and $y_m(k)$ are the DC motor output and the WNN output, respectively.

The optimal Wiener type dynamic neural network parameters should meet the following formula

$$\min_{W_I} \boldsymbol{J_I}(\boldsymbol{w_I},\boldsymbol{t}) = \min_{W_I} \frac{1}{2N}\sum_{i=1}^{N}\left[y(k)-y_m(k)\right]^2 \tag{13}$$

The adaptive learning algorithm of the WNN identifier can be obtained from the gradient descent method as follows:

$$\frac{\partial \boldsymbol{J_I}}{\partial \boldsymbol{W_I}} = -\frac{1}{N}\sum_{i=1}^{N} e_m(k)\cdot\frac{\partial y_m(k)}{\partial \boldsymbol{W_I}} \tag{14}$$

$$\begin{aligned} \boldsymbol{W_I}(\boldsymbol{k+1}) &= \boldsymbol{W_I}(\boldsymbol{k}) + \boldsymbol{\Delta W_I}(\boldsymbol{k}) \\ &= \boldsymbol{W_I}(\boldsymbol{k}) - \eta_I \frac{\partial \boldsymbol{J_I}}{\partial \boldsymbol{W_I}} \\ &= \boldsymbol{W_I}(\boldsymbol{k}) + \eta_I \cdot \frac{1}{N}\sum_{i=0}^{N-1} e_m(k+i)\cdot\frac{\partial y_m(k+i)}{\partial \boldsymbol{W_I}} \end{aligned} \tag{15}$$

The learning algorithm of the weights from the output feedback layer to the output layer d_j is expanded as follows:

$$\frac{\partial y_m(k)}{\partial d_j} = \varphi' y(k-j), j = 1,2,3\cdots q \tag{16}$$

The learning algorithm of the weights from the intermediate input layer to the output layer c_j is expanded as follows:

$$\frac{\partial y_m(k)}{\partial c_j} = \varphi'\cdot x(k-j), j = 0,1,2,\cdots p \tag{17}$$

The learning algorithm of input weights of linear subsystem a_j is expanded as follows:

$$\begin{aligned} \frac{\partial y_m(k)}{\partial a_j} &= \frac{\partial y_m(k)}{\partial rin(k)}\cdot\frac{\partial rin(k)}{\partial a_j} \\ &= \varphi_j'\cdot\left[\sum_{i=0}^{p} c_i\cdot\frac{\partial x(k-i)}{\partial a_j} + \sum_{l=1}^{q} d_l\cdot\frac{\partial y_m(k-l)}{\partial a_j}\right] \\ \frac{\partial x(k)}{\partial a_j} &= -x(k-j) - \sum_{s=1}^{n} a_s\frac{\partial x(k-s)}{\partial a_j}, j = 1,2,\cdots n \end{aligned} \tag{18}$$

The learning algorithm of the hidden layer feedback weights of the linear lock b_j is expanded as follows:

$$\begin{aligned} \frac{\partial y_m(k)}{\partial b_j} &= \frac{\partial y_m(k)}{\partial rin(k)}\cdot\frac{\partial rin(k)}{\partial b_j} \\ &= \varphi_j'\cdot\left[\sum_{i=0}^{p} c_i\cdot\frac{\partial x(k-i)}{\partial b_j} + \sum_{l=1}^{q} d_l\cdot\frac{\partial y_m(k-l)}{\partial b_j}\right] \\ \frac{\partial x(k)}{\partial b_j} &= u(k-j) - \sum_{s=1}^{n} a_s\frac{\partial x(k-s)}{\partial b_j}, j = 1,2,\cdots m \end{aligned} \tag{19}$$

From these evaluations the output of the WNN $y_m(k)$ is determined and the weights which are associated with the Wiener model parameters can be updated.

As mentioned previously, an ideal DC motor can be regarded as a linear dynamic system, with friction as a static nonlinearity.

4. ADAPTIVE PIDNN CONTROL BASED ON WINNER-TYPE

WNN is used for system identification and combined with traditional control algorithm. Based on the conventional PID controller, the neural network is used to update the PID control parameters of the system, and a stable controller with self-adjusting is constructed. The adaptive PID control structure based on Wiener type dynamic neural network identification is shown in Figure 4. The control objective is to tune the parameters in the PIDWNN controller so that the output $y(k)$ of the nonlinear system tracks the desired trajectories $y_d(k)$. At the same time, the neural network identifier takes the input of the controlled object as the input, uses the identification error of the system to tune the network parameters in real time, so that can model the system nonlinear behaviour, and provides the Jacobian matrix of the identification system. The neural network PID controller uses the tracking desired trajectories error and Jacobian matrix to tune the PID control parameters.

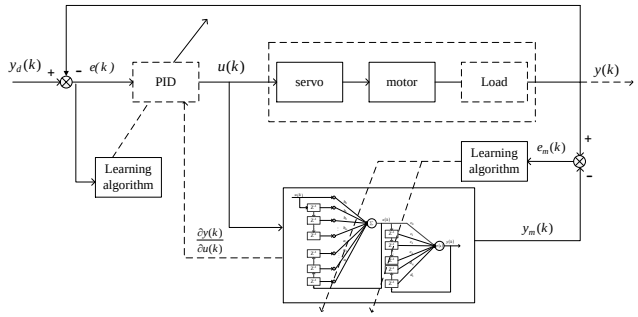


Fig. 4 Adaptive PID-type neural network control based on WNN

In Figure 4, $y_d(k)$ is the desired trajectories output, $y(k)$ is the actual plant output, $e(k)$ is the difference between the desired output and the actual output, $y_m(k)$ is the neural network output and $u(k)$ is the control effort.

The conventional PID control law is obtained from the following formula:

$$e(k) = y_d(k) - y(k) \tag{20}$$

$$xc(1) = error(k) - error(k-1) \tag{21}$$

$$xc(2) = error(k) \tag{22}$$

$$xc(3) = error(k) - 2error(k-1) + error(k-2) \tag{23}$$

$$\triangle u(k) = k_p xc(1) + k_i xc(2) + k_d xc(3) \tag{24}$$

$$u(k) = u(k-1) + \triangle u(k) \tag{25}$$

For the adaptive PIDNN controller, its weights are updated along the negative gradient of a given error function as follows,

$$\begin{aligned} \boldsymbol{J_c}(\boldsymbol{w_c}, \boldsymbol{t}) &= \frac{1}{2N}\sum_{i=1}^{N}\left[y_d(k) - y(k)\right]^2 \\ &= \frac{1}{2N}\sum_{i=1}^{N} e^2(k) \end{aligned} \tag{26}$$

The correction of control parameters is:

$$\begin{aligned} \boldsymbol{W_C}(\boldsymbol{k+1}) &= \boldsymbol{W_C}(\boldsymbol{k}) + \boldsymbol{\Delta W_C}(\boldsymbol{k}) \\ &= \boldsymbol{W_C}(\boldsymbol{k}) - \eta_C \frac{\partial J_C}{\partial W_C} \\ &= \boldsymbol{W_C}(\boldsymbol{k}) + \eta_C \cdot \frac{1}{N}\sum_{i=1}^{N} e(k)\frac{\partial y(k)}{\partial u(k)} \cdot \frac{\partial u(k)}{\partial \boldsymbol{W_C}} \end{aligned} \tag{27}$$

Therefore, the update of each control parameter is:

$$k_p(k+1) = k_p(k) + \eta_c \frac{1}{N}\sum_{i=1}^{N} e(k)\frac{\partial y}{\partial u} xc(1) \tag{28}$$

$$k_i(k+1) = k_i(k) + \eta_c \frac{1}{N}\sum_{i=1}^{N} e(k)\frac{\partial y}{\partial u} xc(2) \tag{29}$$

$$k_d(k+1) = k_d(k) + \eta_c \frac{1}{N}\sum_{i=1}^{N} e(k)\frac{\partial y}{\partial u} xc(3) \tag{30}$$

In equations (28)-(30), $\frac{\partial y}{\partial u}$ denotes the sensitivity of the plant output with respect to its input (Jacobian information). The sensitivity cannot be calculated directly from the output of the nonlinear system since the precise mathematical model is usually unknown in many practical systems. In general, since the WNN was trained (off-line or online), there is $\frac{\partial y_m}{\partial u} \approx \frac{\partial y}{\partial u}$ .Therefore, the system sensitivity Jacobian information can be calculated as:

$$\begin{aligned} \frac{\partial y_m(k)}{\partial u(k)} &= \frac{\partial y_m(k)}{\partial rin(k)} \cdot \frac{\partial rin(k)}{\partial u(k)} \\ &= \varphi_j' \cdot \left[\sum_{i=0}^{p} c_i \cdot \frac{\partial x(k-i)}{\partial u(k)} + \sum_{l=1}^{q} d_l \cdot \frac{\partial y_m(k-l)}{\partial u(k)}\right] \end{aligned} \tag{31}$$

Where

$$\frac{\partial x(k)}{\partial u(k)} = b_0 - \sum_{s=1}^{n} a_s \frac{\partial x(k-s)}{\partial u(k)}, j = 1,2,3\cdots n$$

5. SIMULATION VALIDATION

Firstly, a PMSM connected to a mechanical load drive system is established with Matlab/Simulink. The simulation model comprehensively considers the external load and system friction, including static friction, Coulomb friction, viscous friction and other factors. The Specifications of the PMSM are in table 1.

Table. 1 Specification of the PMSM

Motor characteristics	Parameters	Values	Unites
Motor rated voltage	-	48	V
Motor rated current	-	11	A
Motor rated torque	-	1.43	Nm
Motor rated speed	-	2500	RPM
Motor torque constant	Kt	0.13	Nm/A
Motor terminal resistance	Rm	0.21	Ω
Motor rotor inductance	Lm	0.00047	H
Motor viscous damping coefficient	Bm	0.61e-6	Nms/rad
Motor rotor inertia	Jm	0.61e-5	Kgm^2
Stiffness coefficient of harmonic driver	Kts	3.6e5	Nm/rad
Harmonic load inertia	JL	0.001	Kgm^2
Reduction ratio	N	100	-

Secondly, the mathematical model of adaptive PIDNN controller is established. In this paper, the controller is verified by simulation and the results are analyzed under the conditions of constant external load and variable external load. Wiener type dynamic neural network adopts a three-layer network structure, in which the input of the nonlinear static block are the intermediate variable $x(k)$, as well as the three times feedback of $x(k)$ and the previous time feedback of the output $y_m(k)$. First, initialize a small set of system control parameters. In the simulation setup, the control algorithm is implemented at a frequency 10KHz sampling rate.

(1) WNN for Off-line system identification, to test identification performance of WNN for the DC motor with nonlinear friction, an open-loop test is performed with a sin function. The system identification results are shown in Figure 5, where the WNN could identify the plant output. It is clear that WNN could identify the nonlinear friction.

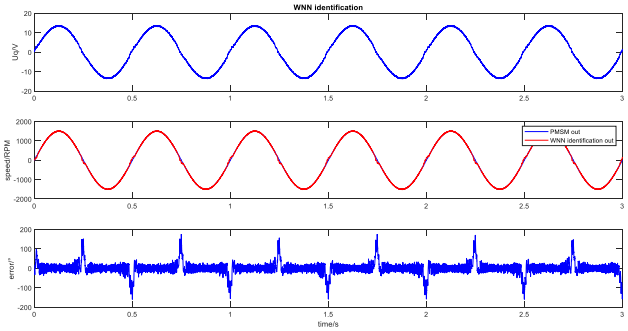


Fig. 5 DC motor voltage, plant output, WNN identification, plant and identification error

(2) Under the given friction model and external load condition, A sinusoidal signal is set as velocity 1500 rpm and frequency 2Hz. A square wave is set as $\pm$500 rpm and frequency 0.25Hz. The motor velocity adaptive PIDNN control simulation results are shown in Figure 6 and Figure 7.

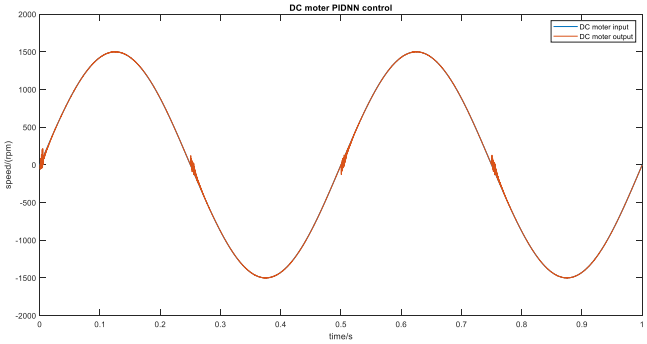


Fig. 6 DC motor speed sin signal and adaptive PIDNN control output (time varying nonlinear friction)

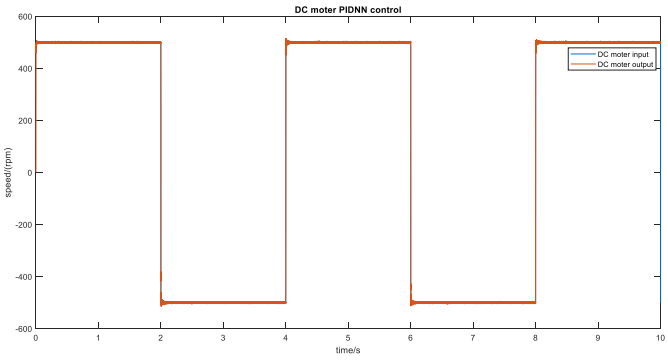


Fig. 7 DC motor speed square signal and adaptive PIDNN control output (time varying nonlinear friction)

After the gradual learning and adjustment of the neural network, the control system tends to be stable. It can be seen from the simulation results in Figure 6 and 7, the PMSM output is also gradually stable close to the command value, and the control result is ideal. In this control process, the self adjustment of control parameters is realized through neural network intelligent control, so as to achieve the ideal control effect, avoid the problems caused by cumbersome manual parameters adjustment and improper parameters, realize the intelligent management of system control.

(3) The law of the system at a given speed under variable load is sinusoidal signal, which velocity is 1500 rpm and frequency is 2Hz. In the control process, a sudden external load change is set from 0.6s to 0.72s, which represents the impact of external interference on the system. The results are shown in figure 8 and 9.

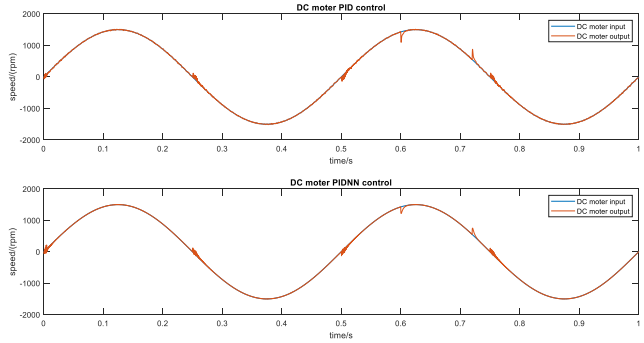


Fig. 8 Simulation results of PID and PIDNN controller (Sudden change of external load and time varying friction)

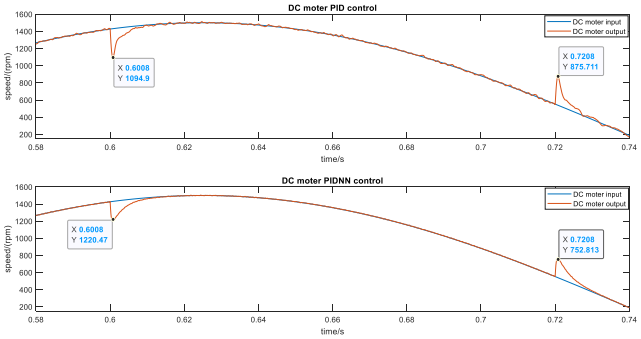


Fig. 9 Simulation results at 0.6~0.72s
(Sudden change of external load and time varying friction)

The figures illustrate that the PMSM system controlled by PIDNN controller has a better tracking performance than the PID controller. In the case of sudden change of external load, the system output of the traditional PID controller has obvious oscillation and the control performance decreases, which shows that the adaptability of the traditional PID controller is poor. In the case of sudden change of external load, the self-adjusting PID control algorithm using Wiener type dynamic neural network can still maintain good control performance and stable system output by adjusting control parameters through its own learning ability. It is verified that the control algorithm has good adaptability and robustness.

6. CONCLUSION

In this study, Firstly the principle and characteristics of DC motor drive system with static, stick slip and Coulomb friction are introduced. Secondly, the structure and principle of PID controller based on Wiener type dynamic neural network identification are introduced. Wiener type dynamic neural network is used as a forward identifier to identify the DC motor motion online and provide Jacobian information of system dynamic characteristics for PID controller in real time to tune the control parameters to facilitate adaptive control of the system. Through the simulation of MATLAB and Simulink, it is verified that the PIDNN controller based on Wiener type dynamic neural network identification could continuously optimizes the parameters in the control process, avoids the tedious adjustment of traditional PID and the blindness of parameter optimization to forms a stable and adaptive controller. When the external load changes, the control structure can not only realize the optimization process of initial parameters, but also eliminate the interference of load change to the system through the self-learning function of neural network. It is verified that the PIDNN controller has good adaptability and robustness and realizes the intelligent control of nonlinear time-varying system. Furthermore, the approach could be used to identify and control other electrical or mechanical systems.

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