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Speed-Regulating System for Induction Motor and Inverter based on Hammerstein Model and Neural Network Control

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Abstract

A novel control strategy based on Hammerstein model and neural network for the speed-regulating system of the induction motor and inverter is proposed in this paper. First, Hammerstein model was used to model the speed-regulation system of the induction motor and inverter. Auto-regressive and moving average (ARMA) model was used to identify the dynamic linear module of Hammerstein model of the speed-regulating system. Second, the ARMA model was used as a reference model for identification of the inverse model of static nonlinear neural network (NN) module of Hammerstein model in the framework of the model reference adaptive control method. For the load disturbance issue, two control strategies, online learning neural network direct inverse control and the traditional PI close-loop control strategy were studied. Simulations show that the inverse control based on Hammerstein model and NN is effective and the online learning neural network direct inverse control strategy for the speed-regulating system with load disturbance has higher performance.

Keywords: *Hammerstein model; Inverter; Induction motor; Neural network; ARMA*

1. Introduction

The speed-regulating system of induction motor and inverter (SSIMI) widely used in industrial fields is a complex nonlinear system. The traditional PID control is difficult to meet the requirements of high performance control [1]. SSIMI has been studied by many researchers. The nonlinear time-delay characteristics of hysteresis current control PWM inverter was discussed in SSIMI [2]. For the nonlinear problem of SSIMI, the α-th order neural network inverse system was designed to control SSIMI [1, 3-6]. Cascaded with the α-th order neural network inverse system which is obtained by training, the original system can be represented by an approximate pseudolinear system. Then the close loop controllers can be designed respectively according to the linear system theory. However, Several factors such as the time-delay of inverter and load disturbance were ignored in [1, 3]. And the approximate pseudolinear system was designed as pure integrators resulting in difficulties of realizing open loop control.

Hammerstein model is a typical nonlinear system model with a specific structure, which consists of a static nonlinear module and a dynamic linear module [7]. The model can be used to model many nonlinear systems. Some research results about Hammerstein model applied in the fields of motor model and control have been achieved. The parameters identification method of permanent magnet synchronous motor based on Hammerstein model was proposed in [8].The newton’s method was used for identification of the direct and quadrature inductances from the nonlinear

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static module of Hammerstein model. The Hammerstein model based on radial functions neural network was applied in modeling traveling wave ultrasonic motor [9]. The application of Hammerstein model in modeling DC motor was discussed in [10]. Coulomb friction and dead zone nonlinearities of DC motor was described by the nonlinear static module of Hammerstein model.

For the nonlinear nature of the speed-regulation system of SSIMI, a novel control strategy based on Hammerstein model and neural network was proposed in this paper. In the strategy, Auto-regressive and moving average (ARMA) model was used to identify the dynamic linear module of the speed-regulating system. Moreover, the ARMA model was used as a reference model for identifying the inverse model of static nonlinear module in the framework of the model reference adaptive control method. Finally, for the existing of load disturbance, online learning neural network direct inverse controller was studied and compared with PI controller.

2. Speed-regulating System of the Induction Motor and Inverter

Three phase induction motor mathematical model can be expressed by the five order state equation in rotating two-phase coordinate as follows [3, 11].

$$\begin{cases} \dot{\omega}_{\mathrm{r}} = \dfrac{\mathrm{n}_p{}^2 L_m}{J L_r}(\psi_{rd}\,\mathrm{i}_{sq} - \psi_{rq}\,\mathrm{i}_{sd}) - \dfrac{\mathrm{n}_p}{J} T_L \\ \dot{\psi}_{rd} = -\dfrac{1}{T_r}\psi_{rd} + (\omega_1 - \omega_{\mathrm{r}})\psi_{rq} + \dfrac{L_m}{T_r}\mathrm{i}_{sd} \\ \dot{\psi}_{rq} = -(\omega_1 - \omega_{\mathrm{r}})\psi_{rd} - \dfrac{1}{T_r}\psi_{rq} + \dfrac{L_m}{T_r}\mathrm{i}_{sq} \\ \dot{\mathrm{i}}_{sd} = -\dfrac{1}{T_s}\mathrm{i}_{sd} + \omega_1\,\mathrm{i}_{sq} + \dfrac{1}{T_s}\mathrm{i}_{sd}^{*} \\ \dot{\mathrm{i}}_{sq} = -\dfrac{1}{T_s}\mathrm{i}_{sq} + \omega_1\,\mathrm{i}_{sd} + \dfrac{1}{T_s}\mathrm{i}_{sq}^{*} \end{cases} \quad (1)$$

where ω_1 is electrical synchronous angular velocity, ω_{r} is rotor electrical angular velocity, i_{sd} and i_{sq} are stator currents in (d,q) axis. i_{sd}^{*} and i_{sq}^{*} are given stator current in (d,q) axis. ψ_{rd} and ψ_{rq} are rotor flux linkage in (d,q) axis. n_p is number of pole-pairs. L_m is mutual inductance. L_r is rotor inductance. J is inertia. T_L is load torque. T_r is rotor time-constant of induction motor. T_s is current lagging time-constant of inverter.

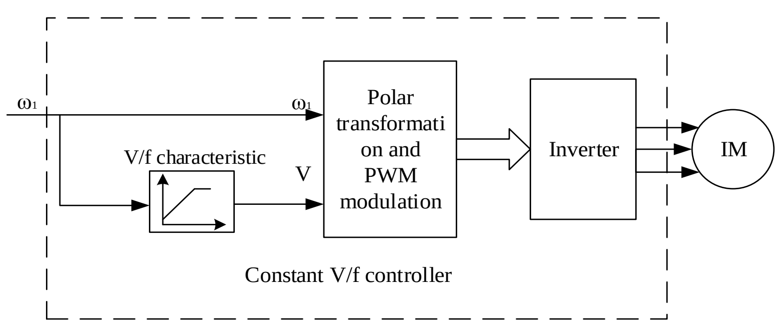


Figure 1. Variable Frequency Speed-regulating System in v/f Mode

An industrial inverter usually works in one of three modes: the V/f mode, the field-oriented mode and the direct torque mode. And the V/f mode is the most widely used because of its light weight, small volume and outstanding performance. The principle chart of variable frequency speed-regulating system in the V/f mode is presented in Figure 1. Since SSIMI is a whole module, a speed response can be obtained once the inverter is given a frequency input which is used as the synchronous angle frequency that can generate a setpoint of voltage amplitude according to the V/f characteristic in nature. V/f control mainly is used to keep the stator's flux linkage unchanged. With two phases voltages of stator in polar coordinates, synchronous angle frequency and voltage amplitude make that the flux linkage of the induction motor stator remains the same [1]. As seen in Figure 1, in consideration of motor startup behavior and protection, the V/f characteristic is usually designed as a nonlinearity curve. In practical application, the amplitude and change rate of input signals of the V/f controller is usually limited. Besides, the delay in the inverter makes the nonlinearity of the SSIMI more complex.

The fluctuation characteristics of load T_L to rotor electrical angular velocity ω_{r} were studied in the next part. When the speed response of the induction motor reaches steady state, equation (1) can be written as

$$\dot{\omega}_{\mathrm{r}} = \frac{\mathrm{n}_p{}^2 L_m}{J L_r}(\psi_{rd}\,\mathrm{i}_{sq} - \psi_{rq}\,\mathrm{i}_{sd}) - \frac{\mathrm{n}_p}{J}T_L = 0 \quad (2)$$

$$\frac{\mathrm{n}_p L_m}{L_r}(\psi_{rd}\,\mathrm{i}_{sq} - \psi_{rq}\,\mathrm{i}_{sd}) = T_L \quad (3)$$

under the condition of the rotor field-oriented, $\psi_r = \psi_{rd}, \psi_{rq} = 0$, $\omega_1 = \omega_{\mathrm{r}} + \frac{L_m}{T_r \psi_r}\mathrm{i}_{sq}$,

then i_{sq} can be written as $\mathrm{i}_{sq} = (\omega_1 - \omega_{\mathrm{r}})\frac{T_{\mathrm{r}}}{L_r}\psi_r$, so Eq.(3) is rearranged as

$$\omega_{\mathrm{r}} = \omega_1 - \frac{T_L L_r{}^2}{\mathrm{n}_p T_{\mathrm{r}} L_m \psi_r{}^2} \quad (4)$$

When the speed response reaches steady state, rotor field-oriented ψ_r is a constant. In addition, L_r, n_p, T_r and L_m in equation (4) are invariable, the relationship between the speed response of induction motor and setpoint ω_1 of inverter is linear while load T_L is invariable. But load T_L disturbance will affect the speed response.

3. Speed-regulating System for Induction Motor and Inverter based on Hammerstein Model and Neural Network

3.1. Hammerstein Model

A typical structure of Hammerstein model (see Figure 2) consists of a static nonlinear element $N(\cdot)$ in series with a dynamic linear element $G(\mathrm{z})$ [12]. In Figure 2, $\mathrm{u(k)}$, $v(\mathrm{k})$ and $y(\mathrm{k})$ denote the input, internal and output signals at time k of a SISO system respectively.

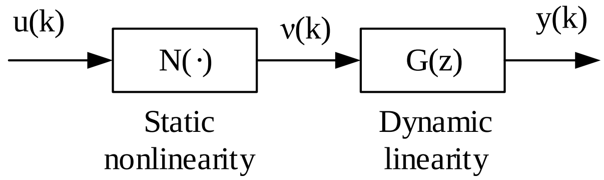


Figure 2. The Structure of Hammerstein Model

The SSIMI can be described by a Hammerstein model. For the lowpass property of the induction motor, the linear dynamic module of Hammerstein model can be identified using an ARMA model and the nonlinear static module can be approximated using neural network. The proposed control strategy of the SSIMI based on a Hammerstein model is showed in Figure 3.

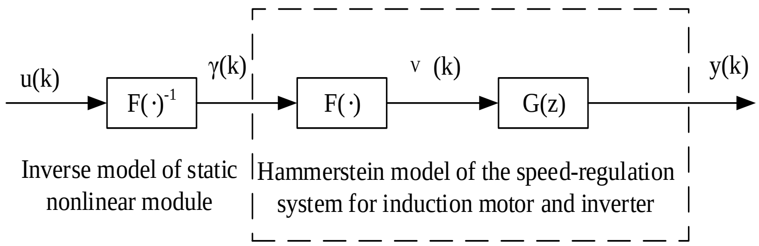


Figure 3. Direct Inverse Control for Speed-regulating System

The SSIMI cascaded with the NN inverse model of the static nonlinear module can be viewed as an approximate pseudolinear system. So the controller of the pseudolinear system can be designed on linear system theory.

3.2. Identification of the Linear Dynamic Module

Because of the lowpass property of the SSIMI, the linear dynamic module of the SISO system in Figure 1 can be identified on the step response [13]. In Figure 2,the change of $\nu(\mathrm{k})$ and $\mathrm{u(k)}$ is synchronous [14]. If $\mathrm{u(k)}$ denotes a step signal, then $\nu(\mathrm{k})$ denotes a synchronous step signal. Assume that the linear dynamic module $G(\mathrm{z})$ is a system and its steady-state gain is 1 for convenience. Giving the SSIMI a step signal, the linear model of the original system can be identified using an ARMA model when the output of the system reaches steady state.

3.3. Identification of the Inverse Model of the Nonlinear Static Module

Any static neural network inverse model can be used to offset the nonlinear characteristic of the SSIMI in this paper. Three layers MLN network inverse model was adopted for indicating the suitability of the proposed method. The excitation function of hidden neuron is monotonic smooth hyperbolic tangent function:

$$f(\mathrm{x}) = \frac{\mathrm{e}^{2x} - \mathrm{e}^{-2x}}{\mathrm{e}^{2x} + \mathrm{e}^{-2x}} \tag{5}$$

The output layer is composed of neuron with linear threshold excitation function [15, 16].

The initial connection weights of the MLN network can be obtained by training on the input and output of the SSIMI offline. It is important to note that the exciting signal of the system should be reasonable. For the aim is to identify the inverse of the static nonlinear module, stairstep signal is chosen. The exciting signal and output response of the SSIMI are shown in Figure 4.Under the condition of the previous assume, the neural network inverse model of the nonlinear static module can be trained on the steady output and corresponding input in Figure 4.

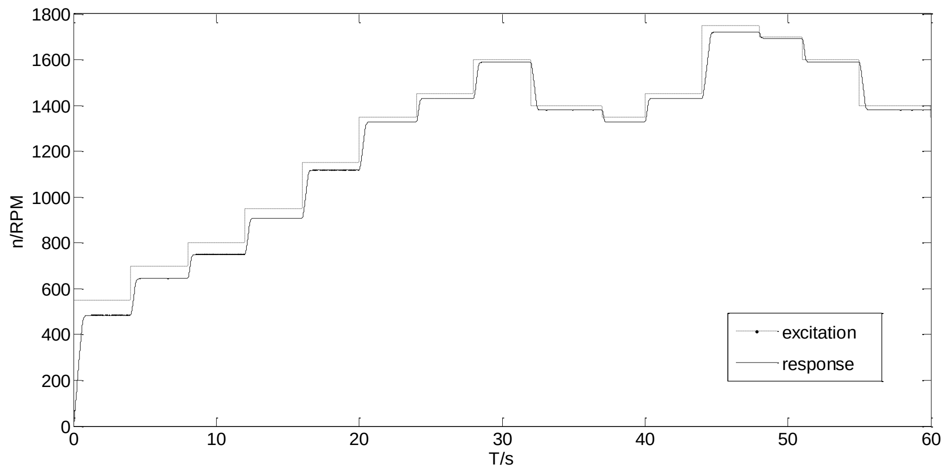


Figure 4. Speed Input and Output of Speed-regulating System

3.4. Identification and Control of the Online Learning Neural Network Inverse Model based on Model-reference

In a practical application, the load disturbance is inevitable, which affect the control performance of neural network direct inverse control. So online learning neural network direct inverse control is designed to improve the control performance. Online learning neural network direct inverse model can compensate the nonlinearity of the SSIMI by online adjusting the connection weights of the NN inverse model .The structure of the proposed online learning neural network inverse model control is shown in Figure 5. The error between the outputs of identified linear dynamic model and pseudolinear system was used to adjust the NN inverse model online. And the conjugate gradient optimization method is applied in training neural network inverse model online.

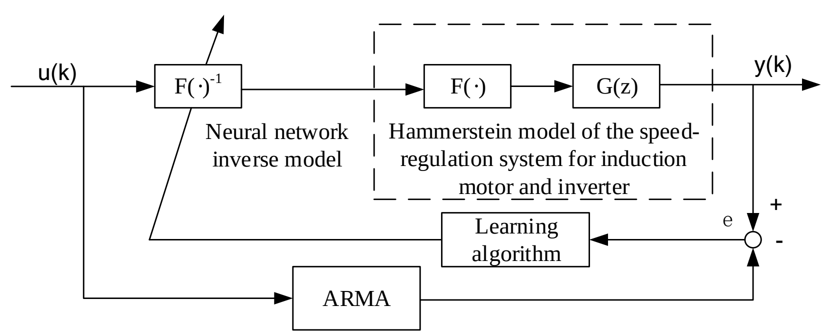


Figure 5. Online Direct Inverse Control for Speed-regulating System based on NN

3.5. Identification and Control of the Traditional PI Close-loop

For the load disturbance problem, the traditional PI close-loop control strategy was also studied (see Figure 6). The PI controller was employed to offset the system modelling errors causing by load disturbance.

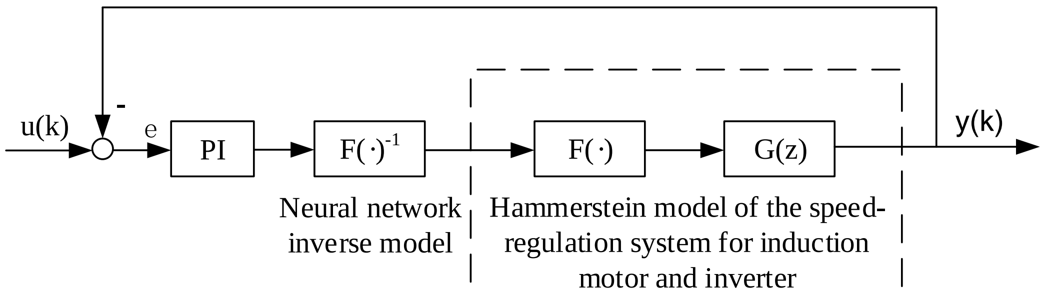


Figure 6. PI Close-loop Control for Speed-regulating System

4. Simulation

4.1. Three Phase Induction Motor Parameters

The threes phase induction motor is a kind of squirrel cage motors. Parameters are as follows: nominal power P_e and nominal voltage U_e are 2.2kW and 220/380V respectively. The number of pole-pairs n_p is 2.The stator resistance R_s and inductance L_s are 0.435 Ω and 0.0022H respectively. The rotor resistance R_r and inductance L_r are 0.816 Ω and 0.002H respectively. The mutual inductance L_m is 0.006931H.And the inertia J is 0.089 $\mathrm{kg}m^2$.

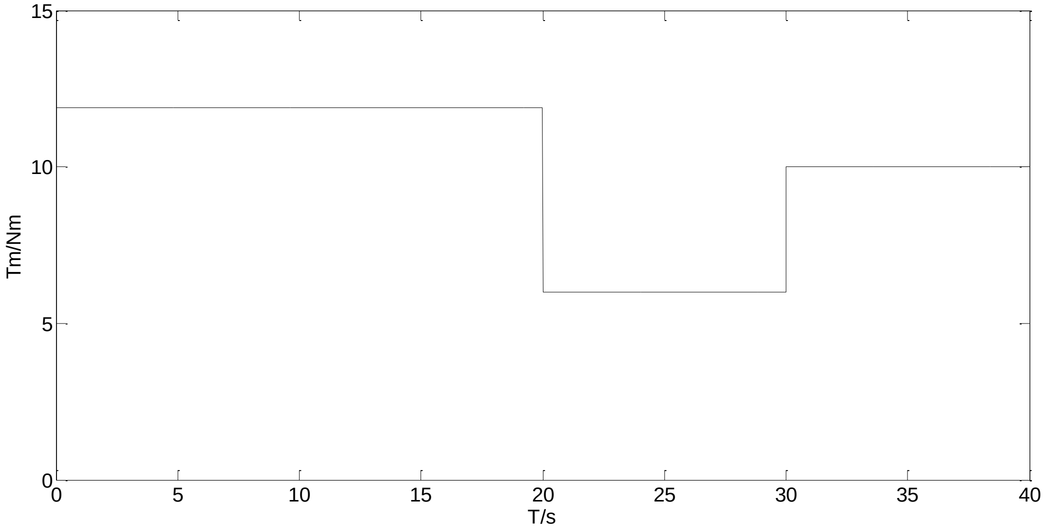
4.2. Simulation Results

The linear dynamic module of the SSIMI is obtained (see equation (6)) using the method in Section 2.2.

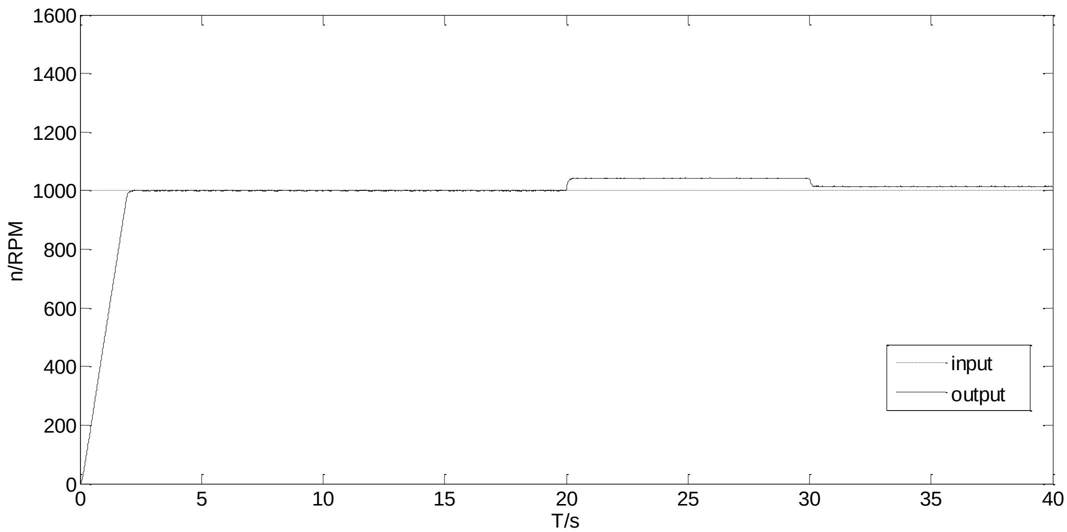
$$G(\mathrm{z}) = \frac{-0.0042191z + 0.013158}{z^2 - 1.8981z + 0.90736} \qquad (6)$$

The rate of change of the frequency generated according to the V/f characteristic was limited and was shown in the initial parts of curves in Figure 7-15.

(1) Simulations of NN direct inverse control strategy



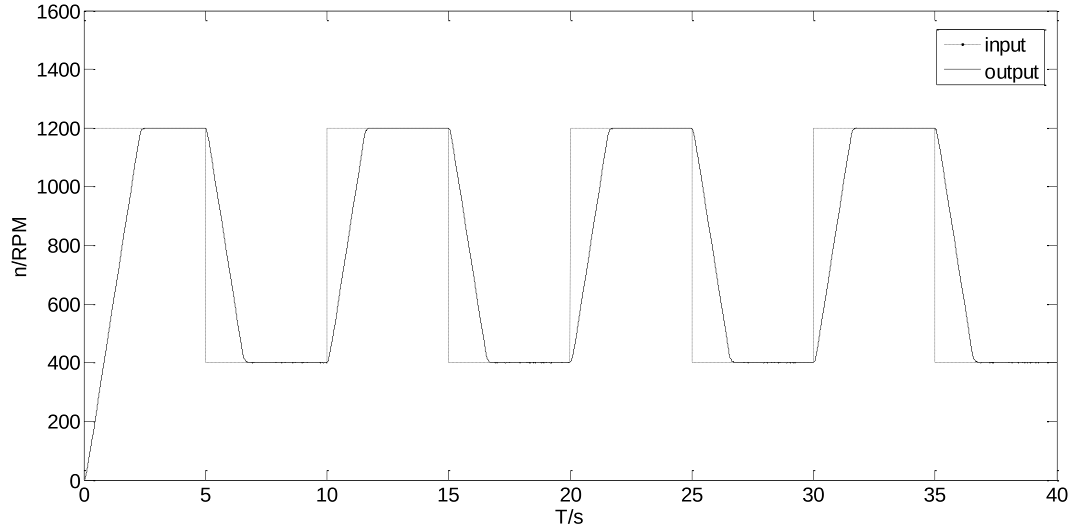
(a) Dynamics of Load Disturbance



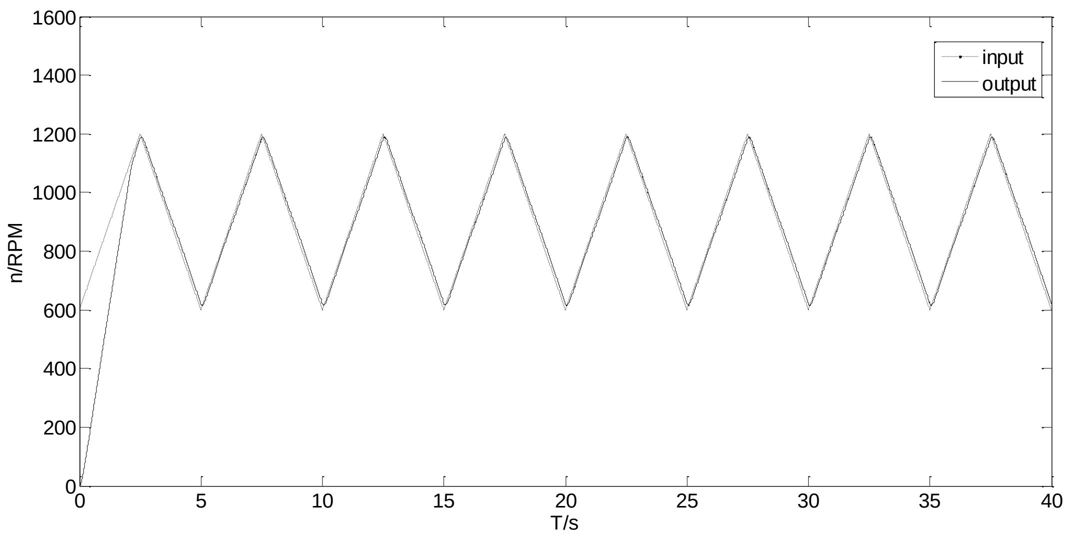
(b) Speed Response

Figure 7. Speed Response in NN Direct Inverse Control with Load Disturbance

With the load decreased to 6 *N*m from 11.9 *N*m at 20 seconds, then increased to 10 *N*m in Figure 7(a), the speed response curves of neural network direct inverse control are shown in Figure 7(b). Those indicate that the load disturbance affects the performance of neural network direct inverse control obviously. The main reason is that the neural network inverse model was trained with specific load and the trained model cannot be corrected online.



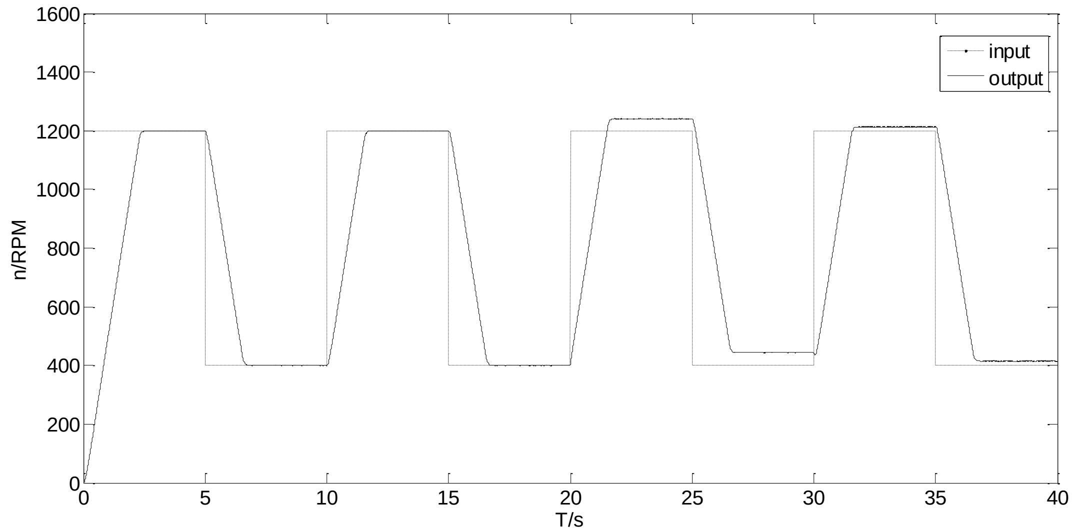
(a) Square Wave Input and Speed Response



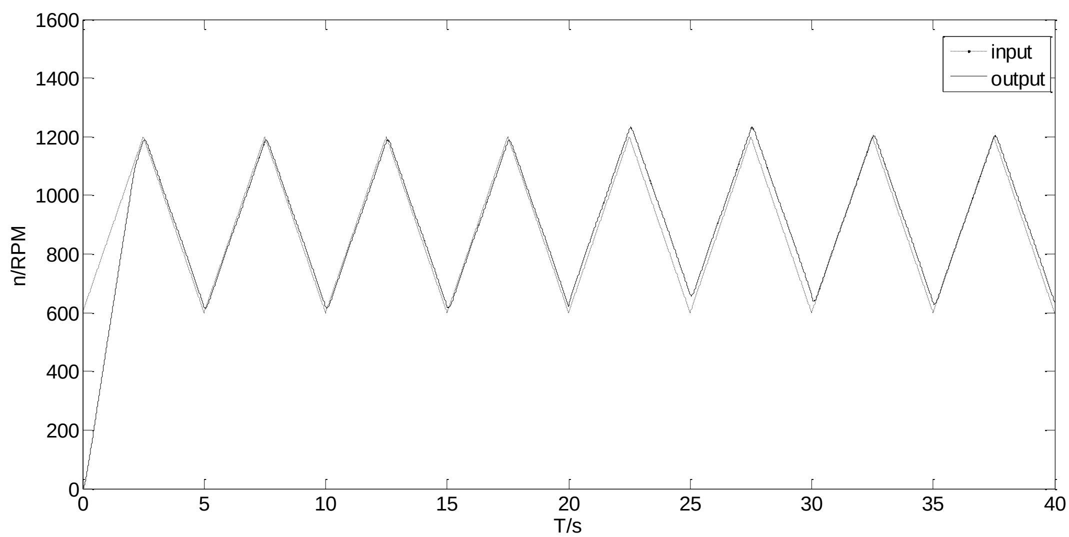
(b) Triangular Wave Input and Speed Response

Figure 8. Speed Response in NN Direct Inverse Control with Constant Load

With unchanged load, when the input signals are square wave and triangular wave, the speed response curves of the NN direct inverse control system are shown in Figure 8(a) and Figure 8 (b) respectively. From Figure 8, it can be concluded that the NN direct inverse control with constant load has a good track precision.



(a) Square Wave Input and Speed Response



(b) Triangular Wave Input and Speed Response

Figure 9. Speed Response in NN Direct Inverse Control with Variable Load

With the load decreased to 6 *N*m from 11.9 *N*m at 20 seconds, then increased to 10 *N*m at 30 seconds, when the input signals are square wave and triangular wave, the speed response curves of neural network direct inverse control are shown Figure 9(a) and Figure 9(b). It can be found that the speed response of neural network direct inverse control cannot track the input signal well when load changes.

(2) Simulations of online NN direct inverse control strategy

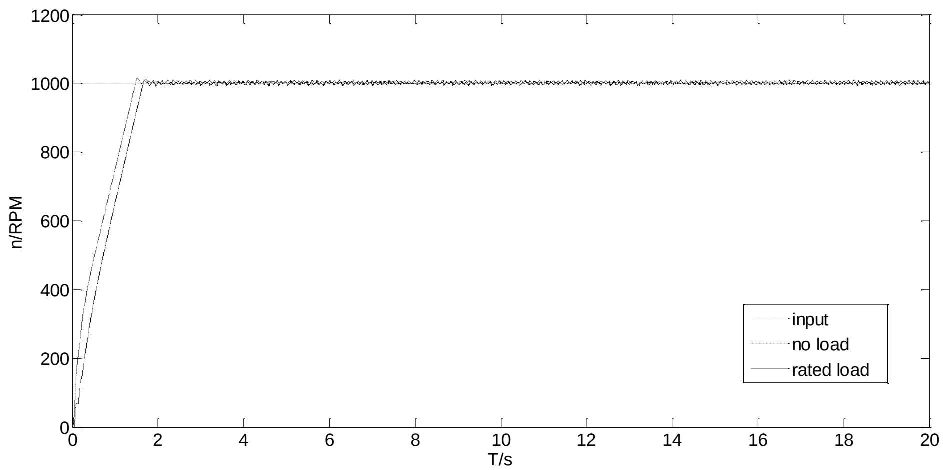


Figure 10. Speed Response in Online NN Direct Inverse Control with/without Rated Load

Figure 10 shows the speed response curves of online learning neural network inverse control with no load and rated load. The curves show that the load has little effect on the online learning neural network inverse control system.

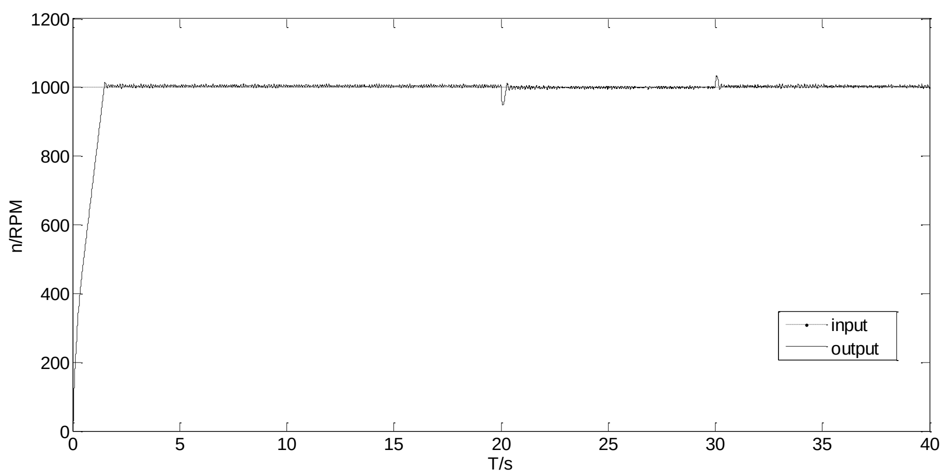
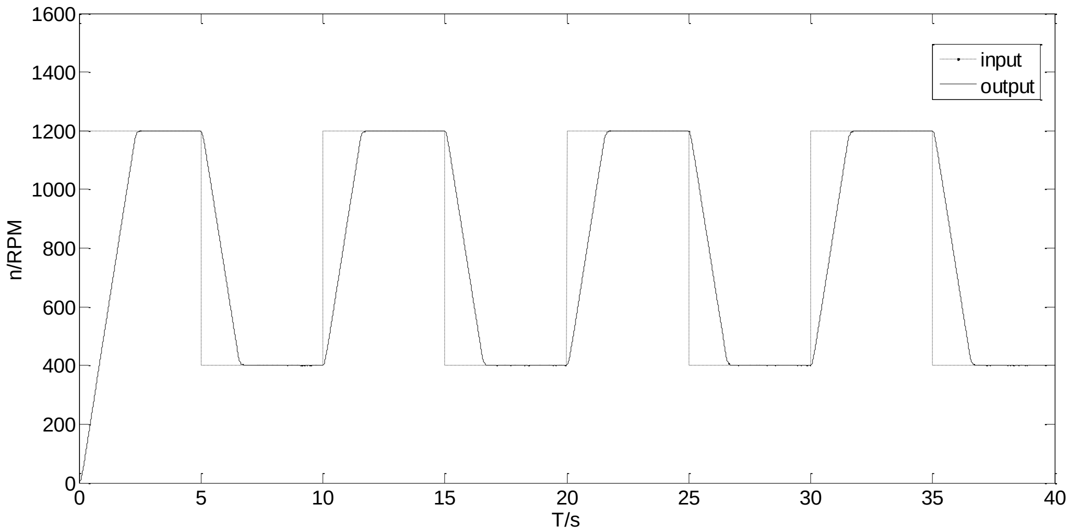
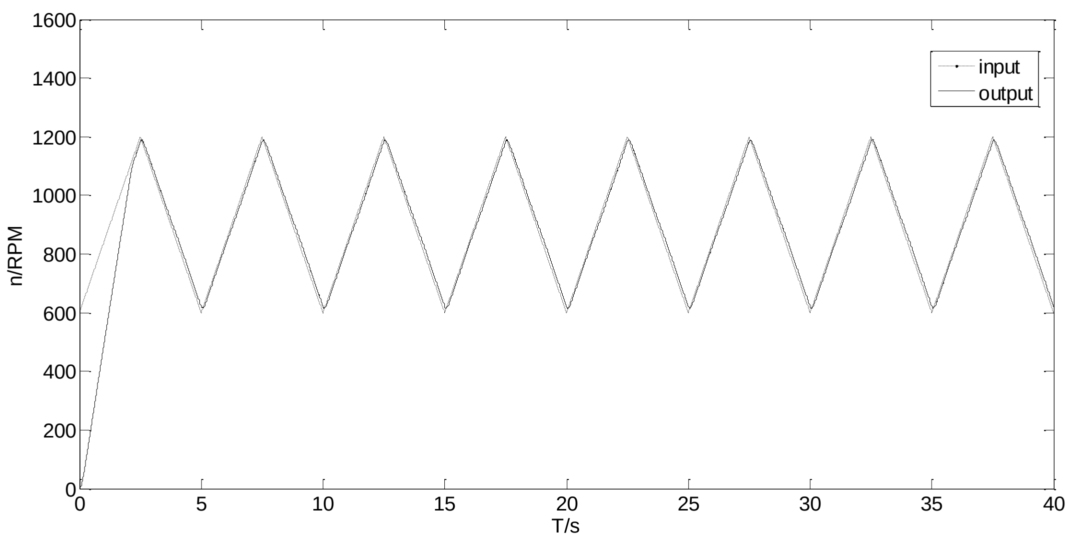


Figure 11. Speed Response in Online NN Direct Inverse Control with Variable Load

With the load decreased to 6 *N*m from 11.9 *N*m at 20 seconds, then increased to 10 *N*m at 30 seconds, the speed response curves of online NN direct inverse control strategy are presented in Figure 11, which shows that the load has little effect on the online learning neural network inverse control system.



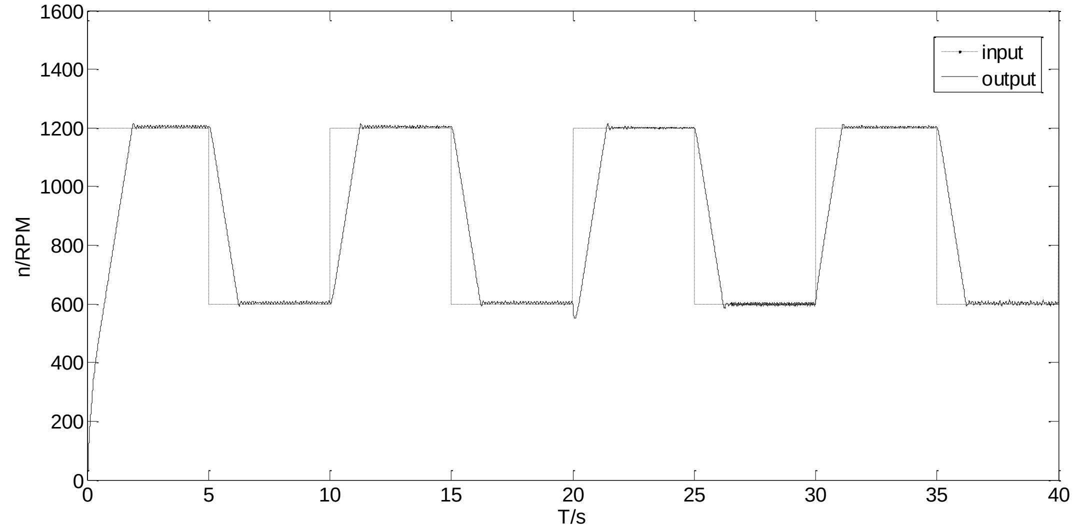
(a) Square Wave Input and Speed Response



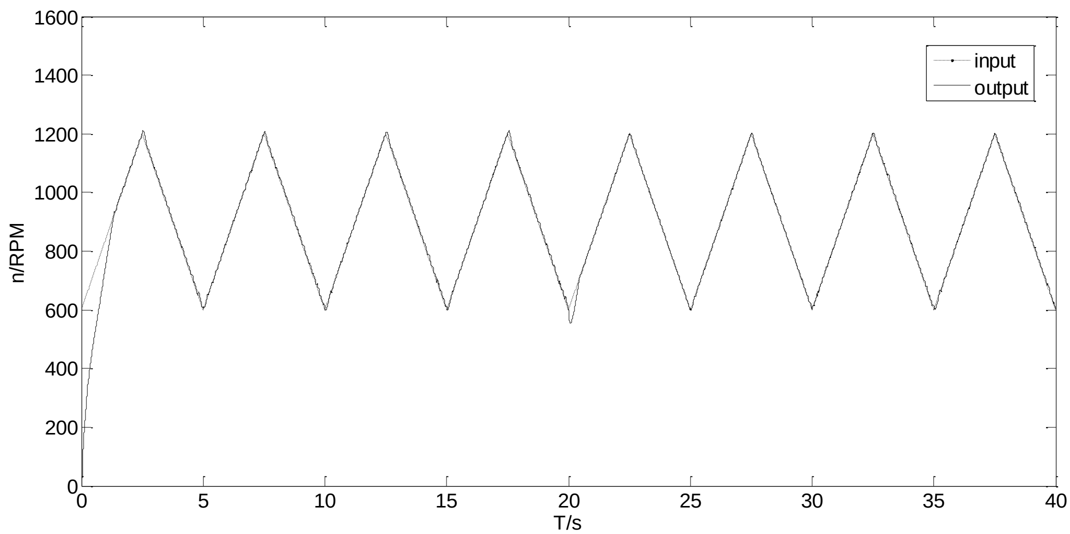
(b) Triangular Wave Input and Speed Response

Figure 12. Speed Response in Online NN Direct Inverse Control with Constant Load

With unchanged load, the input signals are square wave and triangular wave ,the response curves of the online NN direct inverse control strategy are shown in Figure 12(a) and Figure 12(b) respectively. From Figure 12, it can be concluded that the online NN direct inverse control with constant load has a good track precision.



(a) Square Wave Input and Speed Response

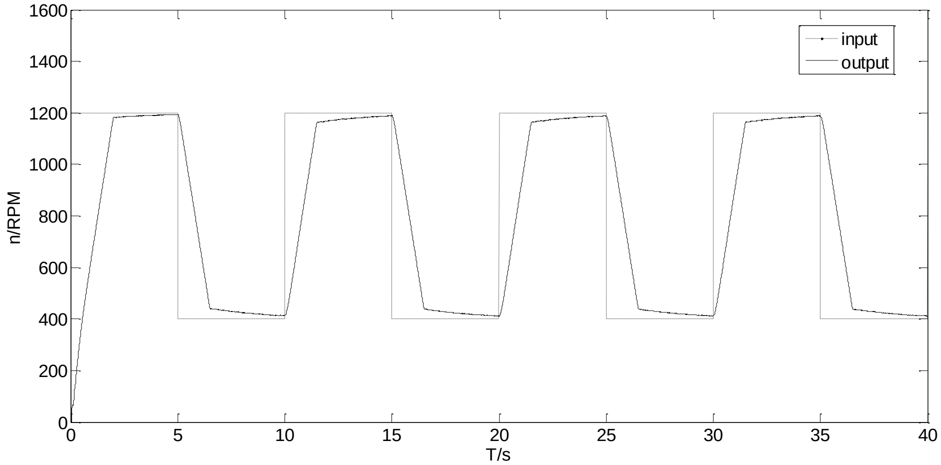


(b) Triangular Wave Input and Speed Response

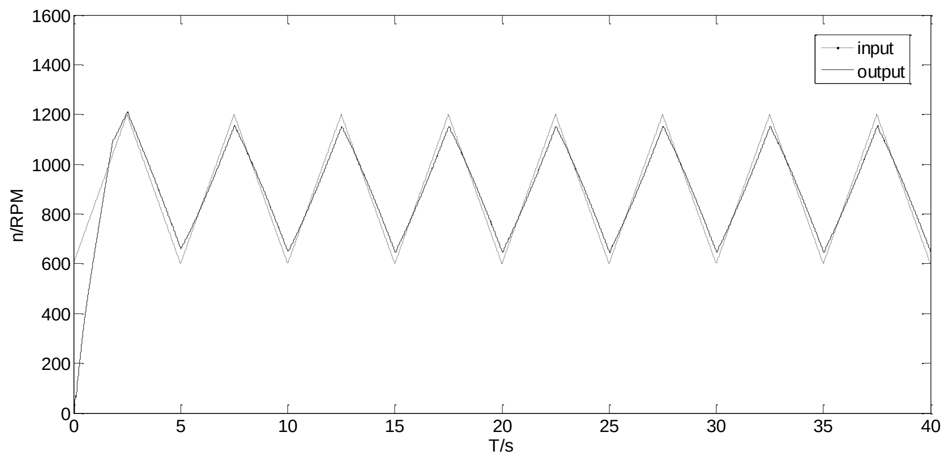
Figure 13. Speed Response in Online NN Direct Inverse Control with Variable Load

With the load decreased to 6 Nm from 11.9 Nm at 20 seconds, then increased to 10 Nm at 30 seconds, when the input signals are square wave and triangular wave, the response curves of the online NN direct inverse control strategy are shown in Figure 13(a) and Figure 13(b) respectively. From Figure 10-13, it can be found that the response of online neural network direct inverse control system has good robustness in tracking input signals.

(3) Simulations of PI close-loop control



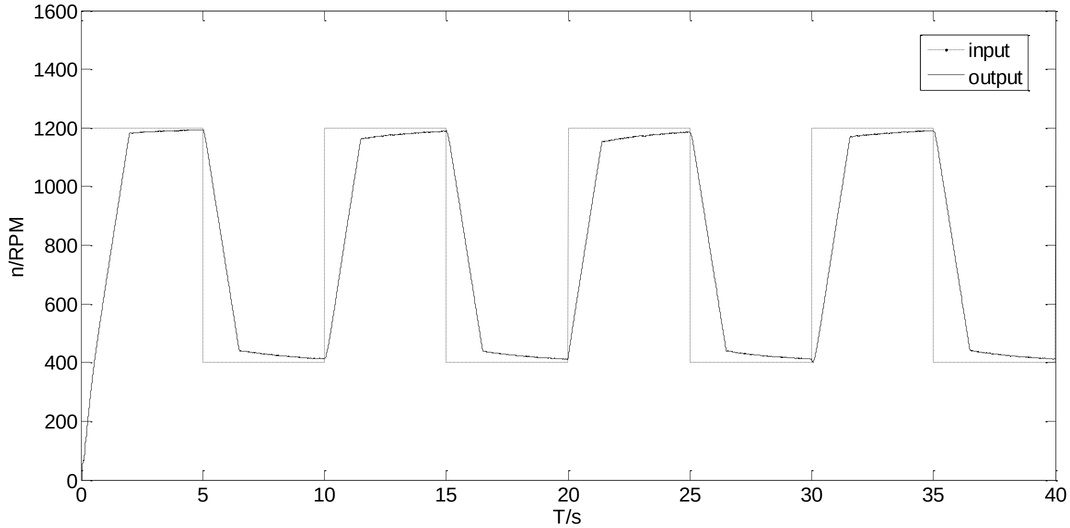
(a) Square Wave Input and Speed Response



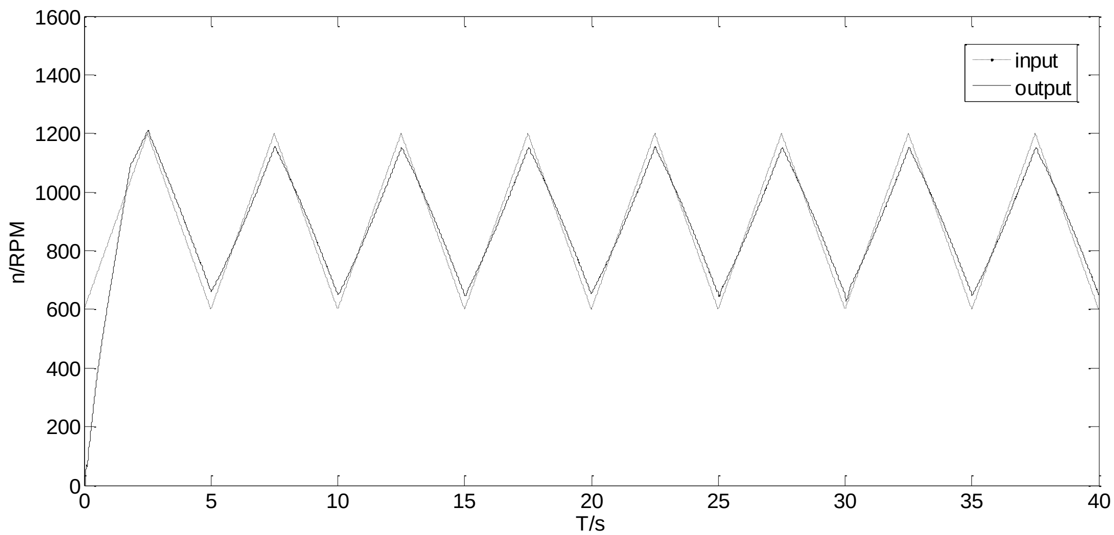
(b) Triangular Wave Input and Speed Response

Figure 14. Speed Response in PI Close-loop Control with Constant Load

With constant load, the input signals are square wave and triangular wave, the speed response curves of the PI close-loop control are shown in Figure 14(a) and Figure 14(b) respectively. The parameters of PI controller are adjusted to different input signals. When the input signal is square wave, K_P is set to 2 and K_I is set to 1. When the input signal is triangular wave, K_P is set to 4 and K_I is set to 3. From Figure 14, the tracking ability of PI close-loop control is not so satisfactory compared with both NN direct inverse control and online NN direct inverse control.



(a) Square Wave Input and Speed Response



(b) Triangular Wave Input and Speed Response

Figure 15. Speed Response in PI Close-loop Control with Variable Load

With the load decreased to 6 *N*m from 11.9 *N*m at 20 seconds, then increased to 10 *N*m at 30 seconds, square wave and triangular wave response curves of PI close-loop control are shown in Figure 15(a) and Figure 15(b) respectively. The parameters of PI controller are set as the same to the above mentioned. The pictures show that the PI control has considerable robustness against the load disturbances. However, the tracking precision is not as satisfactory as that of online NN direct inverse control strategy.

The above results show that the online learning control strategy based on Hammerstein model and neural network for the SSIMI can reach the aim of high performance control compared with neural network direct inverse control strategy and PI close-loop control strategy. Simulations were implemented on Matlab/Simulink.

5. Conclusion

For the nonlinear nature of the speed-regulating system of the induction motor and inverter, a novel control strategy based on Hammerstein model and neural network is proposed. Auto-Regressive and Moving Average (ARMA) model was used to identify the dynamic linear module of the speed-regulating system, and it was used as a reference model for identification of the inverse model of static nonlinear module in the framework of the model reference adaptive control method. For load disturbance issue, online learning neural network direct inverse controller and PI controller were both studied. In addition, the trained NN inverse model is a static model, and it is easy to realize and can be used in open loop control in comparison with the NN α-th order inverse model. Simulations show the feasibility of the proposed control strategy for speed-regulating system based on Hammerstein model.

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