JPE 4-1-4

Simple Neuro-Controllers for Field-Oriented Induction Motor Servo Drives

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ABSTRACT

In this paper, the position control of a detuned indirect field oriented control (IFOC) induction motor drive is studied. A proposed Simple–Neuro-Controllers (SNCs) are designed and analyzed to achieve high-dynamic performance both in the position command tracking and load regulation characteristics for robotic applications. The proposed SNCs are trained on-line based on the back propagation algorithm with a modified error function. Four SNCs are developed for position, speed and *d-q* axes stator currents respectively. Also, a synchronous proportional plus integral-derivative (PI-D) two-degree-of-freedom (2DOF) position controller and PI-D speed controller are designed for an ideal IFOC induction motor drive with the desired dynamic response. The performance of the proposed SNCs and synchronous PI-D 2DOF position controllers for detuned field oriented induction motor servo drive is investigated. Simulation results show that the proposed SNCs controllers provide high-performance dynamic characteristics which are robust with regard to motor parameter variations and external load disturbance. Furthermore, comparing the SNC position controller with the synchronous PI-D 2DOF position controller demonstrates the superiority of the proposed SNCs controllers due to attain a robust control performance for IFOC induction motor servo drive system.

Keywords: Indirect Field Orientation Control (IFOC), 2DOF PI-D position controller, SNC, Induction Motor Drive

1. Introduction

Induction machine servo drive system is considered high-performance when the rotor position, rotor speed and stator currents can be controlled to follow a reference for tracking at all times. A track is a desired time history of the motor current, speed or position. This servo drive system is essential in many applications such as robotics, actuation, numerically controlled machinery and guided manipulation

Manuscript received September 29, 2003; revised January 4, 2004.

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Manuscript received September 29, 2003; revised January 4, 20 † Corresponding Author: fayez@eri.sci.eg where precise control is required. Previously, *dc* machines were used in variable speed and position control applications because of the possibility of controlling their flux and torque independently. However, *dc* machines have many disadvantages. To overcome the *dc* machines disadvantages, the induction machines can be used because of its simple and rugged structure, easy maintenance and economical operation. The induction motor can be controlled similar to a *dc* motor using field oriented control (FOC) strategy ^[1-2]. However, difficulties are found from modelling uncertainties due to parameter variations, magnetic saturation and load

disturbances. To ensure high dynamic performance various

control strategies for field oriented induction motor drive

have been reported in the literature. Conventional control schemes with PID have gained the widest acceptance in high-performance servo drives. However, the induction machine parameters variation causes a degradation in the dynamic response for disturbance rejection and tracking performance with these control schemes.

To overcome the drawbacks of the conventional cont rolle and to achieve high-dynamic performance, research in a tificial intelligent (such as neural network) as a cont oller has become increasingly prevalent.

A neural network can be a feedforward or a feedback A feedforward multi-layer neural network usually cons sts of input layer, output layer and one or more hidd in layers of neurons. It is well known that the neural networks need to be trained and its training is time cons iming. High convergence accuracy and high conver genc: rate are desirable for the training of the neural network. The most popular training algorithm for a mult -layer neural network is the back propagation [3-9]. In th s paper, a simple-neuro-controller(SNCs) are design ed at d analyzed. Four SNCs are developed for position, spee l, d-q axis stator currents respectively. Each SNC cons sts of only one weight and one neuron with a linear hard limit activation function. The SNC is trained on -line based on the back propagation algorithm with a mod fied error function. In spite of their simple constru ctior, the obtained results show that the SNCs can provide a fa t and accurate dynamic response in tracking and distu bance rejection characteristics under parameter varia At the same time, a reduction of the computation time has been occurred as a result of the simple constru ction of the four SNCs. The simulation results have demonstrated that robust control performances both in command tracking and load regulation are achieved by the prop)sed SNCs controllers when detuning occurs and then improve the dynamic behavior compared with the synchro nous PI-D 2DOFC position controller.

The results of the simulation confirm the effectiveness of the proposed SNCs controllers and its superiority as compared with the synchronous PI-D 2DOF position controller for IFOC induction machine drive system. Also, the results—demonstrate that the proposed SNCs control scheine has robust position response and can rapidly cancil the load disturbance.

2. Induction Machine Model for Position Control

The block schematic of IFOC-based induction mach ine servo drive with inverter controlled using space vector modulation (SVM) technique is shown in Fig. 1. The Figure shows that four feedback loops in the control system. The inner is the current feedback loop, the middle is the speed feedback loop and the outer is the position feedback loop. Also, the diagram includes a current regulated pulse width modulation (CRPWM) inverter with SVM technique (CRSVMPWM), indirect field orientation controller (IFOC), decoupling controller, proposed SNCs for *d-q* stator current controllers, speed controller and position controller. The ideal and detuned models of the induction motor and various control blocks are presented in the following section.

2.1 Nominal Parameters Model

The state equation of the nonlinear dynamic d-q model of the induction machine at the synchronous reference frame is expressed as follows ^[1,2].

$$\frac{d}{dt} \begin{bmatrix} i_{qs}^{e} \\ i_{ds}^{e} \\ \lambda_{qr}^{e} \\ \lambda_{dr}^{e} \end{bmatrix} = \begin{bmatrix} -k_{ss} & -\omega_{e} & \frac{k_{m}}{\tau_{r}^{*}} & -k_{m}\omega_{r} \\ \omega_{e} & -k_{ss} & k_{m}\omega_{r} & \frac{k_{m}}{\tau_{r}^{*}} \\ \frac{L_{m}}{\tau_{r}^{*}} & 0 & -\frac{1}{\tau_{r}^{*}} & -\omega_{sl} \\ 0 & \frac{L_{m}}{\tau_{r}^{*}} & \omega_{sl} & -\frac{1}{\tau_{r}^{*}} \end{bmatrix} \begin{bmatrix} i_{qs}^{e} \\ i_{qs}^{e} \\ \lambda_{qr}^{e} \\ \lambda_{dr}^{e} \end{bmatrix} + \frac{1}{\sigma L_{s}} \begin{bmatrix} V_{qs}^{e} \\ V_{ds}^{e} \\ 0 \\ 0 \end{bmatrix} (1)$$

$$T_{e} = \frac{3}{2} \cdot \frac{P}{2} \cdot \frac{L_{m}}{L} (\lambda_{qr}^{e} i_{qs}^{e} - \lambda_{qr}^{e} i_{ds}^{e})$$
 (2)

$$T_e = \frac{J}{(P/2)} \frac{d^2}{dt^2} \theta_r + \frac{\beta}{(P/2)} \frac{d}{dt} \theta_r + T_L$$
 (3)

2.2 Detuned Parameters Model

For facilitating the analysis and design of the proposed controllers, a model representing the dynamic behavior of a detuned IFOC for induction machine is developed. Since the detuning of IFOC is mainly due to the variations of the rotor time constant, the decoupling between the torque command and flux command is no ideal and thus the torque response becomes oscillatory and sluggish. From equations (1-3), we can derive the perturbed model of the induction machine as given by equations (4-6).

2.3 IFOC Dynamic Model (Decoupling Controller)

The IFOC dynamic model for the induction machine (torque, slip angular frequency and voltage commands) can be derived from equations (1-2) respectively at $\lambda_{qr}^e = 0$ and $d\lambda_{qr}^e/dt = 0$. The torque equation and slip angular frequency for rotor field orientation are given in equations (7, 8) while the voltage commands (decoupling controller) of the indirect field orientation controller (IFOC) are given in equations (9-12).

$$\frac{d}{dt} \begin{bmatrix} \Delta i_{qs}^{e} \\ \Delta i_{ds}^{e} \\ \Delta \lambda_{qr}^{e} \\ \Delta \lambda_{dr}^{e} \end{bmatrix} = \begin{bmatrix} -k_{ss} & -\omega_{eo} & \frac{k_{m}}{\tau_{r}} & -k_{m}\omega_{ro} \\ \omega_{eo} & -k_{ss} & k_{m}\omega_{ro} & \frac{k_{m}}{\tau_{r}} \\ \frac{L_{m}}{\tau_{r}} & 0 & -\frac{1}{\tau_{r}} & -\omega_{slo} \\ 0 & \frac{L_{m}}{\tau} & \omega_{slo} & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} \Delta i_{qs}^{e} \\ \Delta \lambda_{dr}^{e} \\ \Delta \lambda_{dr}^{e} \end{bmatrix} + \frac{1}{\sigma L_{s}} \begin{bmatrix} \Delta V_{qs}^{e} \\ \Delta V_{ds}^{e} \\ 0 \\ 0 \end{bmatrix} (4)$$

$$\Delta T_e = K_t \begin{pmatrix} \lambda_{dro}^e \Delta i_{qs}^e - \lambda_{qro}^e \Delta i_{ds}^e \\ -i_{dso}^e \Delta \lambda_{qr}^e + i_{qso}^e \Delta \lambda_{dr}^e \end{pmatrix}$$
 (5)

$$\Delta T_e = \frac{J}{(P/2)} \frac{d^2}{dt^2} \Delta \theta_r + \frac{\beta}{(P/2)} \frac{d}{dt} \Delta \theta_r + \Delta T_L$$
 (6)

$$T_e = \frac{3}{2} \cdot \frac{P}{2} \cdot \frac{L_m^2}{L_r} i_{ds}^{e^*} i_{qs}^{e^*} \tag{7}$$

$$\omega_{sl} = \frac{1}{\tau_r} \cdot \frac{i_{qs}^{e^*}}{i_{ds}^{e^*}} \tag{8}$$

$$V_{qs}^{e^*} - e_{qs}^{e^*} = \left(L_s \sigma \frac{d}{dt} i_{qs}^{e^*} + R_s i_{qs}^{e^*} \right)$$

$$\tag{9}$$

$$e_{qs}^{e^*} = \left(L_s \sigma + L_m^2 / L_r\right) \omega_e \ i_{ds}^{e^*} \tag{10}$$

$$V_{ds}^{e^*} + e_{ds}^{e^*} = \left(L_s \sigma \frac{d}{dt} i_{ds}^{e^*} + R_s i_{ds}^{e^*} \right)$$
 (11)

$$e_{ds}^{e^*} = \left(L_s \sigma + L_m^2 / L_r\right) \omega_e \, i_{qs}^{e^*} \tag{12}$$

where,

 i_{ds}^{v} : Exciting current component of d-axis

 i_{as}^e : Torque current component of q-axis

 λ_{dr}^e , λ_{ar}^e : d-axis and q-axis components of rotor flux

 K_t : Torque constant, $K_t = (3P/4) \cdot (L_m^2/L_r) \cdot i_{ds}^{*}$

 σ : Leakage flux coefficient, $\sigma = (L_{s}L_{r} - L_{m}^{2})/L_{s}L_{r}$

 L_s : Stator windings self inductance

 L_r : Rotor windings self inductance

 L_m : Mutual inductance

: Detuned rotor time constant, $\tau_r = L_r / R_r$

 τ_r^* : Nominal rotor time constant, $\tau_r^* = (L_r/R_r)^*$

 ω_{sl} : Slip angular frequency

 ω_n : Natural frequency

 $e_{ds}^{e^*}$, $e_{ds}^{e^*}$: d-q-axes components of back e.m.f

 $V_{ds}^{e^*}$, $V_{ds}^{e^*}$: d-q-axes components of the stator voltages

: Constant, $k_{ss} = (1/\sigma \tau_s + 1 - \sigma/\sigma \tau_r)$

 K_m : Constant, $K_m = L_m / \sigma L_s L_r$

 τ_s' : Constant, $\tau_s' = \sigma \tau_s$

 τ_r : Constant, $\tau_r = \sigma \tau_r$

3. On-Line Trained Simple Neuro-Controller (SNC)

In this section, a proposed simple neuro-controller (SNC) with learning ability on-line and simple structure is described. Its training is on-line based on a modified error function that depends on the input variable and the output variable and its derivative. The modified error function is used to improve the performance of the SNC which is trained on-line by the back propagation algorithm [10-12]

3.1 Back Propagation Algorithm with a Modified Error Function

The neural network needs to be trained to generate multiple input-output matching pattern. The training of the neural network is basically a process of finding the local minimum of a predefined objective function. The most popular training algorithm is the Bake Propagation (BP). The training can be off-line, on-line or combination of both. The input and output of a neuron j are given by the following equations.

$$S_{pj} = \sum_{i} W_{ji} O_{pi} + \phi_{j} \tag{13}$$

$$O_{pi} = F(S_{pi}) \tag{14}$$

The BP 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 de

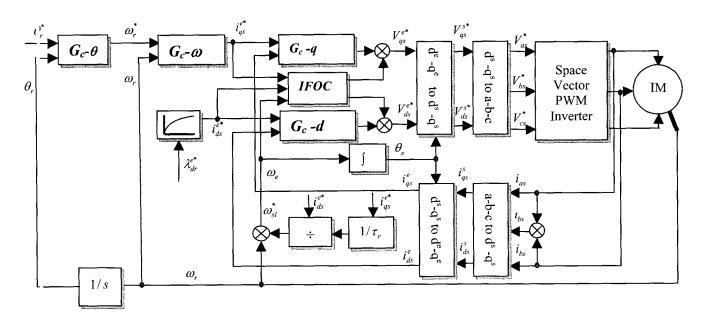


Fig. 1. Schematic block diagram of the IFOC induction machine drive system.

sired 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:

$$V_{ii}(t+1) = W_{ii}(t) + \Delta W_{ii}(t)$$
 (15)

$$L W_{ii}(t) = \varepsilon \delta_{gi} O_{gi}$$
 (16)

$$\epsilon_{pj} = -\frac{\partial E_p}{\partial O_{pj}}.\tilde{F}(S_{pj})$$
(17)

The error function normally used in the standard BP algorithm is given by:

$$I_{p} = \frac{1}{2} \sum_{i} (t_{pj} - O_{pj})^{2}$$
 (18)

V'hen neuron j is an output layer,

$$\frac{\partial E_p}{\partial O_{pi}} = (t_{pj} - O_{pj}) \tag{19}$$

V hen j is in hidden layer,

$$\frac{\partial E_p}{\partial O_{pi}} = \sum \delta_{pk} W_{kj} \tag{20}$$

The traditional error function is given in equation (19). The modified error function is based on the traditional error function, the error between the input and output variables, and the change of the controlled output.

Therefore, equation (19) can be modified to the following equation to provide the modified error function (mef).

$$\frac{\partial E_p}{\partial O_{pj}} = \left[(t_{pj} - O_{pj}) - \frac{dO_{pj}}{dt} \right]$$
 (21)

where,

 S_{pj} : input of neuron j for pattern p O_{pj} : output of neuron j for pattern p W_{ij} : weight from unit i to unit j

 t_{pj} : target input

 E_p : error function for pattern p

 ε : learning rate

F : sigmoid activation function

t : time

 δ_{ni} : error term for unit j

 ϕ_j : bias

3.2 Simple Neuro-Controller (SNC)

The SNC consists of only one weight and one neuron with a linear hard limit activation function as shown in Fig. 2. The SNC output can be derived from Fig. 2 as follows:

$$u = xW - \phi \tag{22}$$

Based on the BP algorithm, the bias and weight change

are given by the following equations:

$$\Delta W = \varepsilon.mef.x \tag{23}$$

$$\Delta \phi = -\varepsilon.mef \tag{24}$$

3.3 The Proposed Modified Error Function

The proposed modified error function (mef) is obtained by adding a term (kdy/dt) opposite to the traditional error (x-y) to change the overall error of the system and then speed up the system output response to its target. Also, the mef is used to modify the weight W and bias ϕ on-line as given by equations (22-25) and as shown in Fig. 2.

$$mef = \left[(x - y) - k \frac{dy}{dt} \right] \tag{25}$$

where,

u : the controller outputy : the controlled variable

x : reference input

k: constant

mef: the modified error function, f(x, y, ky')

Based on equations (22-25), the SNC weight update depends on two parameters named k and ε . For each controller these two parameters are selected by trial and error based on the author experiences.

3.4 Training Process

The SNC is trained on-line directly from the system inputs and outputs. There is no need to determine the states of the system and reference model or parameters identification. From the inputs and outputs of the system, the *mef* computes the error which is back propagated the SNC to update its weights and then the SNC outputs is calculated.

4. Design of the On-Line Trained Simple Neuro-Controllers (SNCs)

This section provides the design of a four SNCs, *d-q* axes stator current controllers speed controller and position controller.

4.1 Design of SNC Current Controllers 4.1.1 Q-axis SNC Current Controller (G_c-q)

The proposed SNC-q controller has $i_{qs}^{e^*}$ as the controller input, and i_{qs}^e as the controlled variable. The *mef* of the SNC-q current controller is given by equation (21). Using this function along with equations (23-24), the controller output can be calculated as given in equation (21).

$$mef_q(t) = e_q(t) - k_q \frac{d}{dt} i_{qs}^e$$
 (26)

$$e_{q}(t) = \left(i_{qs}^{e^{*}}(t) - i_{qs}^{e}(t)\right) \tag{27}$$

4.1.2 D-axis SNC Current Controller (Gc-d)

Similarly, the *mef* of SNC-d current controller is given by equation (28). The controller output can be calculated from the weight, bias and the *mef* given by equation (28), the controller output can be calculated.

$$mef_d(t) = e_d(t) - k_d \frac{d}{dt} i_{ds}^e$$
 (28)

$$e_{d}(t) = \left(i_{ds}^{e^{*}}(t) - i_{ds}^{e}(t)\right)$$
 (29)

4.2 Design of SNC Speed Controller (G_c-ω)

Similar to the current controllers, the proposed SNC speed controller has ω_r^* , ω_r as the controller input and the controlled variable respectively. The *mef* of the SNC- ω speed controller is given by the following equation.

$$mef_{\omega}(t) = e_{\omega}(t) - k_{\omega} \frac{d}{dt} \omega_{r}$$
(30)

$$e_{\omega}(t) = \left(\omega_r^*(t) - \omega_r(t)\right) \tag{31}$$

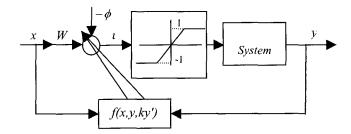


Fig. 2. Single neuron configuration.

4.3 Design of SNC Position Controller (G_c-θ)

Also, the proposed SNNC- θ controller has θ_r , θ_r as the controller input and the controlled variable

respectively. The SNNC- θ error function is given by the fellowing equation:

$$mef_{\theta}(t) = e_{\theta}(t) - k_{\theta} \frac{d}{dt} \theta_{r}$$
 (32)

$$e_{\theta}(t) = \left(\theta_r^*(t) - \theta_r(t)\right) \tag{33}$$

5. Design of the Proposed PI-D 2DOF Controller

In this section, the analysis and design procedures of different conventional controllers are carried out for a comparison purpose. The PI-D and PI-D 2DOF speed at diposition controllers respectively are designed. The PI controllers has been designed in [1-2]. The design dopends on the desired response technique.

5.1 PI-D Speed Controller

According to block diagram shown in Fig. 3, the closed loop transfer function at $T_L(s) = 0$ is given by:

$$\frac{\omega_r(s)}{\omega_r^*(s)} = \frac{K(K_p^\omega s + K_i^\omega)}{s^3 + \tau_{2\omega} s^2 + \tau_{1\omega} s + KK_i^\omega}$$
(34)

where.

$$\begin{aligned} &\tau_{1\omega} = (1/\tau_{sr}^{'}\tau_{m} + KK_{p}^{\omega}/\tau_{sr}^{'}), \ \tau_{2\omega} = (1/\tau_{sr}^{'} + 1/\tau_{m} + KK_{d}^{\omega}) \\ &K = (K_{t}K_{j}K_{q}/\tau_{sr}^{'}), \ K_{j} = P/2J, \ K_{q} = \tau_{sr}^{'}/\sigma L_{s} \\ &\tau_{m} = J/\beta, \ \tau_{sr}^{'} = \tau_{s}^{'}\tau_{r}^{'}/(\tau_{r}^{'} + \tau_{s}^{'}(1-\sigma)) \end{aligned}$$

Using the third order performance index based on the IT AE robust technique which has the following equation, we can determine the controller parameters as follows.

$$\frac{C(s)}{R(s)} = \frac{\omega_n^3}{s^3 + 1.75\omega_n s^2 + 2.15\omega_n^2 s + \omega_n^3}$$
(35)

From equations (34 and 35), we can determine the controller parameters as follows.

$$K_p^{\omega} = \frac{2.15\omega_n^3 \tau_{sr}^{'} - 1/\tau_m}{K\tau_{sr}^{'}}$$
 (36)

$$\zeta_i^{\omega} = \frac{\omega_n^3}{\kappa} \tag{37}$$

$$\zeta_d^{\omega} = \frac{\left(1.75\omega_n - 1/\tau_{sr} - 1/\tau_m\right)}{K} \tag{38}$$

5.2 PI-D 2DOF Position Controller 5.2.1 Feed-back Controller

The type of feedback controller is proposed as a PI-D controller while the feed forward controller is designed based on the desired closed loop response. According to block diagram shown in Fig. 4, the closed loop transfer function at $T_{i}(s) = 0$ is given by the following equation.

$$\frac{\theta_{r}(s)}{\theta_{d}(s)} = \frac{K_{t}K_{j}(K_{p}^{\theta}s + K_{i}^{\theta}).(K_{p}^{\omega}s + K_{i}^{\omega})/\tau_{2\omega}}{s^{4} + \tau_{3\theta}s^{3} + \tau_{2\theta}s^{2} + \tau_{1\theta}s + \hat{K}K_{i}^{\theta}}$$
(39)

Using the fourth order performance index based on the ITAE robust technique which has the following equation, we can determine the controller parameters as follows.

$$\frac{C(s)}{R(s)} = \frac{\omega_n^4}{s^4 + 2.1\omega_n s^3 + 3.4\omega_n^2 s^2 + 2.7\omega_n^3 s + \omega_n^4}$$
(40)

From equations (39 and 40), we can determine the controller parameters as follows.

$$K_p^{\theta} = \frac{2.7\omega_n^3 \cdot \tau_{2\omega} - \omega_n^4 \cdot \tau_{2\omega} \cdot K_p^{\omega} / K_i^{\omega}}{K_i K_i K_i^{\omega}}$$
(41)

$$K_i^{\theta} = \frac{\tau_{2\omega}.\omega_n^4}{K_i K_i K_i^{\omega}} \tag{42}$$

$$K_d^{\theta} = \frac{\left(2.1\omega_n \cdot \tau_{2\omega} - \tau_{1\omega}\right)}{K_t K_i K_i^{\omega}} \tag{43}$$

5.2.2 Feed-forward Controller

According to block diagram shown in Fig. 4 with PI-D 2DOF controller, the closed loop transfer function with pre-filter and at $T_{L}(s) = 0$ is given by:

$$\frac{\theta_{r}(s)}{\theta_{r}^{*}(s)} = \frac{K_{t}K_{j}(K_{p}^{\theta}s + K_{i}^{\theta}).(K_{p}^{\omega}s + K_{i}^{\omega})/\tau_{2\omega}}{s^{4} + \tau_{3\theta}s^{3} + \tau_{2\theta}s^{2} + \tau_{1\theta}s + K_{i}^{\omega}}.G_{ff}(s)$$
(44)

Accordingly, we can obtain the feed forward controller transfer function that has the following relation from equations (40 and 44).

$$G_{ff}(s) = \frac{\omega_n^4 \cdot \tau_{2\omega}}{K_i K_j (K_p^{\theta} s + K_i^{\theta}) \cdot (K_p^{\omega} s + K_i^{\omega})}$$
(45)

Equation (45) is a tow lag compensators but to speed up the response we propose a lead-lag compensator. As given by equation (46).

$$G_{ff}(s) = \tilde{K} \cdot \frac{(1 + \tau_{lead}s)}{[1 + (K_{\rho}^{\rho} / K_{i}^{\theta})s]}$$
(46)

where,

$$\begin{aligned} \tau_{lead} > (K_p^{\theta}/K_i^{\theta}), & \stackrel{\approx}{K} = \omega_n^4 \tau_{2\omega}/K_i K_j K_i^{\theta} \\ \tau_{3\theta} = (\tau_{1\omega} + K_i K_i K_i^{\theta})/\tau_{2\omega}, & \stackrel{\hat{K}}{K} = K_i K_i K_i^{\omega}/\tau_{2\omega} \end{aligned}$$

$$\tau_{1\theta} = (K_i K_j K_i^{\omega} K_d^{\theta} + K_i K_j K_i^{\omega} K_p^{\theta})/\tau_{2\omega}$$

$$\tau_{1\theta} = (K_i K_j K_p^{\omega} K_d^{\theta} + K_i K_j K_i^{\omega} K_p^{\theta})/\tau_{2\omega}$$

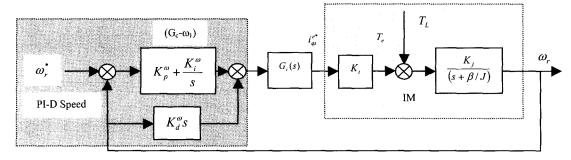


Fig. 3. Block diagram of induction machine speed control with PI-D controller.

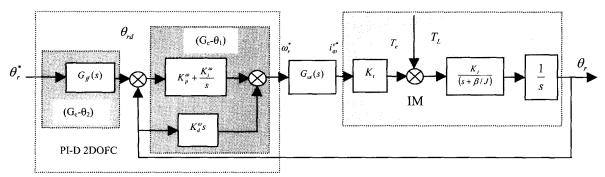


Fig. 4. Block diagram of induction machine position control with PI-D 2DOF controller.

6. Simulation Results of the Drive System

The simulation of the proposed control scheme for IFOC induction machine drive system has been carried out using PCMATLAB package. The dynamic performance of the drive system for different operating conditions has been studied with the application of the four SNCs to the d-q currents, speed and position loops and then compared with the conventional controllers. Taking into conside ration the parameter variations of the induction machine, the drive system performance has been tested under load changes and set-point variations.

6.1 Dynamic Performance Under Different Loads

The dynamic performance of the drive system under the disturbances of step change in reference position and step change in load is shown in Fig. 5 and Fig. 6. Fig. 5

illustrates the dynamic response of the drive system with the application of SNCs and the dynamic response of the drive system with the conventional PI-D 2DOF position controller at the same conditions is illustrated in Fig. 6. Fig. 5 and Fig. 6 show the position tracking, speed response. and load current response, regulation performance under nominal parameters. At t=1.5 sec, an external load of 10 N.m is applied to the drive system for both controllers. It is obvious that the proposed SNCs provide a rapid and accurate response for the reference within 0.55 sec. Also, the SNCs quickly return the position to the command position within 0.55 sec under full load with a maximum dip of 0.01 radian. While the position response of the conventional control scheme provides a slow response for the reference of about 1 second and has a long recovery time of 1 second and large dipping in position of about 0.43 radian under load changes as shown in Fig. 6. Fig. 7 and Fig. 8 prove that

the IFOC is achieved during load changes ($\chi_{dr}^e = \chi_r^{e^*}$ and $\chi_{qr}^e = 0$). Also, Fig. 7 illustrates that the proposed SNCs cortrol scheme provides robust performance than the corventional PI-D 2DOF controller. The dynamic performance introduced through Fig. 5 to Fig. 8 reveals that the proposed SNCs control scheme has an extremely quick position response and is influenced slightly by the load disturbance.

6.2 Influences of Parameter Variations

The position response and the load regulation per formance of the proposed SNCs and the conventional controller are shown in Fig. 9 to Fig. 12 respectively under parameter variation of the machine. It can be seen that from these figures that the drive system with SNCs controllers is insignificantly affected by variations in the induction machine parameters while the drive system response with the PI-D 2DOF controller shows a significant effect of the parameter variations.

7. Conclusion

In this paper, a SNC control system design for IFOC of induction machine drive system has been presented. The SNC control constitute a simple structure that is applied to the induction machine drive system. In spite of the sim ple structure of SNCs, the obtained results show that those cor trollers can provide a fast and accurate dynamic response in tracking and disturbance rejection chara cte istics under parameter variations. At the same time, a reduction of the computation time has been occurred as a result of the simple construction of the four SNCs. The preposed SNC controller can compensate the induction mathine drive system at nominal values and is ins gnificantly affected by variations in the induction ma:hine's parameters. The position response of this pre posed SNC control scheme was influenced slightly by the load disturbance, whether the system parameters var ed or not. However, the position response of the corventional control scheme did have a long recovery time. Simulation results demonstrate that the proposed SNC control scheme has a robust position response and can rapidly cancel a load disturbance and its superiority

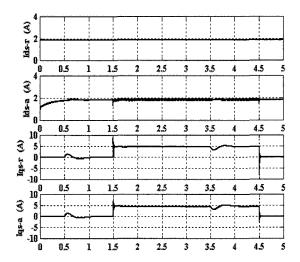
compared with the PI-D 2DOFC position controller for IFOC induction machine drive system.

8. Appendix

Table 1 shows the machine parameters measured by means of no-load and locked rotor tests.

Table 1. Machine parameters

1.5 kW, 4 poles, 380 V/3.8 A, 50 Hz $R_s = 6.29 \,\Omega, R_r = 3.59 \,\Omega, \quad L_s = L_r = 480 \,mH, L_m = 464 \,mH, M_s = 464 \,mH, M_s = 464 \,mH, M_s = 464 \,mH, M_s = 464 \,mH$



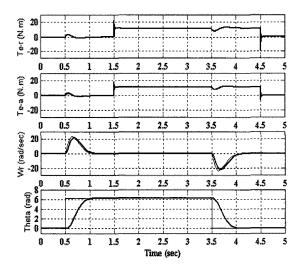


Fig. 5. Dynamic performance of the current, speed and position with the proposed SNCs controllers.

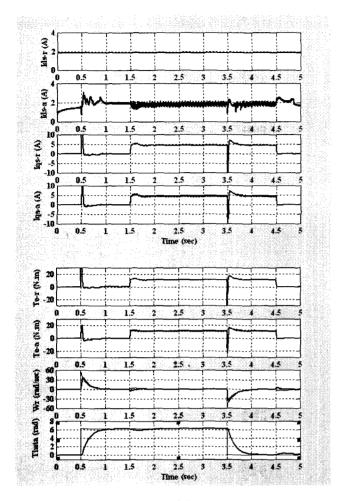


Fig. 6. Dynamic performance of the current, speed and position with the proposed conventional PI-D 2DOF position controller.

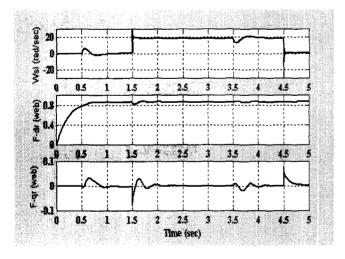


Fig. 7. Dynamic performance of the variables, ω_{sl} , λ_{dr}^{e} , λ_{dr}^{e} for the SNCs controllers.

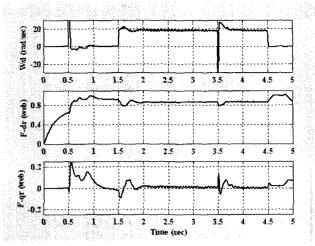


Fig. 8. Dynamic performance of the variables, ω_{sl} , λ_{dr}^e , λ_{qr}^e for the proposed PI-D 2DOF controller.

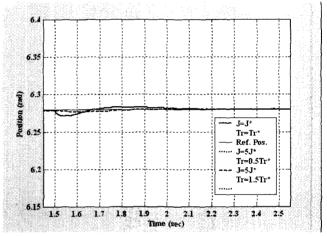


Fig. 9. Load regulation performance under parameter variations with the proposed SNCs controllers.

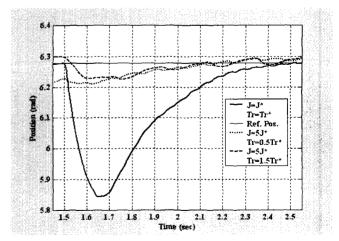
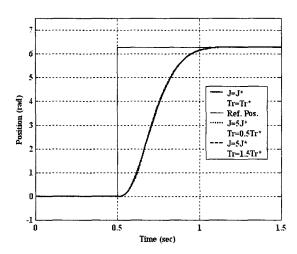


Fig. 10. Load regulation performance under parameter variations with the proposed PI-D 2DOF controller.



ig. 11. Step response performance under parameter variations with the proposed SNCs controllers.

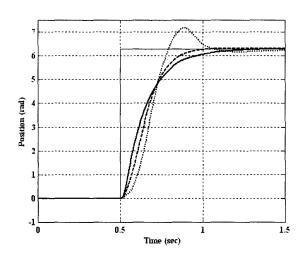


Fig. 12. Step response performance under parameter variations with the proposed PI-D 2DOF controller.

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