

Control of Induction Motor Drive using Artificial Neural Network

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ABSTRACT - The induction motor drive is a dynamic nonlinear system with uncertainty in the machine parameters. The aim of this study is to improve tracking performance of the induction motor drive. A method for controlling induction motor drive is presented with conventional Proportional-Integral (PI) controller and Artificial Neural Networks (ANNs) controller. MATLAB/SIMULINK software is used to develop a three phase induction motor model. Also the performances of the two controllers have been verified. The ANN is trained so that the speed of the drive tracks the reference speed. It is found that with the use of the ANN controller the performance and dynamics of the induction motor are enhanced as compared with that of a conventional PI controller.

Keywords: Artificial Neural Networks, Control, P.W.M (Pulse Width Modulation), Back propagation, vector control

المستخلص - المحرك الحثي عبارة عن نظام ديناميكي لا خطي بثوابت غير مؤكدة. هدف هذه الدراسة هو تحسين أداء التتبع للمحرك الحثي. طريقة التحكم في المحرك الحثي تم توضيحها بالمتحكم التقليدي التناسبي التكاملي و المتحكم الشبكي العصبي الاصطناعي. أستخدم البرنامج MATLAB/SIMULINK لبناء نموذج للمحرك الحثي ثلاثي الطور. و تم التحقق من أداء المتحكمين. دربت الشبكة العصبية الاصطناعية حتى تتبعت سرعة المحرك السرعة المرجعية. لقد وجد أن باستخدام المتحكم الشبكي العصبي الاصطناعي يكون الأداء الديناميكي للمحرك الحثي قد تحسن مقارنة بالمتحكم التقليدي التناسبي التكاملي.

INTRODUCTION

In many industrial drives advanced digital control strategies for the control of field-oriented induction motor drives with a conventional speed PID controller, have gained the widest acceptance in high performance AC servo system [1-4]. However, in certain applications such as steel mills and paper mills robotics, machine tools, the drive operates under a wide range of load change characteristics. Under such conditions, the system parameters vary substantially leading in most of the cases to load disturbance. To overcome this drawback, the control algorithm should include a complicated computation process to eliminate the variations in the load disturbance. However, the control algorithms applicable to these systems have become increasingly more complicated, requiring extensive computations for real-time implementation. In recent years, Artificial Neural Network intelligent and fuzzy logic controllers have gained great importance and proved their dexterity in many respects [5-8].

Recently, many techniques have been developed for induction motor drives and hence very good control performances have been achieved. Among the existing techniques, the most commonly used one is the Proportional-Integral (PI) controller. The PI controller is very easy to be implemented; although it cannot lead to good tracking and regulating performance simultaneously. Further; its control performance parameters are sensitive to the system parameters variations and load disturbances.

In much motor control applications, direct control of torque is highly desirable, since a system with a fast response to changes in torque is very beneficial. The field oriented control (FOC) or vector control theory is the foundation base for certain new special control methods for induction motor drives. With this control method, it becomes feasible that induction motors can successfully replace the expensive DC motor.

The most important aspect of a field-oriented control of induction motor is the transformation of the stator currents into a torque producing component (the quadrature q) and a flux-

producing component (the direct path d). To enable the flux producing current component to align with the rotor magnetic flux, the accurate estimation of a transformation parameter called the unite vector is required. However, if these unite vector can be correctly determined, and then the AC drive performance will depend on the effectiveness in producing the appropriate torque command. This control technique is very sophisticated in implementation that exploits the conventional controllers.

Through the years artificial neural networks have been developed with both biological ideas and control applications in mind, and the theories of the brain and nervous system have used ideas from control system theory. The motivation for control system design is often to optimize costs such as the energy used or the time taken for a given control action. Control actions designed with minimum cost are said to make up optimal control. The problem of approximating to an optimal control in a practical way can be addressed with the use of neural network methods [9].

Principles of Artificial Neural Networks are that ANNs use a dense interconnection of computing nodes to approximate nonlinear functions [10]. Each node constitutes a neuron and performs the multiplication of its input signals by constant weights, sums up the results to finally map the sum to a nonlinear activation function g ; the result is then transferred to its output. A recurring ANN network is organized in layers: an input layer, one or more hidden layers and an

output layer and at least one feedback loop. A Multi Layer Perception (MLP) consists of an input layer, several hidden layers, and an output layer [3]. Node i , also called a neuron in a MLP network is shown in Figure 1. It includes a summer and a linear activation function g .

The inputs x_k , where k ranges from digit '1' to digital 'k', the neuron are multiplied by weights w_{ki} and summed up together with the constant bias term θ_i . The resulting i_n is the input to the activation function g . The activation function is originally chosen to be a relay function, but for mathematical convenience a hyperbolic tangent (tanh) or a sigmoid function are most commonly used [11]. The mathematical model of a neuron is given by:

$$y_i = g_i = g\left(\sum_{j=1}^N W_{ji} \cdot X_j + \theta_i\right) \quad (1)$$

MODELING OF INDUCTION MOTOR

The space vector model of the induction motor is the lumped-parameter model with the largest use in the study and design of electrical drive applications. It is common to consider as a first approximation that the rotor windings and the stator windings have a sinusoidal distribution inside the motor and no magnetic saturation is present. Therefore, the magneto-motive force (MMF) space harmonics and slot harmonics are neglected. Although saturation is not taken into account, the model is considered to yield acceptable results for the study of common electric drive applications.

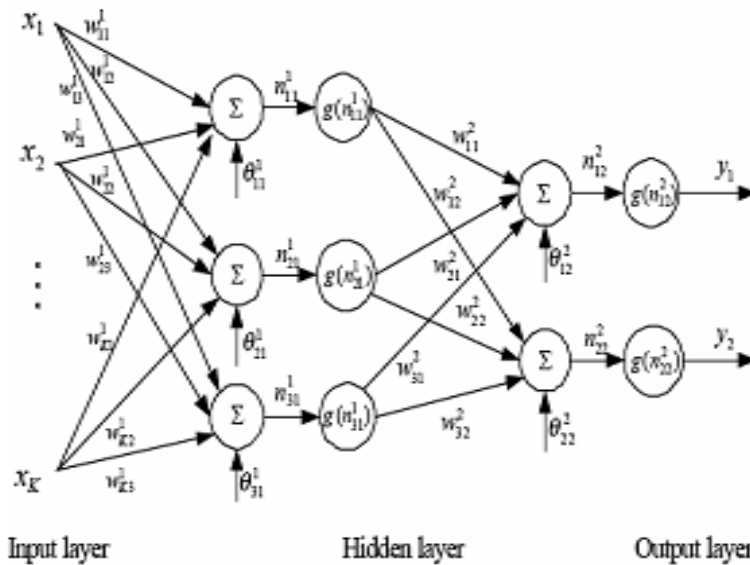


Figure 1: A Multi-Layer Perception (MLP) network with one hidden layer

The induction motor space vector model is derived from the basic electrical equations describing each of the stator windings and each of the rotor windings^[12].

The indirect vector control method is very popular in industrial applications. Figure 2 shows the phasor diagram of explaining indirect vector control.

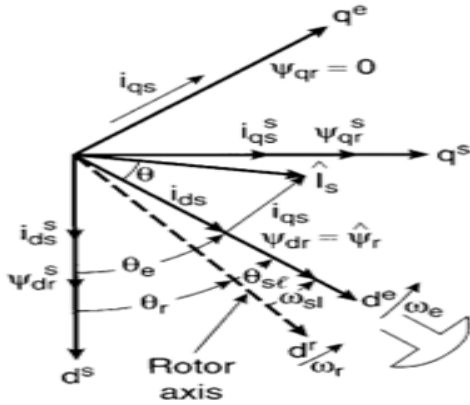


Figure 2: Indirect vector control

The $d^s - q^s$ axes are fixed on the stator, but the $d^e - q^e$ are rotating ahead of the $d^r - q^r$ axes by the positive slip angle θ_{sl} corresponding to slip frequency, ω_{sl} . Since the rotor pole is directed at the d^e axis and $\omega_e = \omega_r + \omega_{sl}$, the rotor flux position θ_e can be written as

$$\theta_e = \int \omega_e dt = \int (\omega_r + \omega_{sl}) dt = \theta_r + \theta_{sl} \quad (2)$$

The rotor pole position is not absolute, but it is slipping with respect to the rotor frequency ω_{sl} .

The phasor diagram suggests that for decoupling control, the stator flux component of current i_{ds} should be aligned with the d^e axis, and the torque component of current i_{qs} should be on the q^e axis, the rotor circuit equations given in^[13] are reproduced as (3) and (4).

$$\frac{d\psi_{dr}}{dt} + R_r i_{dr} - (\omega_e - \omega_r) \psi_{qr} = 0 \quad (3)$$

$$\frac{d\psi_{qr}}{dt} + R_r i_{qr} - (\omega_e - \omega_r) \psi_{dr} = 0 \quad (4)$$

The rotor flux linkage (ψ_{dr}, ψ_{qr}) expressions can be given as:

$$\psi_{dr} = L_r i_{dr} + L_m i_{ds} \quad (5)$$

$$\psi_{qr} = L_r i_{qr} + L_m i_{qs} \quad (6)$$

From the above equations, the rotor d and q axis currents can be written as

$$i_{dr} = \frac{1}{L_r} \psi_{dr} - \frac{L_m}{L_r} i_{ds} \quad (7)$$

$$i_{qr} = \frac{1}{L_r} \psi_{qr} - \frac{L_m}{L_r} i_{qs} \quad (8)$$

The rotor current in equation (3) and (4), which are inaccessible, can be eliminated with the help of equations (7) and (8) as:

$$\frac{d\psi_{dr}}{dt} + \frac{R_r}{L_r} \psi_{dr} - \frac{L_m}{L_r} R_r i_{ds} - \omega_{sl} \psi_{qr} = 0 \quad (9)$$

$$\frac{d\psi_{qr}}{dt} + \frac{R_r}{L_r} \psi_{qr} - \frac{L_m}{L_r} R_r i_{qs} - \omega_{sl} \psi_{dr} = 0 \quad (10)$$

Where, $\omega_{sl} = \omega_e - \omega_r$ has been substituted. For decoupling control, it is desirable that:

$$\psi_{qr} = 0 \quad (11)$$

That is,

$$\frac{d\psi_{qr}}{dt} = 0 \quad (12)$$

So, that the total rotor flux $\hat{\psi}_r$ is directed at d^e axis. Substituting the above conditions in equations (9) and (10) getting:

$$\frac{L_r}{R_r} \frac{d\hat{\psi}_r}{dt} + \hat{\psi}_r = L_m i_{ds} \quad (13)$$

$$\omega_{sl} = \frac{L_m R_r}{\hat{\psi}_r L_r} i_{qs} \quad (14)$$

where $\hat{\psi}_r = \psi_{dr}$ has been substituted. If rotor flux $\hat{\psi}_r$ is constant, which is usually the case, then from equation (13):

$$\hat{\psi}_r = L_m i_{ds} \quad (15)$$

A DC machine-like electro-mechanical model of an ideal vector-controlled drive can be driven using equation (13) and the following equations[5]:

$$T_e = \frac{3}{2} \left(\frac{P}{2} \right) \frac{L_m}{L_r} \hat{\psi}_r i_{qs} \quad (16)$$

$$T_e - T_L = \frac{2}{P} J \frac{d\omega_r}{dt} \quad (17)$$

where T_L is the load torque.

PROPORTIONAL INTEGRAL CONTROLLER

Vector-controlled induction motor drive with a conventional proportional integral (PI) speed controller has used extensively in industrial applications, since PI controller is simple, easily implemented and effective if the load

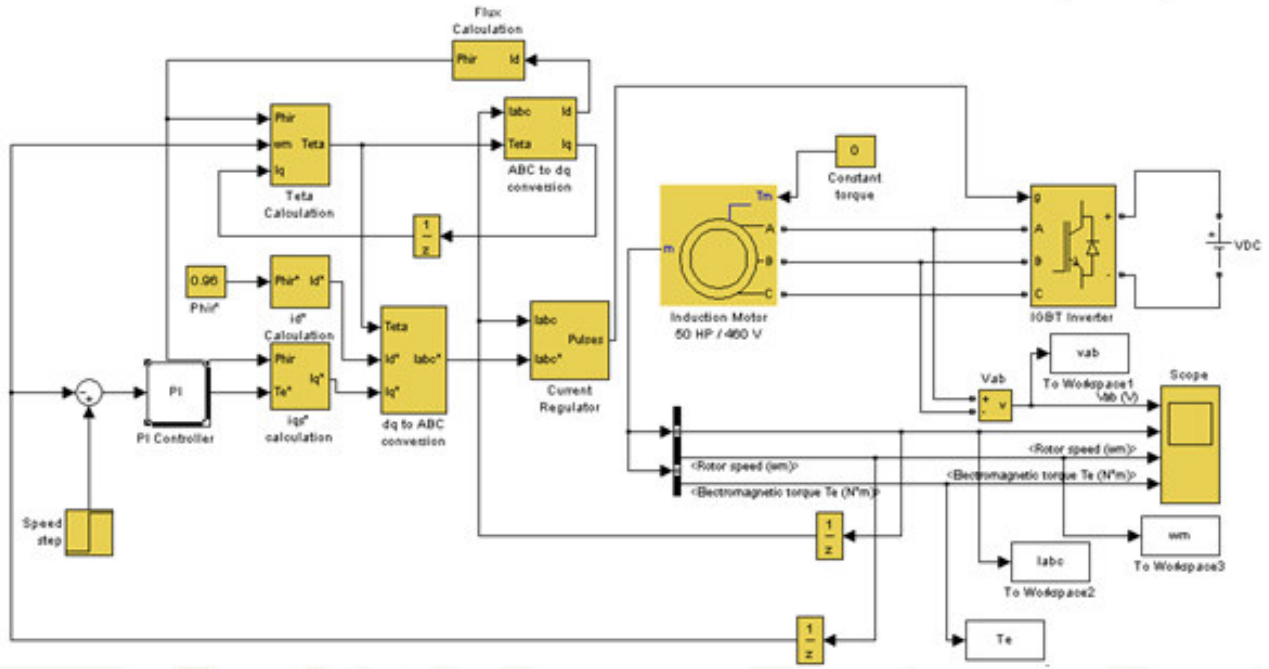


Figure 3: PI control system of induction motor drive

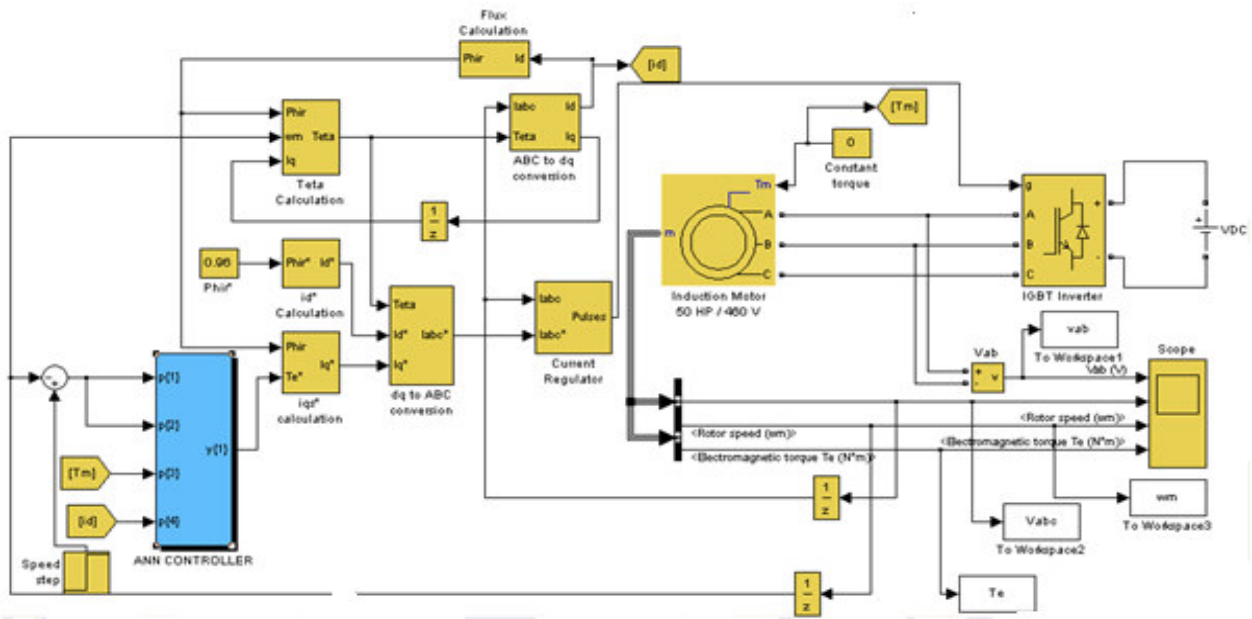


Figure 4: ANN control system of induction motor drive

changes are small and the operating conditions do not force the system too far away from the linearized equilibrium point [14].

The analog transfer function of the proportional-integral (PI) controller is:

$$C(s) = k_p + \frac{k_i}{s} = k_p \frac{s + a}{s} \quad (18)$$

Figure 3 shows the SIMULINK model of the PI control system of induction motor drive.

NEURAL NETWORK CONTROLLER

The ANN is trained by a learning algorithm which performs the adaptation of weights of the

network iteratively until the error between target vectors and the output of the ANN is less than an error goal. The most popular learning algorithm for multilayer networks is the back propagation algorithm and its variants [15]. The latter is implemented by many ANN software packages such as the ANN toolbox in MATLAB [8].

In this paper the ANNs control strategy has been implemented. Neural network has been devised having as inputs the speed error, the speed error change, the load torque, the stator

direct axis current, and as output the reference electromechanical torque.

The conventional *PI* controller shown in Figure 3 is replaced by the neural network controller and the simulation is performed as shown in Figure 4. The ANNs training with TRAINLM is given in Figure 5 and the SIMULINK block of ANN is generated as shown in Figure 6. The ANNs layers are shown in Figure 7 through to Figure 9 accordingly.

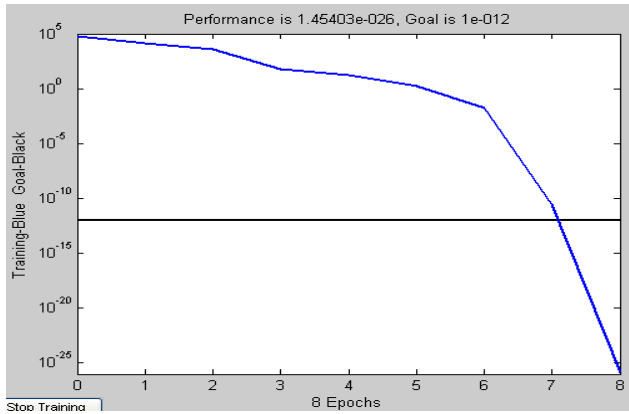


Figure 5: The training ANN

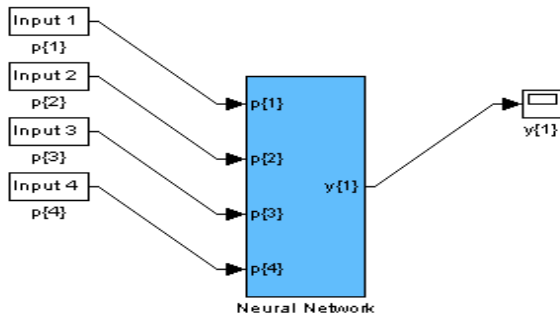


Figure 6: ANN controller

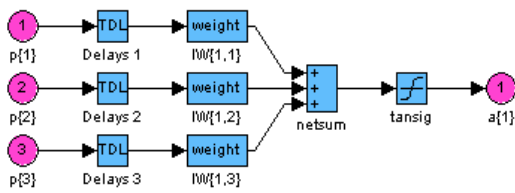


Figure 7: Layer1

SIMULATION RESULTS

The simulation of the system is conducted using SIMULINK Toolbox. The performances of the proposed controllers are evaluated under a variety of operating conditions. The *PI* controller has been tuned using trial and error to obtain a good speed response

with $k_p = 13, k_p = 26$. The simulation results are shown in Figure 10 through to Figure 15. As shown in Figure 10, the speed of the motor with *PI* controller, rises to 90% of its final speed at $t=0.75s$.

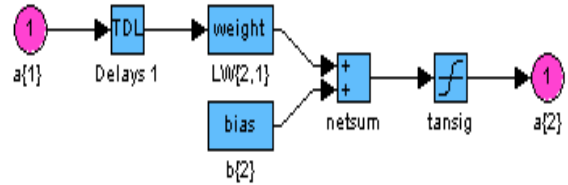


Figure 8: Layer-2

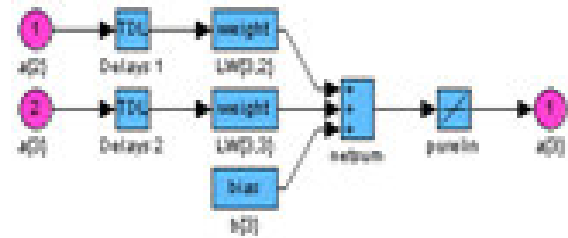


Figure 9: Layer-3

An external force of 2 [Nm] is applied to the induction motor and the speed response is shown in Figure 11, it seen that the result was very successful and the obtained result confirm the validity of the proposed control specifications. As shown in Figure 12, the speed of the motor with ANN controller, rises to 90% of its final speed at shorter time compared with *PI* controller ($t=0.6s$). An external force of 2 [Nm] is applied to the induction motor controlled with ANN controller and the speed is shown in Figure 13. In Figure 14 and Figure 15, one can observe the superior properties of the loop controlled by the NN control and the conventional *PI* controller.

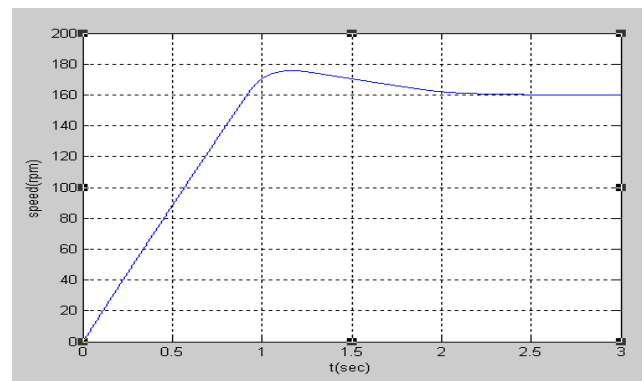


Figure 10: Speed response with *PI* controller at no load

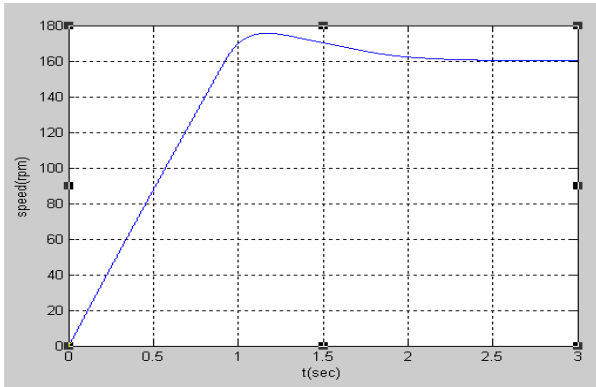


Figure 11: Speed response with PI for 2N.m load torque disturbance

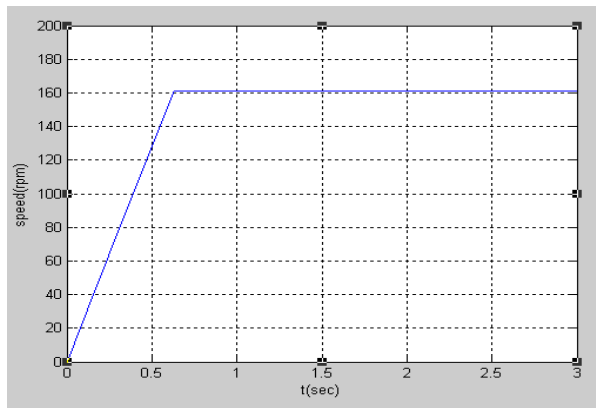


Figure 12: Speed response with ANN controller at no load

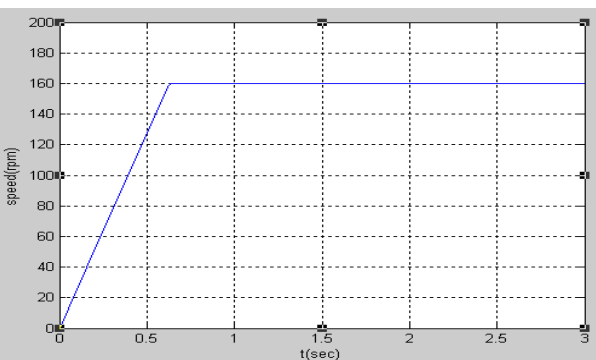


Figure 13: Speed response with ANN for 2N.m load torque disturbance

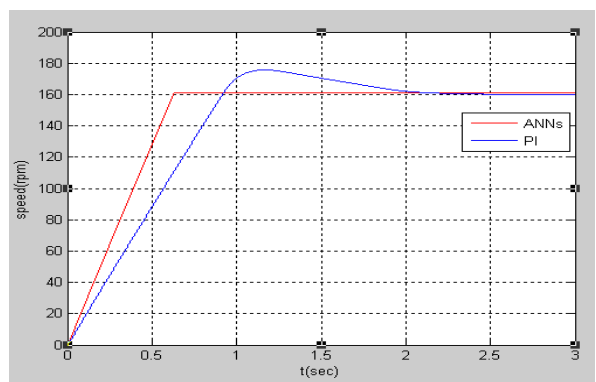


Figure 14: Speed response with PI and ANN controller at no load

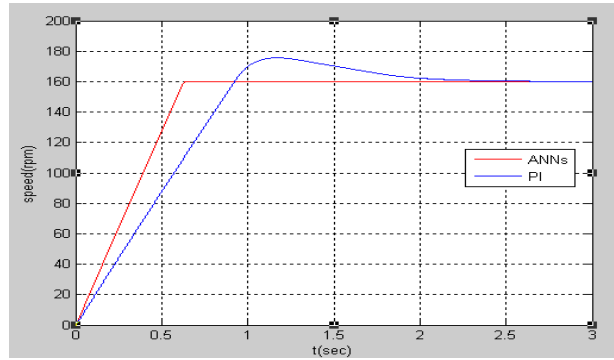


Figure 15: Speed response with PI and ANN controller at 2N.m load

6. CONCLUSIONS

The performance specifications taken into consideration are: the overshoot, rise time, settling time and steady state error. The performance of the proposed controllers has been evaluated under a variety of operating conditions of the drive system, and the results demonstrate the effectiveness of these control structures. A comparative study of the control strategies in term of performance has been conducted. An intelligent control system using a neural network controller has reduced peak overshoot, rise time and settling time compared to the system with a PI controller. It is observed that the speed of the machine remains constant with reduced overshoot using the neural network-based controller. In conclusion, the proposed Artificial Neural Network shows high performance and good control accuracy for the system.

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