Journal of Engineering and Applied Sciences 13 (21): 9156-9163, 2018
ISSN: 1816-949X

Impact of Artificial Neural Network for DC Motor Speed Control Over the Conventional Controller

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Abstract: DC motors are proven enhanced performance while it used in different applications where accurate speed control is demanded. This study emphasises to deploy artificial neural controller for accurate and rapid control of speed. A comparative approach is made to prove the strength of ANN controller over Proportional Integral (PI) controller. MATLAB ANN toolbox and Simulink library is used to emulate the paradigm. Observations are made base on experimental system and the same is revealed more rapid response to speed fluctuation is made by ANN controller under different load circumstances. Neural network is designed to ensure perfect speed regulation after it fed by reference speed and other electrical parameters such as voltage and armature current. Moderated error is detected at ANN controllers of 1e-7 and 8 after 5000 epics of training process.

Key words: PI, ANN, DCM, GA, FL, AC, DC, AI

INTRODUCTION

Industrial applications are presenting large deployment of motor drives of high performance. Such drives are expected to have good speed regulation and dynamic responding to load variation; DC motors are deployed to satisfy such requirement due to their accuracy in terms of speed regulation and control. The precise control characteristics of direct current motors encouraged the manufacturers of different industrial concerns to utilize them in enormous applications such as electric vehicles and robotic devices (Suman and Giri, 2016; Dursun and Durdu, 2016). DC motors are considered as serial input serial output system with good compatibility of mechanical loads, hence, speed control of DC motors can be performed with varying of their terminal voltage with proper scale. Now a days, noticeable efforts are paid by electric manufactures to make the some available AC drives to behave as direct current motors to claim the above advantages and cob with load variation and other practical challenges such as propagation of noise, instant load variation and unpredictable parameters. Such uncertainty makes it difficult for conventional approaches to stand in such challenges.

The Proportional Integral controller (PI) is one of conventional means of speed control that provide a zero error of DC motor's steady state. Such controller is largely deployed in many applications (Benmabrouk *et al*., 2016). From the other hand, revolved techniques are involved recently to provide speed control such methods are underlying with artificial inelegance algorithms such Artificial Neural Networks (ANN), Genetic Algorithm (GA) and Fuzzy Logic (FL) (Killedar, 2016).

ANN is used in control applications of non-linear and linear paradigms; the information process architecture of ANN has made an advantageous property over the classical controllers. The strength of artificial neural network of parallel distribution architecture is lie on flexible learning and mapping of complex functional problems.

Neural controller is termed to the field of plants controlling which is underlying by artificial intelligence; those systems are capable to learn the functional circumstances of real world and so, it is adaptable in any other unknown model of other system. Two kinds of neural controller are proposed in today's researches; adaptive neural network and feed-forward neural network. In this study, offline training is utilized in adaptive neural network controller of three layers.

MATERIALS AND METHODS

Mathematical analysis: The interested model for mathematic representation of this study is DC motor; Fig. 1 is descripting this system. First order Eq. 1 is putted to describe the motor closed loop:

$$\text{Var} = \text{R ar*i ar+L ar*di}\frac{\text{ar}}{\text{dt}}\text{+emf} \tag{1}$$

The reversed Electro Motive Force (EMF) can be written as:

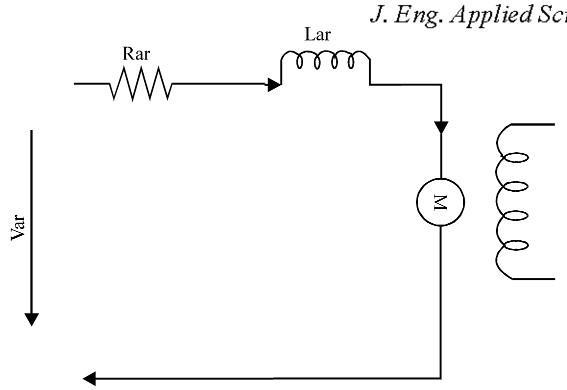

Fig. 1: DC motor equivalent circuit

$$EMF = S\,\omega \tag{2}$$

Where:

Var = The winding voltage that entering armature
EMF = Reversed Electro Motive Force/potential
Iar = Winding current of armature
Rar = Resistance of armature winding
S = Constant of EMF
W = Rotor radian speed

By substitution of Eq. 1-3 can be obtained:

$$Var = R\ ar{*}i\ ar + L\ ar{*}\frac{di\ ar}{dt} + S\omega \tag{3}$$

Torque mechanical can be described as well:

$$\gamma\frac{d\omega}{dt} = -Lq - Lc + L_{EMF} \tag{4}$$

$$Lemf = M{*}i\ ar \tag{5}$$

$$Lq = f{*}\omega \tag{6}$$

By substitution of Eq. 4-6:

$$\gamma\frac{d\omega}{dt} = -(f{*}\omega) - Lc + (M{*}i\ ar) \tag{7}$$

Where:

γ = The moment of inertia in the system
Lq = Load torque
Lc, M = Constant torques

Now, applying of Laplace transform on Eq. 3 will yield the following terms:

$$Var(p) = Ri(p)ar + Lar{*}p{*}Iar(p) + S\omega(p) \tag{8}$$

Table 1: Design parameters for the practical system

Items	Values
Damping factor (f)	0.0218 Nm-sec/rad
Inductance (Lar)	129*(e-3) H
Resistance (Rar)	8 Ω
Damping Resistance (Rd)	1*e(2) Ω
Damping inductance (Rd)	2*e(-1) H
Constant torque (M)	775*e(-3) Nm/A
Electromotive constant	7.75*e(-2) V sec/rad

*Sugnificant value

$$\gamma p\omega(p) = -f\omega(p) + Mi(p) \tag{9}$$

$$i(p) = \frac{Var(p)}{Rar+LarP} - \frac{M}{Rar+LarP}\omega(p) \tag{10}$$

$$\omega(p) = \frac{M}{f+\gamma P} I\ ar(p) \tag{11}$$

By substituting Eq. 11 into 10:

$$\frac{\omega(p)}{Var(p)} = \frac{M}{(Rar+P\ Lar)(\gamma P+f)+M^2} \tag{12}$$

Ultimately, the Eq. 13 of DC motor can be written as:

$$Z(p) = \frac{M}{(Rar+P\ Lar)(\gamma P+f)+M^2} * Var(p) \tag{13}$$

Equation 12 is termed to DC motor transfer function (ratio of angular speed to input voltage). However, the following parameters in Table 1 are considered for our design. Equation 13 will become as:

$$Z(p) = \frac{775*10^{-3}}{259e(-5)p^2+775e(-3)+163e(-3)p} Var(p) \tag{14}$$

By applying Laplace inverse transformation for the Eq.14, the following term will be yielded:

$$\begin{aligned} Z(k) = {} & -532*10^{-3}z(k-2)+994*10^{-5}Var(k-2)+ \\ & 152*10^{-2}z(k-1)+127*10^{-4}z(k-1) \end{aligned} \tag{15}$$

Conventional controller: These methods are implemented base on current regulation and speed regulation; speed and current are detected in machine working conditions by employing a sensors like speed sensor and current sensor which are essential players in conventional methods. Figure 2 is depicting the basic mechanism of speed controller paradigm (Rai and Rai, 2013).

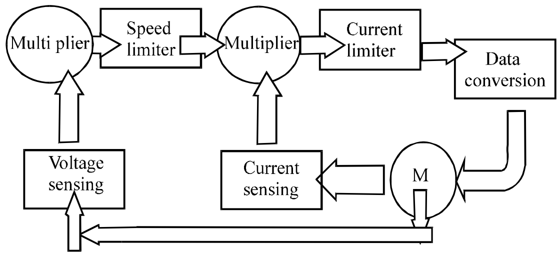

Fig. 2: Common model of controller

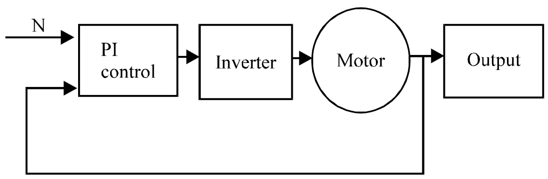

Fig. 3: Proportional integral block diagram for DC motor speed control

PI controller is one of the available conventional means to control DC motor. The structure of PI control is about the existing of position sensor, voltage source inverter or current source invertor that built up with IGBT transistors, Pulse Width Modulator (PWM) to provide a control signals (voltage or current) to trigger the invertor and reference signal generators. The functional PI control may begin to compare the speed value of running motor with its reference value (Mute *et al*., 2015), hereafter, speed error may be yielded from this conversion in PI controller, the term "gains" is required to be updated continuously for applying the designated control. Let's say that ω is rotor speed of running DC motor and ω ref is the reference speed that set in PI controller so speed error can be described as ω error (Fig. 3):

$$\omega eror = \omega\text{-}\omega \text{ ref}$$

Controller is producing a reference torque signal at its output, the winding current is then compared to the reference current to generate speed controller limit.

Artificial neural controller: DC motor can be controlled using artificial intelligence techniques, however, Fig. 4 is depicting the control system based on artificial neural network. Mainly, two functions need to be performed in such control system, terminal voltage and speed (Kumar and Dohare, 2016).

However, ANN controller is required to be trained for voltage and speed emulation. In this control paradigm, data may resource during working conditions of DC motor and feed into ANN for training purpose. In ANN paradigm

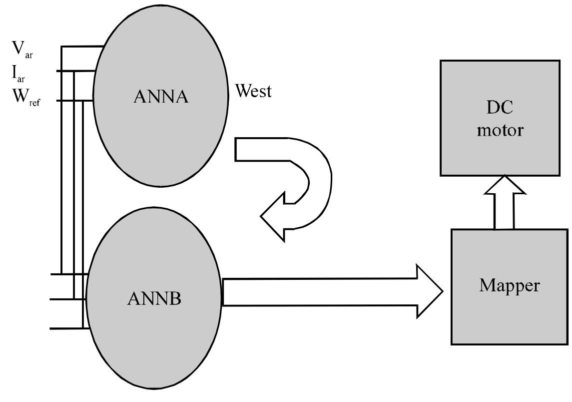

Fig. 4: ANN based controller

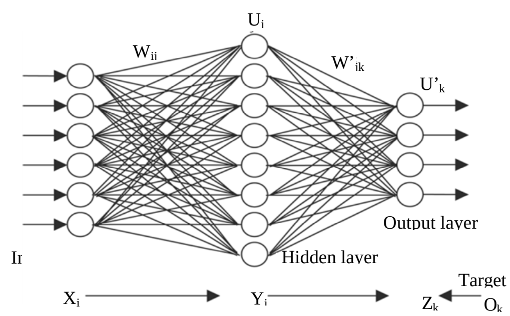

Fig. 5: ANN nodes and neurons paradigm

number of layers is implemented depending on the real-world requirements, nodes are propagating in each layer, every node is performing a function on reception of data from the preceding node, so that, each node is yielding an output that differs from their input. Nodes are connected with each other by logical connections called neurons. Mathematical functions like averaging, integration, multiplication, division, scaling, etc. can be done within nodes (Ren and Chen, 2006). Figure 5 is describing artificial neural network structure.

ANN can learn difficult problems even though large discrimination is existed; in other word, nonlinear problems can be accommodated with neural network.

Neural control design: In order to design a speed control paradigm for DC motor speed governing, the system is investigated and it's found that, two ANN controller is required, ANNA and ANNB. Terminal voltage and armature current data are collected from running machine (Ahmad and Rai, 2014).

ANNA is implemented by three nods to accommodate three different inputs. However, a reference speed is used as an input with current and voltage sets that recorded, so that, we got three inputs to ANNA in return, speed estimation will be yielded by this controller. Table 2 is detailing the design parameter of ANNA (Fig. 6).

Table 2: ANNA design parameters

ANNA/parameters	Values
Inputs	3
Outputs	1
Hidden layers	1
Sweeps of training	5000
Error	$1*10^{-7}$
Training patterns	12.15e2

*Significant values

Table 3: ANNA design parameters

ANNB/parameters	Values
Inputs	4
Outputs	1
Hidden layers	1
Sweeps of training	5000
Error	$1*10^{-8}$
Training patterns	12.15e2

*Significant values

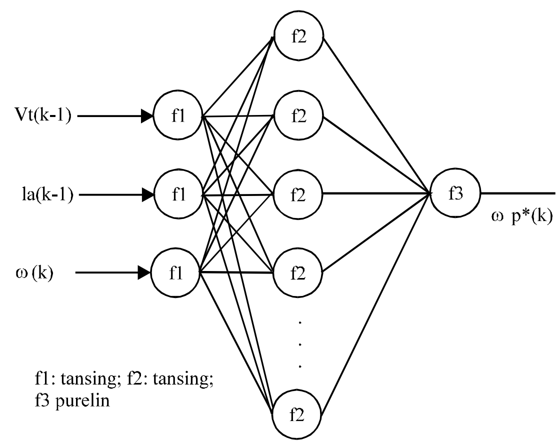

Fig. 6: ANNA controller layers

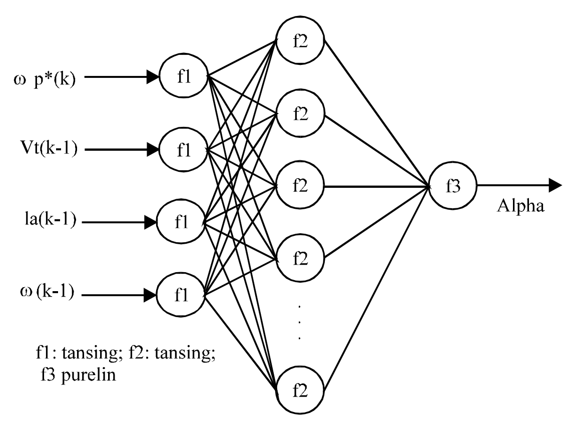

Fig. 7: ANNB controller layers

Now, Fig. 6-9 shows three layers, three inputs and single output (speed estimation). It is essential to state the nature of boundary layers, hence, purelin (linear) activation function is used in output layer while tansig is used with input layer. Other design specifications are tabulated in Table 2.

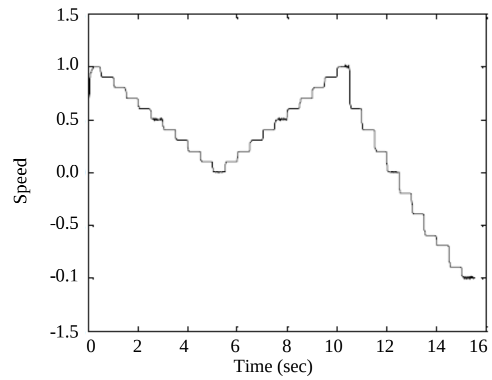

Fig. 8: Set of reference speed (inputs) at ANNA

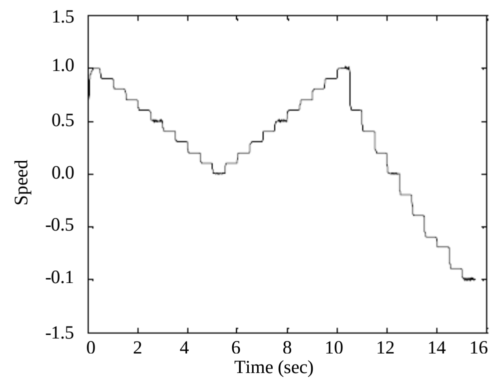

Fig. 9: Output (targeted) speeds of ANNA

The second controller which called ANNB is designed to generate a controller signal that utilized to control the speed of DC motor. Four inputs are fed into controller to generate single output, structure of ANNB is depicted in Fig. 7.

Four inputs such as terminal voltage, armature current, reference speed and the estimated speed from first controller output (ANNA); design parameters of this controller are tabulated in Table 3.

The activation functions of ANNA and ANNB are given in the following:

$$\text{ANNA} = \text{Function}\left[\text{Var}, \text{Iar}, \omega\ \text{ref.}\right]$$

$$\text{ANNB} = \text{Function}\left[\text{Var}, \text{Iar}, \omega\ \text{ref.}, \omega\ \text{est.}\right]$$

After tying all tools and applying the setting parameters as stated above, reference speeds that provided to first controller (ANNA) and the resultant outputs of same controller (west.) are illustrated by Fig. 7-9

Targeted speed are expected to be drawn by DC motor as an output to our program, using of MATLAB to design artificial neural network program to predict this output based on input reference speed and electrical parameters like current and voltage of armature. It is obvious that error is produced which terms to mismatch of input and output. Error found in each controller is tabulated in Table 2 and 3 which were the minimum possible error after training process, parameters of same Table 2 and 3 are set to capture the optimum results in the mentioned error rates.

RESULTS AND DISCUSSION

Two models were implemented using MATLAB Software, we begin with conventional model of PI controller and hereafter artificial neural network controller was used from MATLAB toolbox. However, a DC motor with specifications of Table 1 was simulated in MATLAB Simulink and hence, ANN controllers are also implemented using the specifications of Tables 2 and 3 in MATLAB M file; simulation is executed in hereafter and results are recorded (Fig. 10-25).

Simulation is began with different time fractures, stating from 0 sec through 0.15 sec simulation environments are listed in Table 4 and 5.

Table 4: Simulation sequence and events

Case	Time interval (sec)	Event
1	0.0	W = 1000, T = 3 Fig. (9-12)
2	0.4	W = 2000, T = 3, Fig. (13-16)
3	0.7	W = 500, T = 3, Fig. (17-20)
4	1.2	W = 500, T = 7 Fig. (21-24)

Table 5: Discussion of resulted performance of both controllers

Case	Observation
1	At Fig. 9, torque is controlled by PI paradigm at 0.02 sec whereas; speed is controlled at 0.07 sec. Form the other hand ANN controller was performing same task in 0.01 sec Figure 12 is depicting the speed of case 1 at both PI and ANN controller and same detection is highlighted that ANN is performing quicker speed control
2	Speed and torque are controller at 0.48 sec by PI controller as depicted in Fig. 13 whereas same operation is took place at 0.42 at ANN as in Fig. 14
3	Speed and torque are controller at 0.78 and 0.76 sec, respectively, by PI controller as depicted in Fig. 17 whereas same operation is took place at 0.72 at ANN as in Fig. 18
4	Upon load increment to 7 NM, PI controller will perform speed control at 1.25 sec as in Fig. 21 from the other hand ANN will do the same at 1.2 sec as in Fig. 22

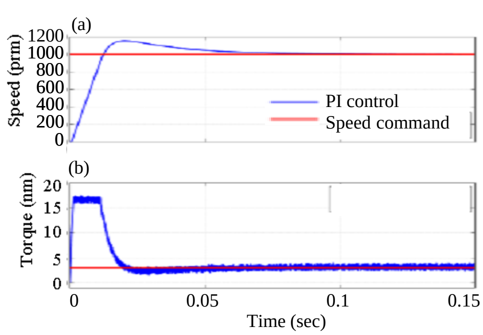

Fig. 10 a, b): PI controller speed and torque response at time interval of 0 sec

Some observations are made on bases of the obtained results, Table 5 is listing the same for all cases.

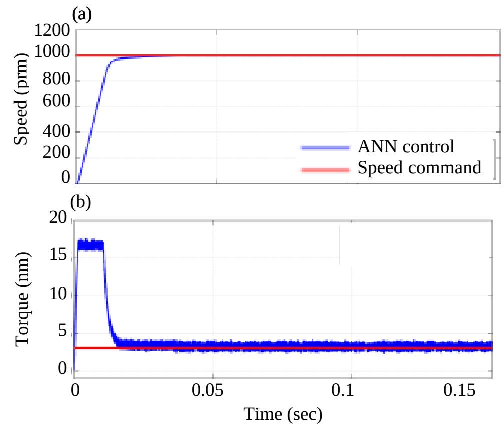

Fig. 11 a, b): ANN controller speed and torque response at time interval of 0 sec

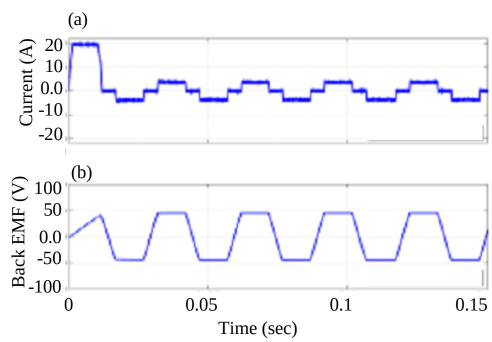

Fig. 12 a, b): ANN controller's back electromotive force and current at time interval of 0 sec

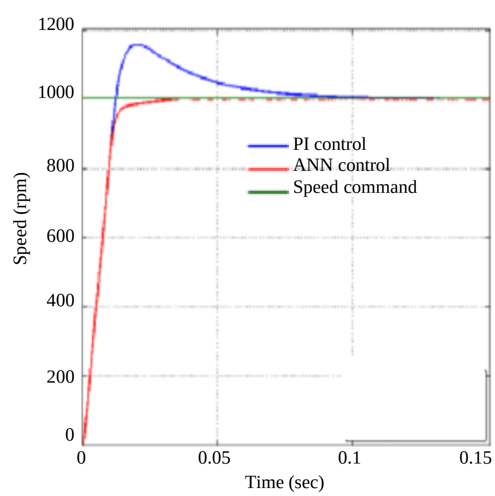

Fig. 13: PI and ANN controller speed control response of time interval 0 sec

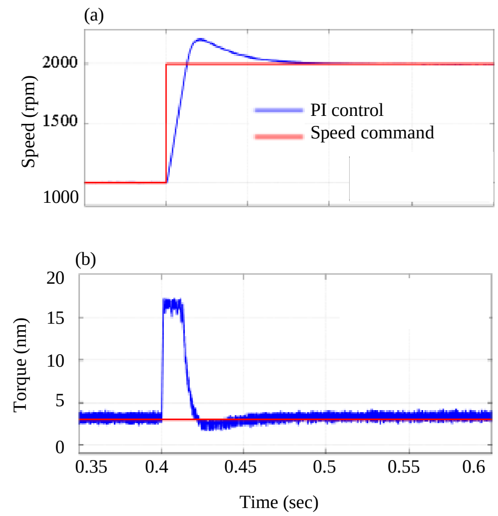

Fig. 14 a, b): PI controller speed and torque response at time interval of 0.4 sec

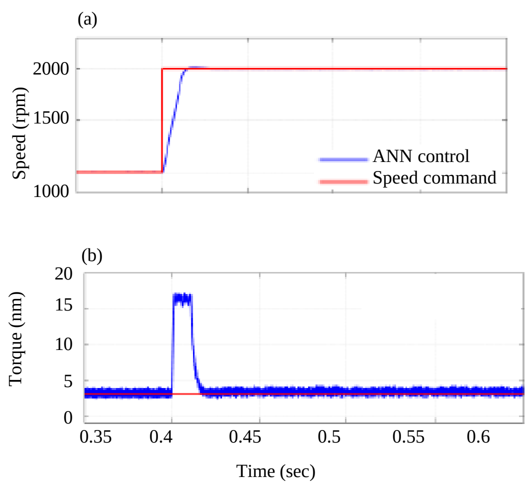

Fig. 15 a, b): ANN controller speed and torque response at time interval of 0.4 sec

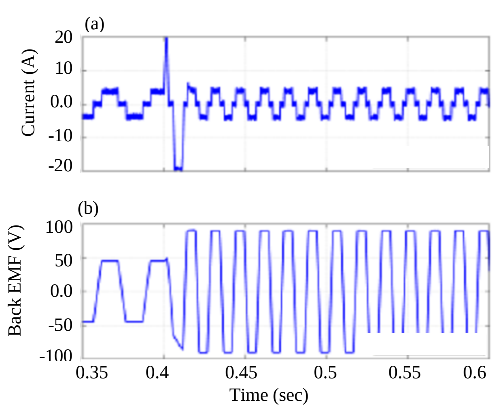

Fig. 16: a, b) ANN controller's back electromotive force and current at time interval of 0.4 sec

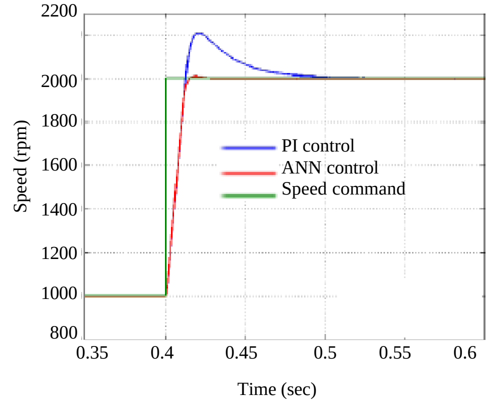

Fig. 17: PI and ANN controller speed control response of time interval 0.4 sec

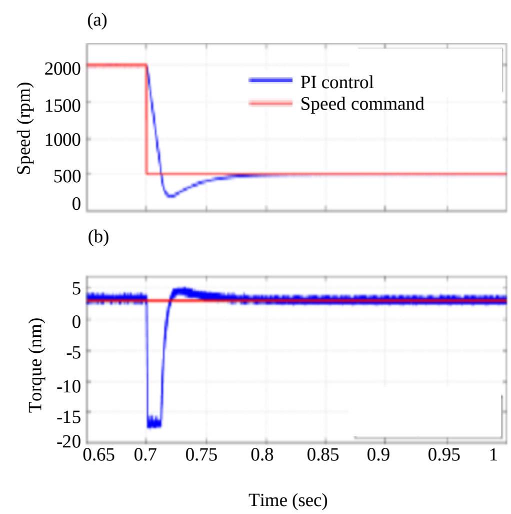

Fig. 18 a, b): PI controller speed and torque response at time interval of 0.7 sec

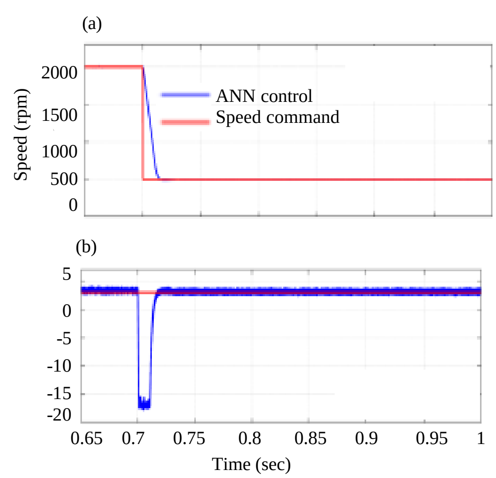

Fig. 19: a, b): ANN controller speed and torque response at time interval of 0.7 sec

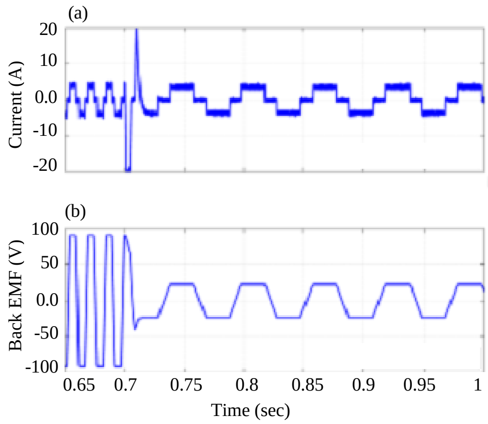

Fig. 20 a, b): ANN controller's back electromotive force and current at time interval of 0.7 sec

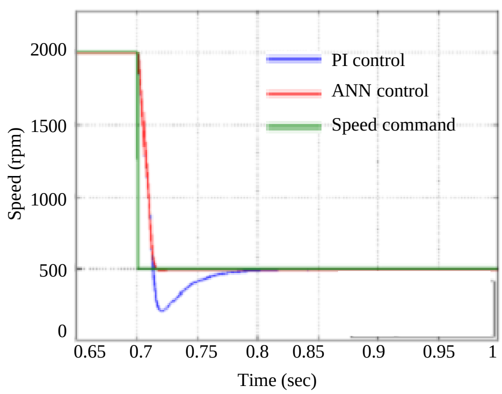

Fig. 21: PI and ANN controller speed control response of time interval 0.7 sec

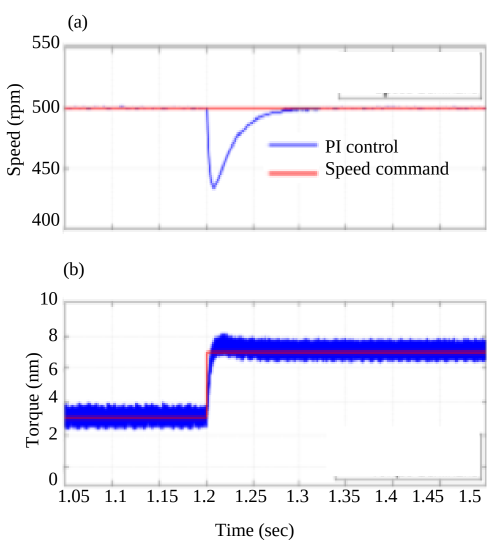

Fig. 22 a, b): PI controller speed and torque response at time interval of 1.25 sec

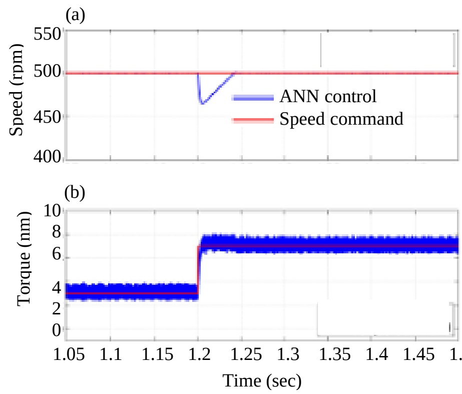

Fig. 23: a, b): ANN controller speed and torque response at time interval of 1.25 sec

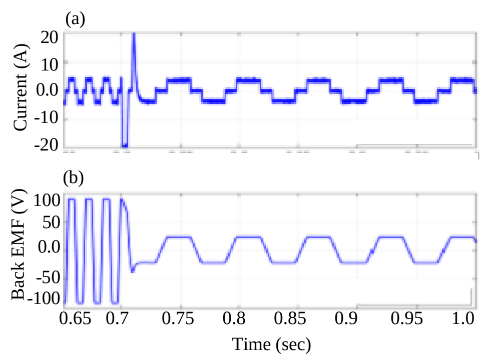

Fig. 24 a, b): ANN controller's back electromotive force and current at time interval of 1.25 sec

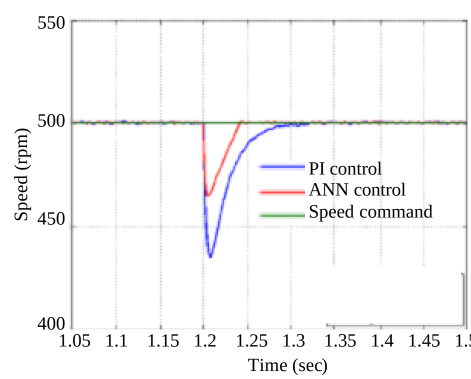

Fig. 25: PI and ANN controller speed control response of time interval 1.25 sec

CONCLUSION

This research is presenting a straight forward approach to synthase the strength of artificial intelligence controller over conventional controller for DC motor speed control. Proportional Integral (PI) controller performance is compared with ANN controller. Results are declared on preceding section, however, all results were proved that ANN controller is drawing enhanced performance over PI conventional controller. Under different working conditions ANN controller is found more quick and accurate in DC motor speed control which become the essential reason to deploy the same in servo systems, form the stability point of view, ANN controller is more reliable due to accurate and quick speed regulation even at load fluctuating.

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