Neural Network Based State Observer with Unknown Terms for Actuator Fault Approximation

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Abstract: In this article, neural network based observer with unknown terms has been implemented for actuator fault approximation in linear systems. All states in a system are not measurable or difficult to measure. In such cases, state observers are used to estimate the states. In this paper, state observer problem with unknown terms is considered. Neural networks are used to approximate the unknown terms in the model. The neural network is trained using back propagation algorithm.The proposed observer is tested on DC motor with various actuator faults such as abrupt, incipient and sinusoidal faults. It is observed that the results obtained for these faults are validated the satisfactory performance of the observer.

Key–Words: State observer, Neural networks, Actuator faults

1 Introduction

State observer is a system, which estimates the internal states of a real time system from measurements of the input and output [1]. It provides foundation for a real time systems. Determining the states is required in solving linear and non-linear control system problems [4]. The states cannot be evaluated by the direct observation. Therefore, the states are observed from the outputs of the system [2]. If a system is observable, it is possible to reconstruct the system states from its output using the state observer [3]. State space representation is an useful in the analysis and design of the control systems. All state variables of the system are not available for measurement [3]. Sometimes it is difficult to measure the state variables. In such situations, the state variables are estimated.

1.1 Literature Survey

The problem of the state vector observation of a linear multi-variable system with unknown inputs has received considerable attention in the last four decades. A comprehensive survey of the nonlinear observer is given in [].

Conventionally, Luenberger observer[5,6] and Kalman filter[7] are used to estimate the states from the model of linear systems. For systems with unknown terms, adaptive observers are used for state estimation of linear systems[8]. Disturbance and nonlinear Luenberger observers for estimating mechanical variables in permanent magnet synchronous motors under mechanical parameters uncertainties is provided in [9].Observers for linear systems with arbitrary plant disturbances is addressed in [10]. Observers for linear systems with unknown inputs is given in [12,13]. Full-order observers for linear systems with unknown inputs is provided in [14],[16],[17], [18].

Recently, neural networks are used for several application in engineering. Multi-layer feed-forward networks are universal approximators that is given in [19]. Other applications of neural networks and sliding mode control are provided in [20-37].

1.2 Observation and Motivation

In many practical systems,only the input and output of a system are measurable.Therefore,estimating the states of a system plays a crucial role in modeling,monitoring or controlling the system. The adaptive learning ability neural networks(NN) makes them powerful tools for identification, observation, monitoring and control of non-linear system without any apriori knowledge about the system dynamics.

State observers are used to estimate the state variables. Approximation of the actuator fault is required for the fault tolerant control (FTC). The state observers are a viable option for approximation of actuator faults in the linear systems. Active fault tolerant control (FTC) requires Fault detection and isolation (FDI) step[]. For FDI fault approximation is key step towards the fault tolerant control. These estimated fault terms information can be used to compensate the fault terms automatically and achieve fault tolerant control of the plant. In this paper proposed ANN observer based fault approximation is used to approximate the additive actuator faults of linear system. The objective here is to develop a state observer which estimates both states and actuator faults simultaneously using multi-layer feed forward neural network.

1.3 Contributions of the article

The contributions of the article are provided below.

1. artificial neural networks (ANN) based observers are used to account for unknown terms the in the plant.
2. simultaneously estimates both the states and unknown additive actuator faults of linear systems
3. Additive actuator faults are combined with inputs of the plant
4. The proposed method is applied DC motor for the purpose of validation

1.4 Organization of the article

The proposed state observer has been developed in MATLAB/SIMULINK. It has been tested on DC motor with various standard faults. The remaining articles is organized as follows. setion 2 describes linear system with unknown actuator fault, a brief description about artificial neural networks is provided in section 3, development of Neural network observer and actuator fault estimation is elaborated in section 04, case studies with various fault conditions are given in section 05 and finally conclusions are provided in the last section.

2 Linear system with unknown actuator fault

A system with unknown actuator fault is represented with the following state space model.

$$\dot{x} = Ax + Bu + Bu_f \tag{1}$$

$$y = Cx \tag{2}$$

Where x is state variable vector. A,B, and C is state variable matrix, u is the input, u_f is the added actuator fault. All the states in a dynamic system are not accessible for measurement. The inaccessible states are to be estimated using state observers. The information of estimated states is used in state feedback control.

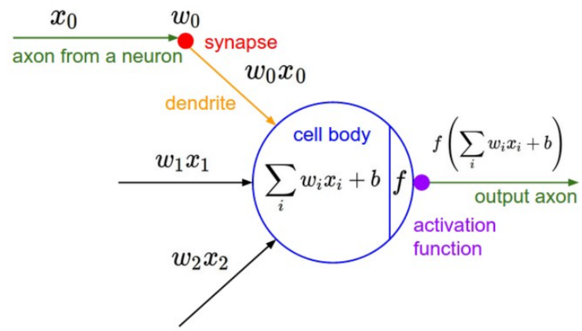

Figure 1: Basic neuron model

3 Neural networks

3.1 back ground

Neural network consists of interconnection of basic units called neurons. The basic artificial neuron is shown in Fig. 01.

The above artificial neuron is represented by the following model.

$$net = \sum_{t=1}^{n} w_i x_i \tag{3}$$

$$y = O(net) \tag{4}$$

$$O(net) = \frac{1}{e^{-\lambda net} + 1} \tag{5}$$

3.2 Multi layer Feed-farward neural network

A feed-farward neural network is considered in this article. Feedforward neural network consists of layers of neurons. First layer is input layer and last layer is output layer. The layers between he input and output layers are called hidden layers. Each layer is connected to its successive layer only. Multi layer feed farward neural network is provided in Fig.02.

I Input node.
W The weight of a connection.
H Hidden node.
HA Hidden node activated.
O Outut node.
OA Output node activated.
B Bias node.

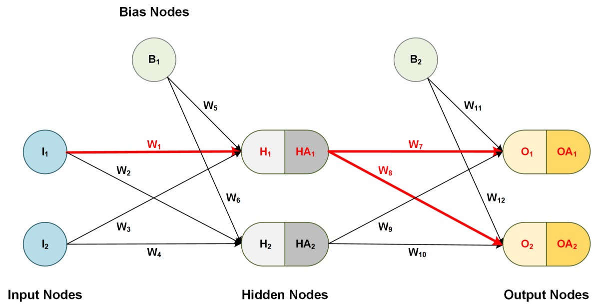

Figure 2: Multi layer feed farward neural network

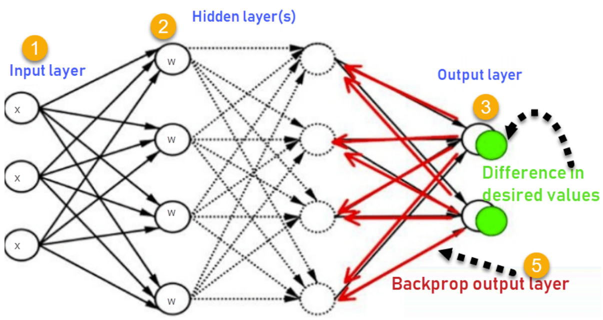

Figure 3: Architecture of back propagation algorithm

e Difference between the output and the desired value.

Multi-layer feed-farward neural networks (MLFFNN) are universal function approximators. For given values of input and output variables, the MLFFNN is trained using supervised algorithms to relate input with output. The back propagation algorithm ha been used in this article to train the neural network.

3.3 Back propagation algorithm

The back propagation algorithm is a generalization of the delta rule for training multi-layer networks (MLN). This algorithm updates the weights w_i of the network by means of successive iterations that minimize the cost function of the error E. Minimization of the error is obtained using the gradient of the cost function, which consists of the first derivative of the function with respect to all the weights. Architecture of back propagation algorithm is shown in Fig.03. Error back propagation algorithm perform gradient descent.This is used to train the neural network in this paper.If dp is the desired output and op is actual output then error

Basic steps involved in the BPA algorithm are provided below.

1. Inputs X, arrive through the pre-connected path
2. Input is modeled using real weights W. The weights are usually randomly selected.
3. Calculate the output for every neuron from the input layer, to the hidden layers, to the output layer.
4. Calculate the error in the outputs i.e Error= Actual Output – Desired Output
5. Travel back from the output layer to the hidden layer to adjust the weights such that the error is decreased.

$$E = \frac{1}{2}\left|d_p - o_e\right|^2 \tag{6}$$

$$\Delta w_{ij} = -n\frac{\partial g}{\partial w_{ij}} \tag{7}$$

4 Development of Neural network observer and actuator fault estimation

4.1 state observer

The state observer for the system (1) is represented as

$$\bar{x} = A\bar{x} + Bu + B\bar{u}_f + L(y - \bar{y}) \tag{8}$$

$$\bar{y} = C\bar{x} \tag{9}$$

$\bar{x}$ is estimated state vector.
$\bar{u}_f$ is estimated additive fault.
$\bar{y}$ is the estimated output.
$\bar{u}_f$ is to be approximated by a multilayer feedforward neural network.

4.2 Error estimation of state and actuator fault

The state estimation error and actuator fault estimation error are given by

The actuator faults are estimated by the neural network

$$u_f = w^T\sigma(x, u) \tag{10}$$

4.3 Weights updation of the neural networks

The weights of the neural network are to be adjusted so that the state estimation error and actuator fault estimation error are converges to zero. The weights are adjusted using error back propagation learning algorithm. The weights are adjusted according to the following equation

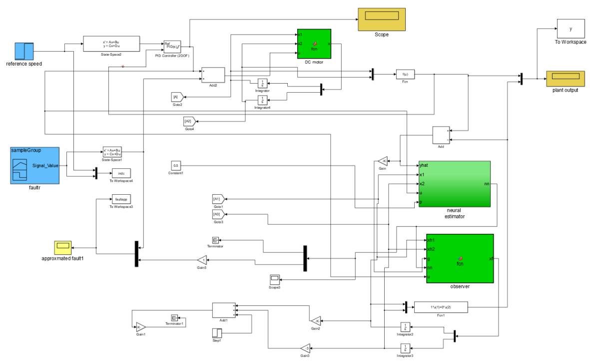

Figure 4: Developed model of the proposed approach

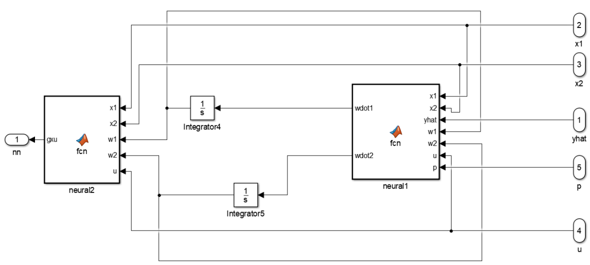

Figure 5: Neural network model

$$\delta w_{ij} = -n \frac{\partial E}{\partial w_{ij}} \tag{11}$$

$$E = \frac{1}{2} \tag{12}$$

4.4 Selection of observer gain

Observer gain is chosen such that matrix A-LC is having eigen values with negative real parts. The plant is controlled using PID controller.The DC Motor is controlled by PID control in the closed loop.

The developed block diagram in simulink is shown in Fig. 04. Three major sub-systems namely DC motor, neural network and are represented with green in colour.

Sub-block of Neural network model is given in Fig. 05. State diagram is shown in Fig. 06.

5 Case study

The proposed algorithm is developed in MATLAB/SIMULNK and executed on a personal computer. The model is validated with various fault conditions. Model of the DC motor is as follows. The state variables are armature current(I_a)and speed (ω). Parameters of the DC motor are adopted from [22] and provided in Table 01.

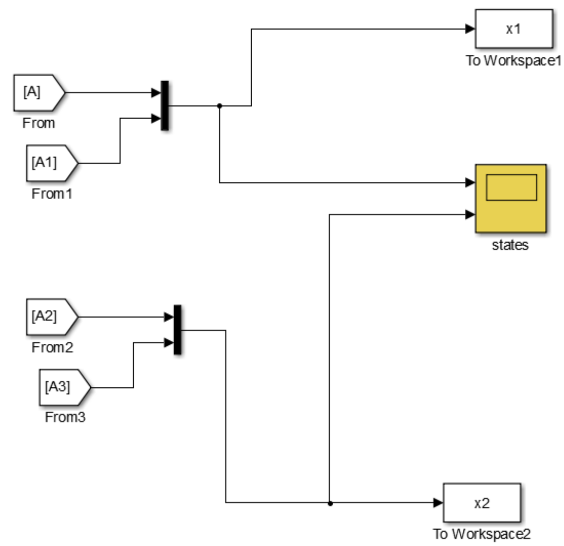

Figure 6: states diagram

Table 1: Parameters of the DC Motor

S.no	variable	Value
1	Resistance (ohm)	8.9
2	Inductance (mH)	99.4
3	B (Nm-sec/rad)	0.003
4	$J(Kg-m^2)$	0.002
5	Constant (K) in volts	1.41
6	Rated voltage in volts	230
7	Rated speed in rpm	1500

With these parameters, the model of DC motor is given in the matrices. A=$(-)\ 1.5705$

$- 14.1851 - 89.5372$
B=$(0)\ 10.0604$

C=(0)

1
L=$(1)\ 5$

Proportional-integral-derivative (PID) controller has been used here to get expected output from the system. It is tuned using MATLAB. The tuned parameters are $K_p = 4.02, K_i = 40, K_d = 0.1$

To validate the model, three cases have been considered.

1. Case 01 Abrupt fault

2. Case 02 Incipient fault

Abrupt Fault specified by

$$f_1(t) = \begin{cases} 0 & 0 \le t \le 50sec \\ 10 & 50 < t \le 100sec \\ 20 & 100 < t \le 150sec \\ 10 & 150 < t \le 200sec \\ 0 & t > 200 \end{cases}$$

Figure 7: Abrupt and Incipient fault

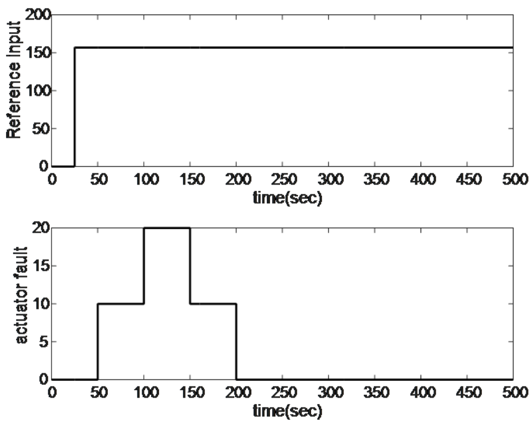

Figure 8: DC motor input with additive abrupt fault and reference input

3. Case 03 Sinusoidal fault

5.1 Case 01 Abrupt Fault

In this case, Abrupt fault is considered. The mathematical expression is given in Fig.7.

Fig.8 specifies the reference input i.e required speed 0f 157 rad per second. It also specifies the actuator fault occuring at the control input i.e the output of the PID controller. The input is applied to the DC motor at 25 seconds and fault occurs at 50 seconds.

Fig.9 depicts the actual fault occurring and the approximation of the fault by neural network for abrupt fault.The curves are in good agreement.

Fig. 10 specifies the actual states and estimated states. It is noticed that the states obtained from the state observer are almost same as the actual states.

The same approach has been extended by changing the type of fault from abrupt fault to incipient fault. The detailed results are given in the preceeding section.

5.2 Incipient fault

In this case, Incipient fault is taken. The mathematical expression is given in Fig.12.

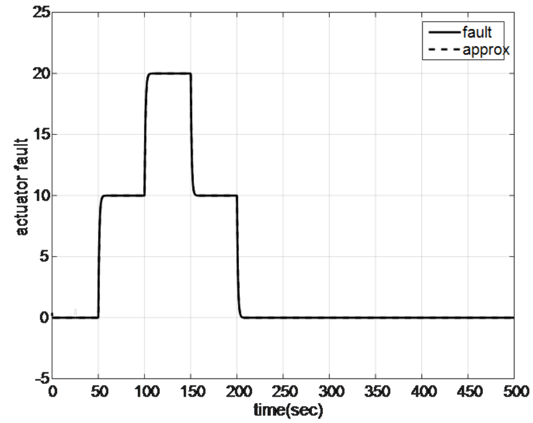

Figure 9: The fault approximation of Neural network.

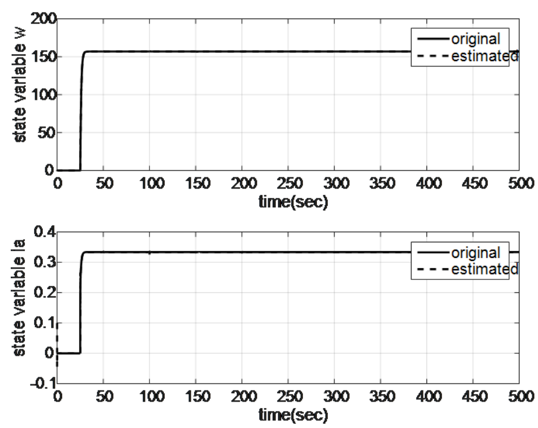

Figure 10: State variables speed and armature current.

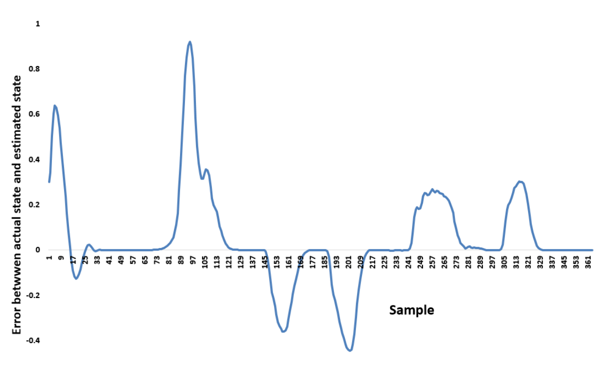

Figure 11: Error between actual and estimated state

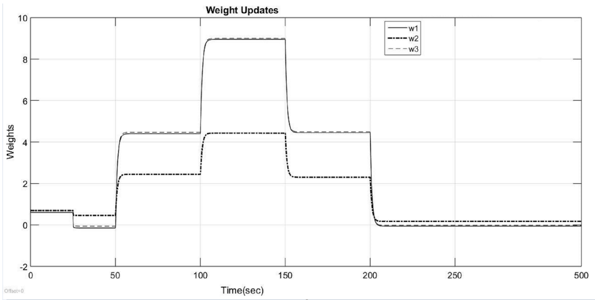

Figure 12: Error between actual and estimated state

$$f_2(t) = \begin{cases} 0 & 0 \leq t \leq 50 \\ 0.667t - 3.333 & 50 < t \leq 200 \\ 10 & 200 < t \end{cases}$$

Figure 13: Incipient fault.

The reference input is provided in Fig. 13. It also specifies the actuator fault occuring at the control input i.e the output of the PID controller. The input is applied to motor at 25 seconds and the fault occurs at 50 seconds.

Fig. 14 depicts the actual fault occurring and the approximation of the fault by neural network for incipient fault.Both the curves are in good agreement.

Fig. 15 specifies the actual states of the motor and estimated states of motors which are armature current ia and w.The observers states are in good agreement with actual states.

5.3 sinusoidal fault

$$f_3(t) = 5 \times sin(\omega t) \tag{13}$$

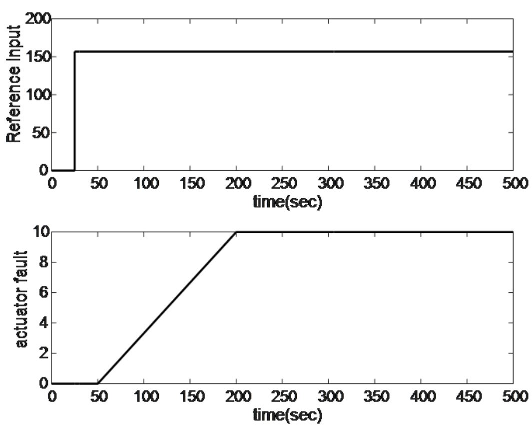

Figure 14: DC motor input with additive incipient fault.

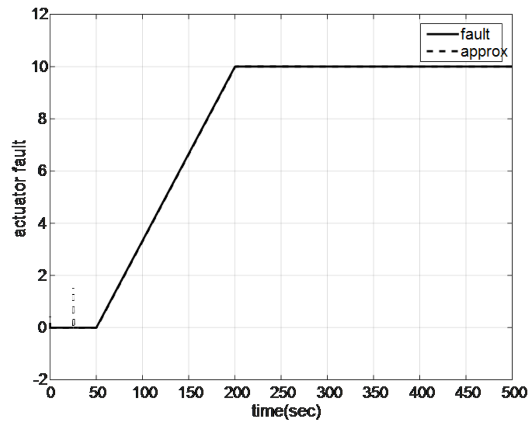

Figure 15: The fault approximation by neural network.

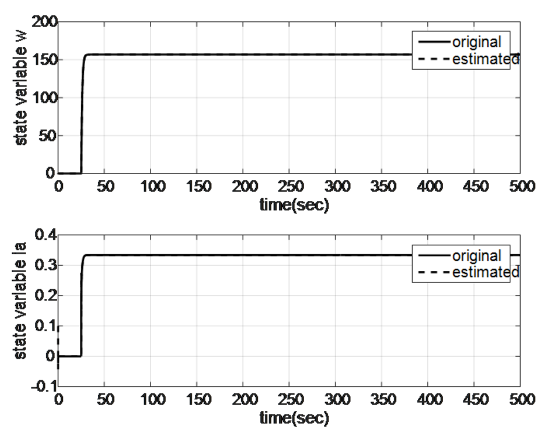

Figure 16: State variables speed and armature current.

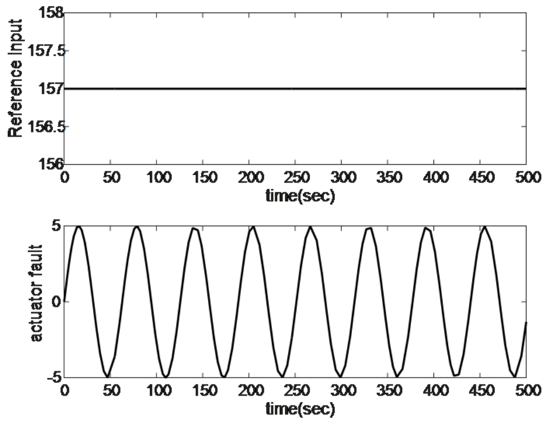

Figure 17: DC motor input with additive sinusoidal fault.

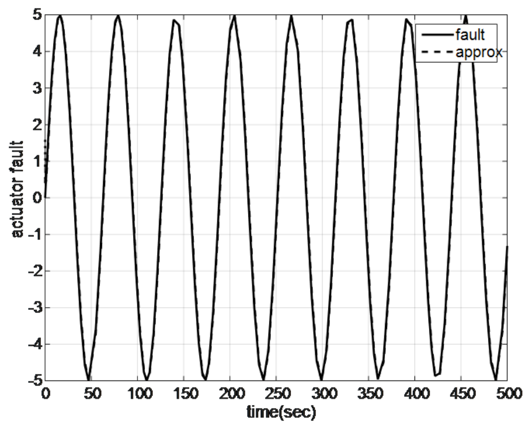

Figure 18: The fault approximation by Neural network.

Fig. 15 specifies the sinusoidal fault applied to the dc motor along with reference speed input. The sinusoidal fault is added with control input i.e the output of PID controller.

Fig. 17 depicts the actual fault occurring and the approximation of the fault by neural network for incipient fault.Both the curves are in good agreement.

Fig. 18 specifies the actual states of the motor and estimated states of motors which are armature current ia and speed w.The observers states are in good agreement with actual states.

6 conclusions

The proposed observer is applied to the DC motor. The DC motor is studied under the effect of abrupt, incipient and sinusoidal actuator faults. Initially system is under no fault situation. Then the state observer is able to estimate the states asymptotically. Faults are applied at 50sec. Under the application of faults, the state observer is able to approximate the faults along with states. The proposed observer is able to approximate unknown terms in the model with the aid of artificial neural networks satisfactorily.

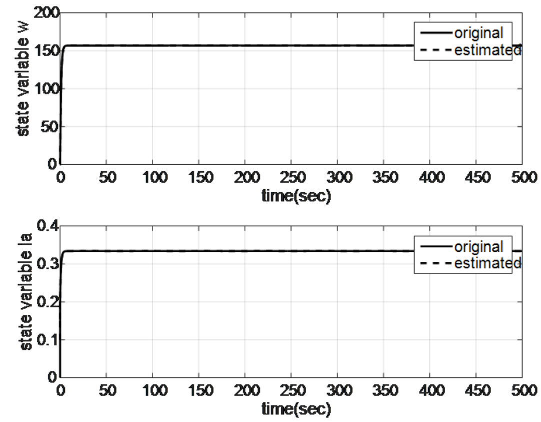

Figure 19: Satate variables speed and armature current.

Acknowledgements: Authors thank GITAM University for providing infrastructure.

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