To Identify a Torque Controller System Approximating a Neural Network Based on Model Reference Technique

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Abstract: In this paper, a system of a torque controller assembly, using a split field winding dc motor, controls the sliding movement of an object, is proposed. This system is identified using the neural network (NN) based model reference technique. At first, a neural network, called plant identification neural network controller (PINNC) is configured by learning the behavior of the torque controller assembly through training the network. The 'process of learning' uses a method of training (trainlm) to train the network. Then the outputs of the proposed system and this PINNC are compared. The knowledge of this comparison is given as feedback to a second neural network controller, called NN-plant or neural network model reference controller (NNMRC). The NNMRC is configured by learning the behavior of a reference model system, provided to it. The 'process of learning' uses a method of training (trainbfgc) to train this network.

The plant identification neural network controller (PINNC) drives the neural network model reference controller (NNMRC) and controls the output of the NNMRC. Ultimately, the neural network model reference controller (NNMRC) or NN-plant identifies the proposed system, the torque controller assembly reliably and successfully.

Keywords: Training a neural network, plant identification, model reference controller

I. INTRODUCTION

The method of neural network (NN) based reference model technique is used now-a-days to identify both linear and non-linear systems. This method is used to analyze the problems related to power systems [7,11], electrical machines[6,9,10,12], control systems [3] and different process plant industries [13].

This paper deals with a system based on the electrical machines. Here, a torque controller assembly [4] is considered to be identified [3,5,8] using a neural network based model reference technique. The torque controller assembly uses a split field windings dc motor. Using mechanical gearing arrangements, the output of the motor is coupled with a sliding platform or bed. The split field windings of the motor controls the torque of the dc motor, thus controls the speed of the dc motor and thus the movement of an object is controlled over a sliding platform. [12,13]The behavior of this complete system is taken under consideration for identification using neural network (NN) based model reference technique, as available with Neural Network Toolbox in MATLAB 7.1. We shall mention the proposed system, the torque controller assembly system, as an 'actual plant' from now.

This neural network based model reference technique requires to realize two different neural network controllers.

A neural network, called plant identification neural network controller (PINNC) is configured first. It learns the dynamics of the actual plant through training this network. The 'process of learning' uses Levenberg-Marquandt (*trainlm*) method of training for training the PINNC.

The outputs of the PINNC and the actual plant are then compared. The knowledge of this comparison is fed back to a second neural network.

The second neural network is provided with a reference model of a plant for its configuration. It generates samples from the reference model for learning the behavior of the reference model through training the network. The 'process of learning' uses quasi-Newton method of training (*trainbfgc*) for training the second neural network.

This second neural network is called neural network plant (NN-Plant) or neural network model reference controller (NNMRC). This receives a feedback from the plant identification neural network controller (PINNC). The plant identification neural network controller (PINNC) drives the neural network model reference controller (NNMRC) and controls the output of NNMRC. Ultimately, the neural network model reference controller (NNMRC) identifies the actual plant, torque controller assembly, successfully.

It is observed that output of our proposed neural network controller (NNMRC) follows the output of the actual plant in very close approximation. The main objectives of the work is as follows:

(i) To realize the plant identification neural network controller (PINNC)

(ii) To realize neutral network plant (NN-plant) or neural network model reference controller (NNMRC),

(iii) The neural network model reference controller (NNMRC) will identifies the actual plant.

In section II, the description of the torque controller assembly, the actual plant is furnished.

In section III, the mathematical model of the actual plant is developed in the state space domain. In section IV, different types of available neural network controllers are described. The section V describes the module of neural network model reference controller (NNMRC). The simulink diagram of the of the proposed scheme has been shown in section VI. In section VII, the design and development of the plant identification neural network controller (PINNC) in the neural network domain is described. In section VIII, the design and development of the NN plant or neural network model reference controller (NNMRC) in the neural network domain is described. In section IX, the simulation diagram of the reference model has been shown. The review of the result has been done in section X. The conclusion takes the section XI. The section XII shows the references.

II. THE DESCRIPTION OF THE TORQUE CONTROLLER ASSEMBLY

The torque controller assembly [4] is equipped with a split field winding dc motor. A gearing arrangement is also added to it to transfer the rotational motion into a sliding or linear motion. A small external body can slide linearly over a platform attached to the motor and gear box. The movement of the small external body can be varied or adjusted for a particular position, varying the torque of the motor. The split field winding is used to change the torque of the motor and thus the speed of the motor can be adjusted. [9,10]

A closed loop control system is considered for controlling the performance of the torque controller assembly system. The displacement or output of the torque controller is compared with a reference input using an error detector. The error thus measured is amplified to a appropriate signal level and again feed to the torque controller to produce the required controlling torque. The output of the motor is coupled to the load through gearing arrangement.

The error detector has a gain (K_e) of value 10 volts/ radian error. The amplifier transconductance (K_a) is considered to be 100 mA /volt. The torque constant (K_T) assumed for the motor is $5x10^{-4}$ Nm/ mA. The coefficient of viscous friction (f) at the motor shaft is of value $5x10^{-4}$ Nm/(rad/sec). The motor is provided to be coupled to the load with a gearing arrangement of ratio (N1/N2)= 20:1. The moment of inertia of the motor (J) is $1.25x10^{-5}$ Kg-m².

The block diagram of the torque controller assembly is shown below:



Fig. 1: Block diagram of the torque controller assembly, the actual plant

III. THE MATHEMATICAL MODEL OF THE ACTUAL PLANT

The mathematical model of the problem, as shown in Fig. 1, has been developed in state-space domain. The state space representation of same has been shown below. [4]

$$\begin{bmatrix} \dot{\mathbf{x}}_1 \\ \dot{\mathbf{x}}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -100 & -10 \end{bmatrix} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \mathbf{u}$$
(1)

$$\mathbf{y} = \begin{bmatrix} 100 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} \tag{2}$$

where, x_1 and x_2 are state vectors. The output of the system is designated by y. here, u is considered to be a scalar and used as a control input. The response of the actual plant (ref. Fig. 1) is shown in Fig. 2.



Fig. 2: Behavior of the actual plant. (ref. eqn. 1 & 2)

IV. DIFFERENT TYPES OF NEURAL NETWORK CONTROLLERS

Neural Network Toolbox in *MATLAB 7.2* offers three methods for identification of different linear and nonlinear system. The methods are as follows: (i) Narma-L2 Controller, (ii) NN Model Reference Controller (ref. Fig. 3), (iii) NN predictive or predictive neural network controller. In this paper, we take the opportunity to utilize of NN Model Reference Controller.

V. THE MODULE OF NN MODEL REFERENCE CONTROLLER (NNMRC).

The module or block diagram of the neural network model reference controller (NNMRC), as available in *Neural Network Toolbox* in *MATLAB 7.1*, is shown in Fig. 3.



Fig. 3: The module of neural network model reference controller (NNMRC)

The Fig. 4, shows the detailed view of the module as shown in Fig. 3. This can also be defined as the 'view under the mask'.



Fig. 4: View under the mask of Fig. 3,

VI. THE SIMULINK DIAGRAM OF THE PROPOSED SCHEME

In Fig. 5, the simulink diagram for the proposed scheme has been furnished. The greenish block is the neural network model reference controller. The actual plant, the torque controller assembly, has been developed in state space domain. This is shown as system/plant and is connected with the model reference controller in one end. The other end of the system/plant is connected to a plotter 'X(2Y)'. The plant has been developed in state space domain based on *MATLAB simulink*.



Fig. 5: Simulink diagram of the proposed system based on *MATLAB*, to get the behaviors of the actual plant and NNMRC

The result of analysis may be observed via the plotter, 'X(2Y)'. The block, called uniform random number is used as the input to the model reference controller. The parameters of this block can be altered for finer adjustment of the response of the plotter. A clock has been to set to decide the time of operation.

VII. DESIGN OF PLANT IDENTIFICATION NEURAL NETWORK CONTROLLER (PINNC)

With the help of *Neural Network Toolbox* based on *MATLAB* 7.1, plant identification neural network controller (PINNC) is configured.

The realization of this neural network learns the behavior of the actual plant. Ten thousand number of samples are used to generate input and output data. The 'process of learning', for understanding the behavior of the PINNC uses Levenberg-Marquandt method (*trainlm*) [1] for training this network. The method of training (*trainlm*) considers 300 epochs. Thus the PINNC is finally realized.

Now, the output of PINNC and output of actual plant is compared. The knowledge of comparison is fed to another NN controller which is configured just after the configuration of PINNC. This second neural network is called neural network reference model controller (NNRMC). This is configured based on a reference model plant, provided to it. This has been illustrated in section-VIII. In Fig. 6, the input data considered for configuring the PINNC are shown.



Fig. 6: Procedure of learning through training (*trainlm*) the plant identification neural network controller (PINNC)

When realization of this neural network (PINNC) undergoes 'learning process' through training (*trainlm*) method, some reports are produced. These are graphical datasheets of training data, validation data and testing data. These data are available and thus required for realization of neural network model reference controller (NNMRC).

Fig.7 reports for the training data obtained through training (*trainlm*) [1] of PINNC and this are available for configuration of the NNMRC.



Fig. 7 : Training data produced during process of learning through training (*trainlm*) of PINNC, available for realization of NNMRC

Fig. 8, shows validation data and Fig. 9, shows the testing data obtained during the process of 'learning'



Fig. 8: Validation data produced during process of learning through training (*trainlm*) of PINNC, available for realization of NNMRC

through 'training (*trainlm*)' of PINNC as before and these are the ready reference required for the configuration of the NNMRC.



Fig. 9: Testing data produced during process of learning through training (*trainlm*) of PINNC, available for realization of NNMRC

The Fig. 10 shows the report which is produced during the training (*trainlm*) of the PINNC.



Fig. 10: Report of training (*trainlm*) the plant identification neural network controller (PINNC)

The process of measurement of the performance index consider the *medium square error* (*MSE*) index. It is seen in the report (shown in Fig. 10) produced during the realization of PINNC that after running the seventh iteration a feasible point of operation has been obtained which corresponds to a value of performance index equal to 1.5×10^{-14} , where, the best result should be a zero value. After 300 number of epoch the performance index attains a value of 0.00. [1]





Fig. 11 shows the comparison of performance characteristics of training, testing and validation related to realization of the PINNC.

VIII. DESIGN OF THE NN PLANT OR NEURAL NETWORK MODEL REFERENCE CONTROLLER (NNMRC)

The realization of the second neural network generates 6000 samples from a model reference plant (ref. Fig.15) developed using simulink based on *MATLAB 7.1*. It undergoes through the 'process of learning' to understand the behavior of this reference model plant. The 'process of learning' uses one of the quasi-Newton types of training (*trainbfgc*) method [1,2] to train the second neural network. Thus the second neural network is configured.

			-
Model Reference Control			
window mep			
Mode	l Refe	rence Co	ontrol
	Network	Architecture	
Size of Hidden Lever	14	No. Delayed Reference inputs 2	
Samping Interval (sec)	0.05	No. Delayed Controller Outputs	
🗖 Normalize Training Data		No.	Delayed Plant Outputs 2
	Train	ing Data 🔹	
Meximum Reference Value	0.7	Controller Training Samples 6000	
Minimum Reference Value 🖡	-0.7		
– Hesiman Pleyal Value (sec) 🖡	2		Reference Model: Brown
– Milman Etheval Value (sec) 🖡	0.1	prmR104	
Erase Generated Data	hpc	rt Deta	Export Data
	Training	Parameters -	
Controller Training Epochs	10	Contro	aller Training Segments 30
Use Current Weights			Use Cumulative Training

Fig. 12: Procedure of learning through training (*trainbfgc*) the Neural Network Model Reference controller (NNMRC)

This network is called NN-plant also. Sometimes it is called the neural network model reference controller (NNMRC).

The Fig. 12 shows the procedure of learning through training (*trainbfgc*) of the NNMRC. The training method (*trainbfgc*) uses ten number of epochs considering 30 numbers of controller training segments.



Fig. 13: Input of model reference plant and comparison of reference model output (blue) and NNMRC output (green)

Fig. 13 shows the samples generated from the reference model plant. The second neural network (NNMRC) produces an output (green). This is compared with reference model output (blue). All of these have been shown in the Fig.13.



Fig. 14: Performance characteristics available during the process of training (*trainbfgc*) of NNMRC

Fig. 14 shows the performance characteristics obtained via process of learning through training (*trainbfgc*) of NNMRC. The performance index is seen to be 0.0117212 obtained after 10 epochs with a zero goal. The characteristics for training, testing and validation coincides to each other.

This NN-plant or neural network model reference controller (NNMRC) identifies the actual plant, [3,5], i.e., the torque controller assembly.

The NNMRC receives a feedback from PINNC continuously. The plant identification neural network controller (PINNC) drives the NNMRC and controls the output of the NNMRC.

IX. THE SIMULATION DIAGRAM OF THE REFERENCE MODEL

A model plant is required for configuration of the neural network model reference controller (NNMRC) as a reference. The process of realization of this neural network generates samples. It learns the behavior of this reference model through training (*trainbfgc*). The 'process of learning' uses a quasi-Newton types of training method '*trainbfgc*' for training of the NNMRC. [1,2]



Fig. 15: Simulink diagram for reference model used for realization of NNMRC

The reference model, used for the realization of NNMRC, is shown in Fig. 15

X. THE REVIEW OF THE RESULT

The first neural network is configured by 'process of learning' of the actual plant through training (*trainlm*) [1,2]

of the same. Thus the PINNC is realized. The second neural network is realized by 'process of learning' the reference model. The 'process of learning' uses quasi-Newton type of training (*trainbfgc*) [1,2] method. Thus the NNMRC is realized. The NNMRC, the second neural network identifies the actual plant. But the performance of NNMRC is always governed by a continuous feedback coming from the PINNC. This feedback includes the information regarding comparison of actual plant output and PINNC output.



Fig. 16: Comparison of outputs of NNMRC (green) and the actual plant (blue)

After configuration of these PINNC and NNMRC, the simulink diagram of the proposed scheme as shown in Fig.5, is allowed to run. It is observed that the NNMRC identifies the actual plant successfully. The result of identification may be observed on the 'X(2Y) plotter as shown in Fig. 16. The characteristic appears in blue color is the output of actual plant (ref. fig. 2). The characteristic appears in green color is the output of neural network model reference controller (NNMRC). Thus the NNMRC identifies the actual plant, the behavior of torque controller assembly. Along the x-axis, a time span of 2 seconds has been considered for better observation of the characteristics. The output of NNMRC follow the non-linear plant [ref. eqns. 1&2] with very close approximation.

XI. CONCLUSION

The 'process of learning' of the PINNC through training (*trainlm*) of the network, produces the reports of three graphical datasheets for training data, validation data and testing data. These are shown in Figs 7, 8 and 9 respectively. A report of performance is also produced along with them as shown in Fig. 10. The performance index is observed to be 0.00 (ref. Fig. 10) after 300 iterations. The performance characteristics obtained via 'process of learning' of the PINNC through training (*trainlm*) of the network are also shown in Fig. 11. These data are available and thus required for realization of the second neural network, i.e., NNMRC.

Fig. 13 shows the report showing graphical datasheet obtained via the 'process of learning' through training (*trainbfgc*) of NNMRC. The performance characteristics obtained via process of training (*trainbfgc*) of the neural network NNMRC are also shown in Fig. 14. The

performance index is seen to be 0.0117212 with Goal equal to zero (ref. Fig. 14).

After completion of realization of the two neural networks, i.e., the PINNC and NNMRC the simulink diagram of Fig. 5 is run and the result has been shown in Fig. 16. This shows the comparison of output responses of NNMRC (green) and actual plant (blue) [ref. Fig. 2].

The output response of NNMRC goes in close approximation with the response of the actual plant, the torque controller assembly.

The plant identification neural network controller (PINNC) will feedback the NNMRC continuously and monitors the output of NNMRC. Ultimately, the neural network model reference controller, NNMRC will identifies the actual plant.

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