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Adaptive Control using Nonlinear Autoregressive-Moving Average-L2 Model for Realizing Neural Controller for Unknown Finite Dimensional Nonlinear Discrete Time Dynamical Systems

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Abstract: This study considers the problem of using approximate way for realizing the neural supervisor for nonlinear multivariable systems. The Nonlinear Autoregressive-Moving Average (NARMA) model is an exact transformation of the input-output behavior of finite-dimensional nonlinear discrete time dynamical organization in a hoodlum of the equilibrium state. However, it is not convenient for intention of adaptive control using neural networks due to its nonlinear dependence on the control input. Hence, quite often, approximate technique are used for realizing the neural supervisor to overcome computational complexity. In this study, we introduce two classes of ideal which are approximations to the NARMA model and which are linear in the control input, namely NARMA-L1 and NARMA-L2. The latter fact substantially simplifies both the theoretical breakdown as well as the practical request of the controller. Extensive imitation studies have shown that the neural controller designed using the proposed approximate models perform very well and in dozens situation even better than an approximate controller designed using the exact NARMA Model. In view of their mathematical tractability as well as their fate in simulation studies, a matter is made in this study that such approximate input-output paragon warrants a detailed study in their own right.

INTRODUCTION

The neural network shape tins be used in control strategies that require a global configuration of the schemes forward or inverse dynamics and these ideal are available in the paradigm of neural networks which have been trained using neural based system identification techniques. Papers by Ramezani and Motlagh[1] and Nguyen *et al*.[2] are some of those that can be referred to as the submissiveness of neural networks for system identification. The generalized education method attempts to produce the inverse of a fortification over the entire state space using off-line workout while in the specialized layout the workout is on-line and uses erroneousness back dissemination through the workshop to learn the plant inverse dynamics over a small operating region. By

Suman and Bhatt[3] their paper is concerned with the design of a loanblend supervisor structure consisting of the adaptive mastery regulation and neural network based education scheme for versions of time changing controller parameters. The global firmness of the closed-loop critique design is guaranteed provided the arrangement of the robot-manipulator movement model is exact. Generalization of the controller over the desired path hiatus has been established using an on-line compression learning scheme. The probability of a neuron-adaptive loanblend control scheme is the high precision and better precision and computationally less intensive control scheme. Also for Self-Tuning Control (STC)[4], used back-propagation trained neural network within a self-tuning sovereignty intrigue to sovereignty Single-Input Single-Output (SISO) response linearizable system. Another approach is given by Sharma[5] where a neural network is used to wind the parameters of a conventional supervisor in an on-line way.

The remarkable learning resources of neural networks is leading to their application in spotting and adaptive control of dynamical systems. A neural network is basically composed of many neurons and interconnections with a particular architecture. Neural networks with relatively complex architectures tend to be more powerful in learning functional mapping but are more difficult to train. The reality that a Multilayer Forward Network (MFN) is widely used is due to the chasing two reasons: it can easily be trained by the generalized delta rule; it able to learn any role with arbitrary desired precision[6-9].

Even though the NARMA patterns consequences in better discovery of the unknown plant, the NARMA-L1 and NARMA-L2 replica may actually backwash in better control. In this paper the identification and control of unknown non-linear dynamic system using NARMA-L2 model is investigated[10].

MATERIALS AND METHODS

Adaptive control using NARAM-L2 model: Here, the aim is controlling an unknown nonlinear system which is based on its input and output data, so that, the system follows desired signal (k). Now, given the object of matching (k) with (k), if we substitute the (k) with (k) in the above approximation equations and solve the resulting equation in terms of u(k), the actual capability of the actuality system can be matched to its optimal value, so the control objective is obtained:

$$y(k+d) = \bar{f}_0\left[y(k), y(k-1), \ldots, y(k-n+1)\right] + \bar{g}_0\begin{bmatrix} y(k), y(k-1), \ldots, y(k-n+1), \\ u(k-1), \ldots, u(k-n+1) \end{bmatrix} u(k) \quad (1)$$

If:

$$y(k+d) = y_r(k+d) \quad (2)$$

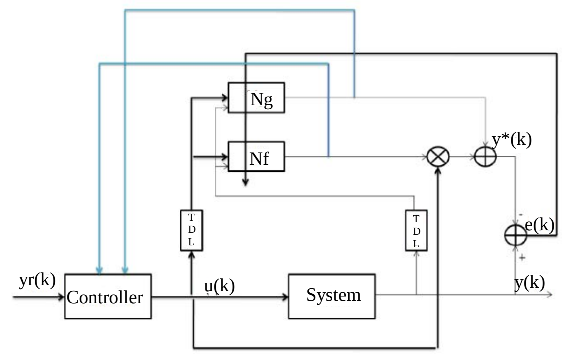

Fig. 1: Block diagram of adaptive control system for NARMA-L2 model

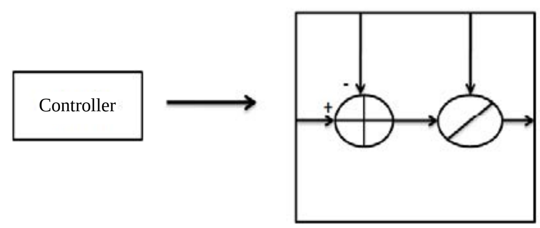

Fig. 2: Algebraic controller

Then:

$$u(k) = \frac{\left[y_r(k+d) - \bar{f}_0\begin{pmatrix} y(k), \ldots, y(k-n+1), \\ u(k-1), \ldots, u(k-n+1) \end{pmatrix}\right]}{\bar{g}_0\begin{pmatrix} y(k), \ldots, y(k-n+1), u(k-1), \ldots, \\ u(k-n+1) \end{pmatrix}} \quad (3)$$

As you can see from Fig. 1 and 2, the supervisor is classic and only performs simple algebra actions based on the neural network signals and does not require a separate neural network for mastery action.

RESULTS AND DISCUSSION

In this section, algorithm design for identification and adaptive control based on NARMA-L2 shape testament be described. MATLAB imitation along with different model of nonlinear method are also provided[11].

Algorithm design for identification: The following steps are considered for identification process:

- Choose the initial stipulation for wi,j and bi, the number of capacity and output sampling, tally of network neurons, activation functions, network learning rates, the quantity of epochs or cycles
- For each input, the exponent of the network is obtained by the sum of cycles

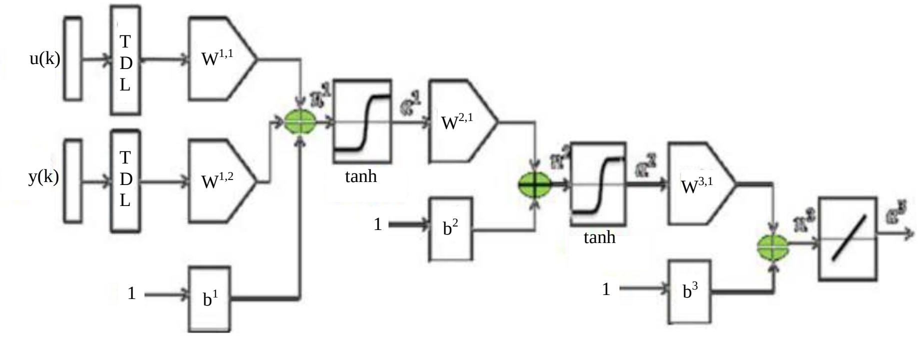

Fig. 3: Neural network with the structure of 3/2, 20,10,1

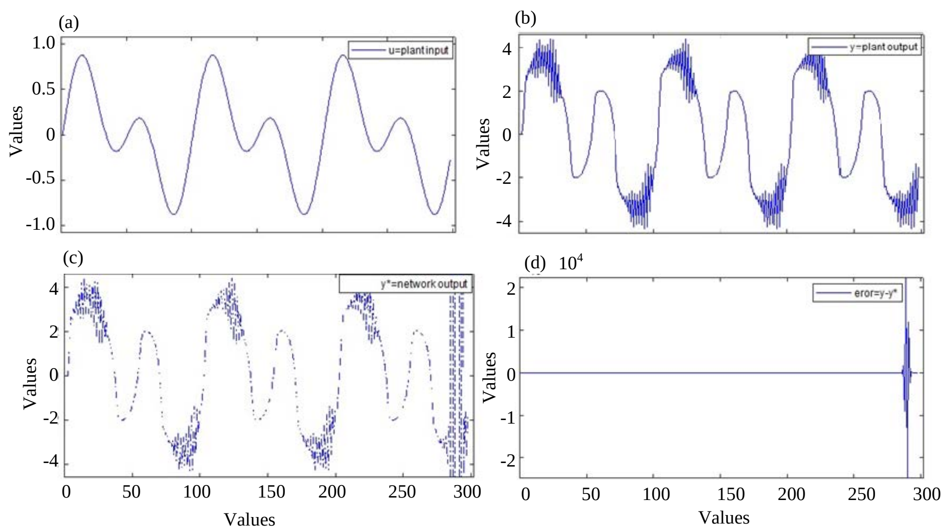

Fig. 4: (a) Plant input (b), Plant output, (c) Network output and (d) Error

- In each cycle, the discovery inaccuracies (y-y*) is obtained which is equal to the output of the system minus the ability of the network)
- Setting network parameters with respect to the spotting error

The neural network used for spotting incentive is shown in Fig. 3. This neural network uses the tanh activation capacity for the first and second layers and the linear activation function for the third layer.

MATLAB simulation: In this sub-section, MATLAB simulation for the identification process is described. The mathematics of neurons in the first rank of the neural network, the second layer, the tally of sampling from the system strength and the tally of sampling from the outline output are assigned as follows:

- S1 = 20; % number of neuron 1%
- S2 = 10; % number of neuron 2%
- dy = 2; % number of delay plant output%
- du = 3; % number of delay plant input%

Identification examples: Two examples have been considered here to show the identification process using NARMA-L2 model.

Example 1: Identification of a first-degree plant that is characterized by the following equation:

$$y(K+1)=\sin\left[y(K)\right]+u(K)*\left(7.5+\cos\left[\left(y(K)*u(K)\right)\right]\right) \quad (4)$$

The experimental results are obtained for different inputs, different training rates and different epochs. Figure 4a shows the first input using the following formula:

$$u=0.75*\left(\sin\left(\frac{2\pi K}{60}\right)+\sin\left(\frac{2\pi K}{120}\right)\right) \quad (5)$$

The output of system based on Eq. 4 and 5 is shown in Fig. 4b with the network output and error output shown in Fig. 4c and d, respectively[12].

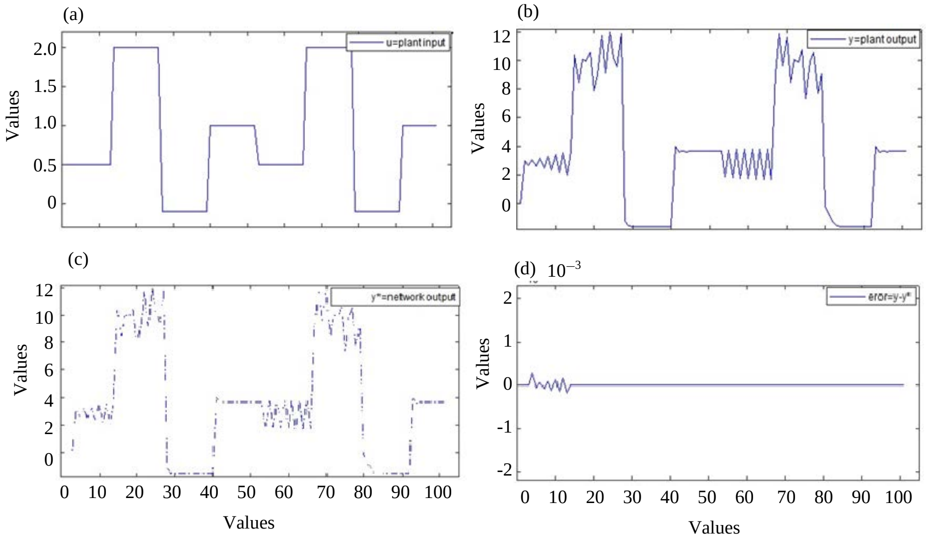

Fig. 5: (a) Plant input, (b) Plant output, (c) Network output and (d) Error

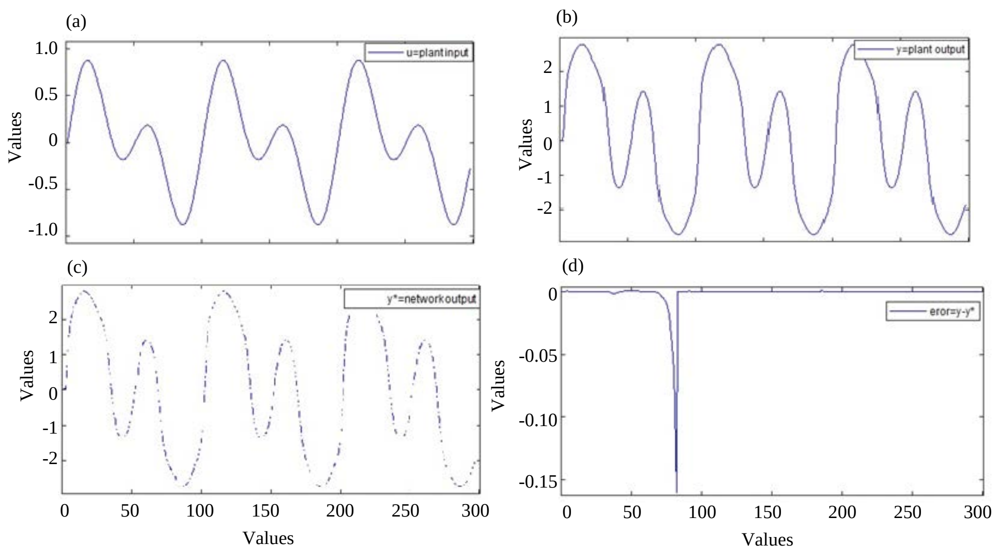

Fig. 6: (a) Plant input, (b) Plant output, (c) Network output and (d) Error

Figure 5a shows the second input for first example using step function. The output of system based on step function as input and Eq. 4 is shown in Fig. 5b. In addition, the identification network output results along with identification errors are shown in Fig. 5c and d. As it can be seen, the identification operation is carried out with high precision.

Example 2: Identification of a second-order plant that is characterized by the following equation:

$$x_1(k+1) = 0.25 * x_1(k) + 2.5\frac{u(k)+x_2(k)}{0.5+(u(k)+x_2(k))^2} \quad (6)$$

$$x_2(k+1) = 0.25 * x_2(k) + u(k)\left(2.5+\frac{u^2(k)}{0.5+x_1^2(k)+x_2^2(k)}\right) \quad (7)$$

$$y(k) = x_1(k) + x_2(k) \quad (8)$$

The plant input is shown in Fig. 6a and the plant output of system based on Eq. 6 and 8 is shown in Fig. 6b. The network output identification results for different epochs and learning rates along with identification errors are shown in Fig. 6c and d. As you can see from the results, for higher learning rates and similar epoch, the network at a higher rate performs better identification.

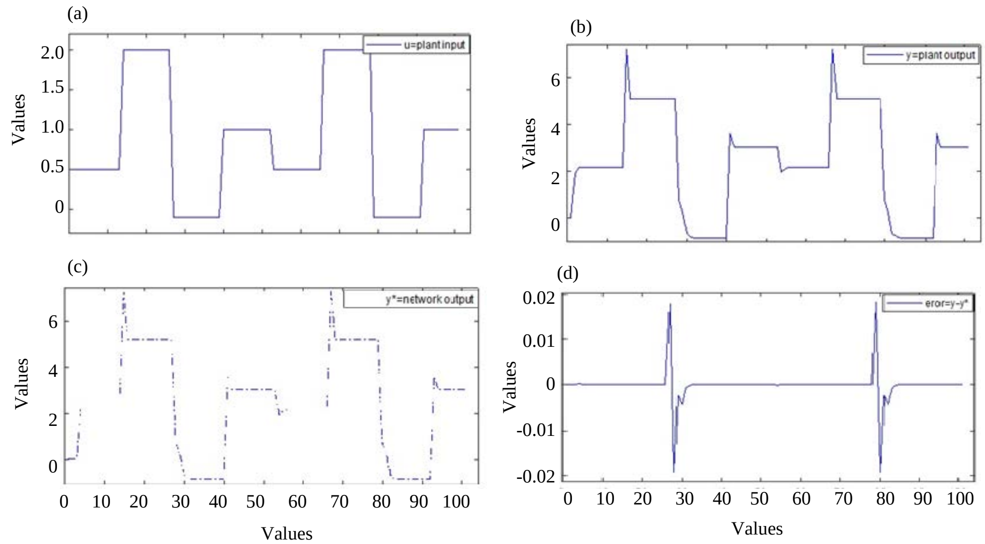

Fig. 7: (a) Plant input, (b) Plant output, (c) Network output and (d) Error

The plant input is shown in Fig. 7a and the plant output of system based on step function as input and Eq. 8 is shown in Fig. 7b. In addition, the network output identification results along with identification errors are shown in Fig. 7c and d. As it can be seen, the identification operation is carried out with high precision.

Algorithm design for adaptive control: The following steps are considered for adaptive control process:

Choose the initial conditions for wi,j and bi, the number of input and output sampling, number of network neurons, activation functions, network learning rates, the number of epochs or cycles. For each reference input, the system input is obtained by the number of cycles:

$$u(k)=\frac{\left[y_r(k+d)-\bar{f}_0\begin{pmatrix}y(k),...,y(k-n+1),\\ u(k-1),...,u(k-n+1)\end{pmatrix}\right]}{\bar{g}_0\begin{pmatrix}y(k),...,y(k-n+1),\\ u(k-1),...,u(k-n+1)\end{pmatrix}} \quad (9)$$

In each cycle, the identification error (y-y*) is obtained which is equal to the output of the system minus the output of the network). Setting network parameters with respect to the identification error.

MATLAB simulation: In this sub-section, MATLAB simulation for the adaptive control process is described. First, the input of the reference is selected and the initial values of the input, the output of the system, are selected as zero. The number of neurons in the first layer of the neural network, the second layer, the number of sampling from the system input and the number of sampling from the system output are assigned as follows:

- S1 = 20; % number of neuron 1%
- S2 = 10; % number of neuron 2%
- dy = 2; % number of delay plant output%
- du = 3; % number of delay plant input%

Adaptive control examples: Two examples have been considered here to show the adaptive control process using NARMA-L2 model.

Example 1: Adaptive control of a first-degree plant that is characterized by the following equation:

$$y(k+1)=\sin\left[y(k)\right]+u(k)*\left(2.5+\cos\left[y(k)*u(k)\right]\right) \quad (10)$$

The experimental results are obtained for plant reference, plant input, plant output and error is shown in Fig. 8a-d, respectively.

Figure 9a-c shows the second reference, the plant input and the plant output for first example using sinusoids functions respectively. In addition, the adaptive control system's errors are shown in Fig. 9d. As it can be seen, the adaptive control operation is carried out with high precision.

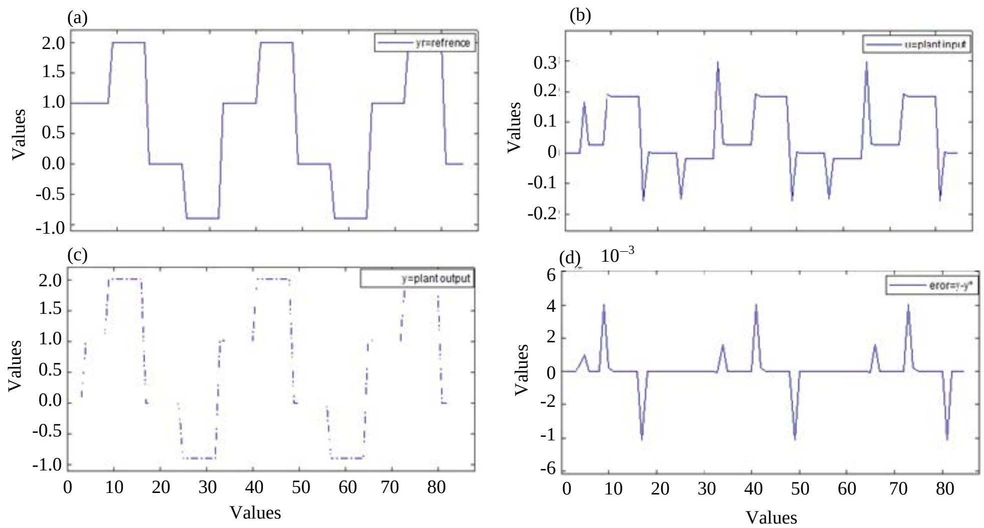

Fig. 8: (a) Reference, (b) Plant input, (c) Plant output and (d) Error

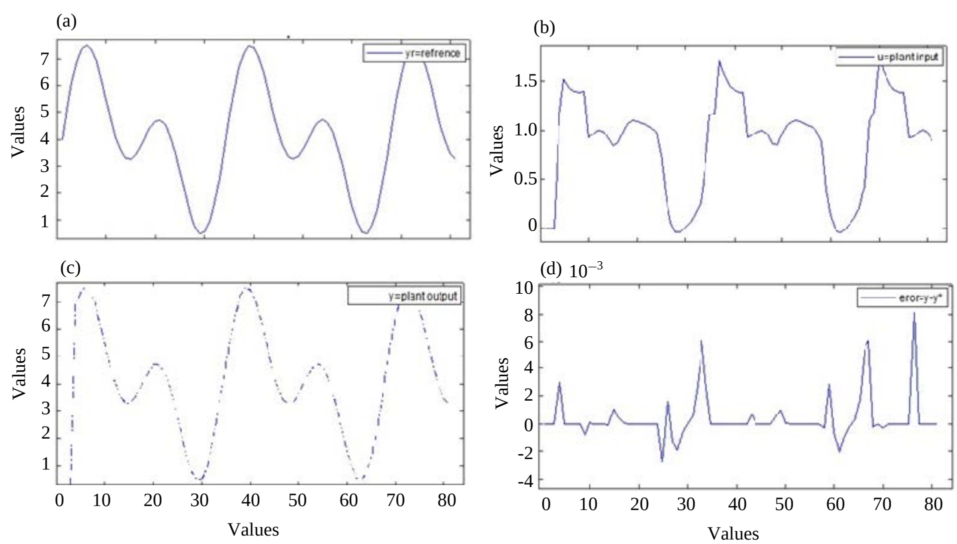

Fig. 9: (a) Reference, (b) Plant input, (c) Plant output and (d) Error

Example 2: Adaptive control of a second-order plant that is characterized by the following equation:

$$x_1(k+1)=0.1*x_1(k)+2\frac{u(k)+x_2(k)}{1+\left(u(k)+x_2(k)\right)^2} \quad (11)$$

$$x_2(k+1)=0.1*x_2(k)+u(k)\left(2+\frac{u^2(k)}{1+x_1^2(k)+x_2^2(k)}\right) \quad (12)$$

$$y(k)=x_1(k)+x_2(k) \quad (13)$$

The experimental results are obtained for plant reference, plant input, plant output and error is shown in Fig. 10a-d, respectively. As it can be seen from the results, the system with higher epoch's results in better tracking of desired output and adaptive control of non-linear system.

Figure 11a-c shows the second reference, the plant input and the plant output for first example using sinusoids functions, respectively. In addition, the adaptive control system's errors are shown in Fig. 10d. As it can be seen, the adaptive control operation is carried out with high precision.

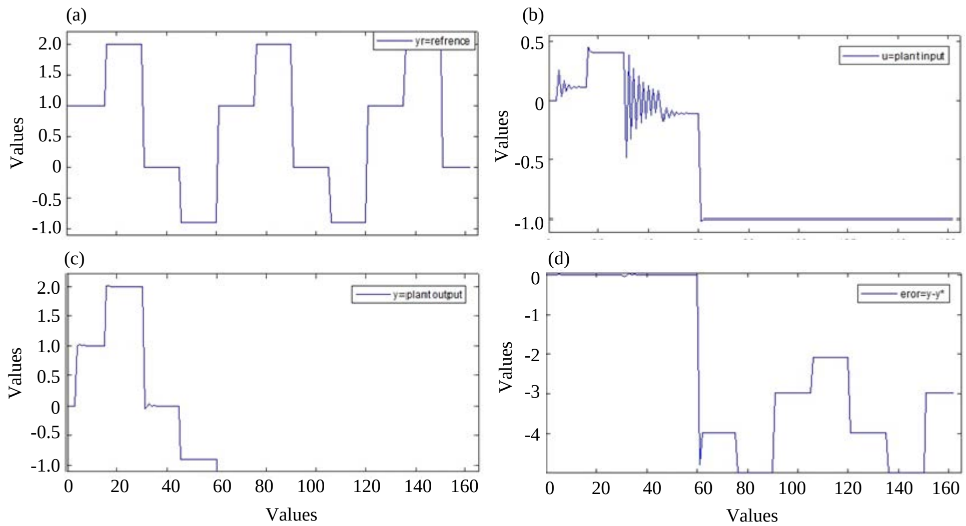

Fig. 10: (a) Reference, (b) Plant input, (c) Plant output and (d) Error

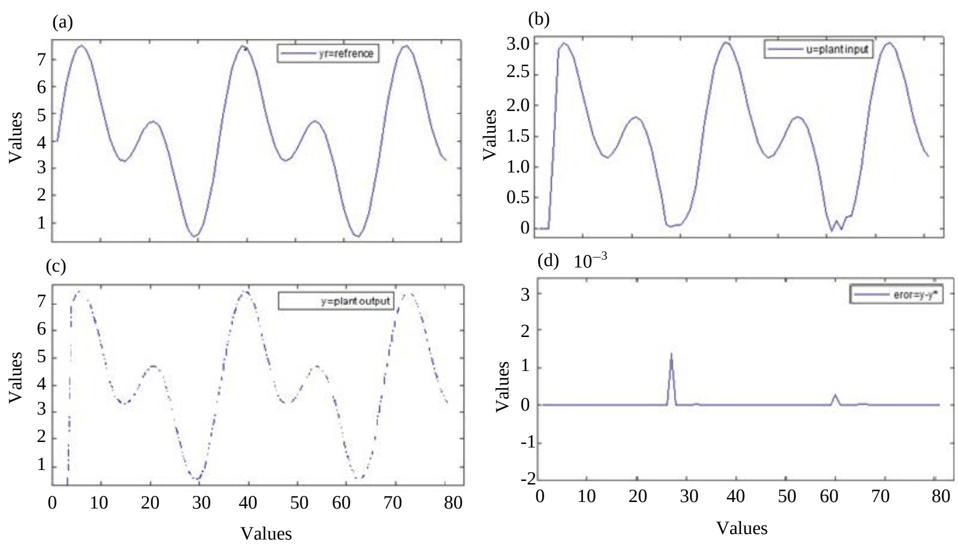

Fig. 11: (a) Reference, (b) Plant input, (c) Plant output and (d) Error

CONCLUSION

From the above discussion, we conclude that by approximating the exact configuration of NARMA for each nonlinear system, we tin sweeps to the approximate pattern of NARMA-L1, NARMA-L2. This approximate exemplar with respect to the actual configuration is not only highly accurate for identification purpose but also make the supervisor a commoner classical controller and no longer obligation a separate neural network for supervisor with its own problems (weight adjustment problems)[13].

Therefore, the adaptive control arrangement has been simplified while the precision is stayed very high and therefore these approximate ideal is usually used in the adaptive dominion of nonlinear systems. Perhaps of greatest extent for the utility of neural networks in the mastery of nonlinear dynamical systems is the reality that the NARMA-L1 and NARMA-L2 replica are more tractable analytically than the NARMA model. If the stability, controllability and observability as well as the null activity of dynamical procedure tins be studied for the castes of organization represented by these approximate models, the consequence can be extended to NARMA ideal using robustness arguments. It is believed that this approach may provide a crankshaft for grappling the stable adaptive dominion problem of nonlinear plants.

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