ISSN: 2766-9823 Volume 1, 2019

Model Reference Adaptive Control based-on Neural Networks for Nonlinear time-varying System

Ayachi ERRACHDI
LARA Automatique, ENIT BP 37, Le Belvédère, Tunis 1002, Tunisia
errachdi_ayachi@ yahoo.fr

Mohamed BENREJEB
LARA Automatique, ENIT BP 37, Le Belvédère, Tunis 1002, Tunisia
mohamed.benrejeb@ enit.rnu.tn

***Abstract*—This paper presents a Direct Model Reference Adaptive Control (MRAC) for nonlinear time-varying system. A mechanism adaptation algorithm is proposed. This corresponding algorithm depends on the error between the actual plant output and the output of the reference model, and also is depending on variable learning rate. The control strategy is based on two-steps; the first is initialization parameters of the controller using reduced number of observation. In the second phase, the parameters of the controller are directly tuned from the training data via the tracking error. The simulation results show that the proposed algorithm is simple to implement and may be extended to multivariable system.**

Keywords—Nonlinear system; neural network; adaptive control; model reference

I. INTRODUCTION

The control of complex dynamic plant is a major concern in control theory [1]. In a consequence, a large number of control structures such as direct inverse control [2], model reference control [3, 4], sliding mode control [5], internal model control [6], feedback linearization [7], backstepping [8], indirect adaptive control [2, 4, 8-13], and direct adaptive control [5, 14-17] have been proposed.

One of these methods may be based on Neural Network (NN). The NNs are used for modeling and control of complex physical systems because of their ability to handle complex input-output mapping without detailed analytical models of the systems [18, 19]. The NN controllers have emerged as a tool for difficult control problems of unknown nonlinear systems [20]. There are several control strategies for neural networks which some of them are: feedforward control, direct inverse control, indirect adaptive control based on NN identification, direct adaptive control with guarantied stability, feedback linearization and predictive control [20-22].

In the industrial process there are many systems having nonlinear properties [20, 23-31]. For instance, the systems to be controlled have constant, unknown or slowly-time uncertain parameters [23-31]. Unless such parameter uncertainty is gradually reduced on-line by an appropriate adaptation or estimation mechanism, it may cause inaccuracy or instability for the control systems [32]. For this reason, an adaptive control is applied in this paper.

The Model Reference Adaptive Control (MRAC) is a technique well established in the framework of linear systems [33]. In the direct MRAC approach, the parameters of the linear controller are adapted directly to drive the plant output to follow a desired reference model. This structure can be extended by utilizing the nonlinear function approximation capability of feedforward neural networks such as the Multi-Layer Perceptron (MLP). The MRAC have been adopted by many researchers in controlling nonlinear plants [3, 4, 34-37]. It is not only applied with neural networks while it is applied else approaches. The neural networks are widely used methods for the characterization of nonlinear systems [19].

As long as, the MRAC is well used in some plants which are with unknown parameters, partially known or tainted by noise. In this paper, the MRAC is proposed for nonlinear time-varying system. The adaptation mechanism of the proposed method is detailed. The neural network provides the capability to describe highly time-varying nonlinear plants. The control strategy used to define the adaptation law is based on the tracking error between the actual plant output and target output, which is the response of the reference model. Then, tuning of the weights is based on the standard delta rule or steepest descent algorithm to minimize the tracking error.

This paper is organized as follows. In the second section, the presentation of the MRAC method is presented. In the third section, the proposed adaptation mechanism is showed. An Example is provided in the forth section, and conclusions are given in the last section.

II. PRESENTATION OF MRAC METHOD

In figure 1, a multilayer Perceptron is taken in order to concept a nonlinear controller which based on neural network [38]. The adopted general structure of MRAC method is showed here. The nonlinear plant is time-varying system. Figure 1 shows the configuration of the MRAC control system.

The used controller is a multilayer Perceptron (MLP) and it contains three layers: the input layer contains N_1 neurons; the hidden layer contains N_2 neurons and one neuron in the output layer. Each neuron of each layer is connected to all neurons of the following layer.

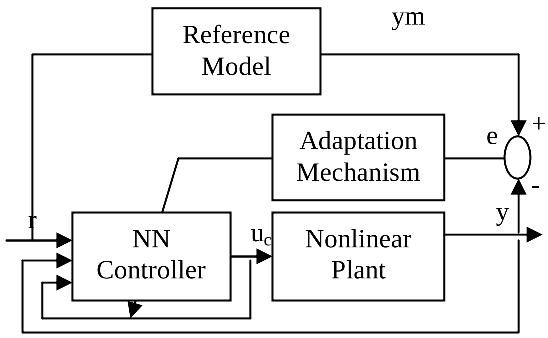

Fig. 1. Model reference adaptive control

The output of the l^{th} node, of the hidden layer, is given by the following equation, ($l = 1,\ldots,N_2$):

$$f(h_l) = f(\sum_{j=1}^{N_1} w_{lj} x_j) \tag{1}$$

with:

$$h_l = \sum_{j=1}^{N_1} w_{lj} x_j$$

The output of the controller is given by the following equation:

$$\begin{aligned} u_c(k) &= \lambda f(\sum_{l=1}^{N_2} f(\sum_{j=1}^{N_1} w_{lj} x_j) z_l) \\ &= \lambda f(\sum_{l=1}^{N_2} f(h_l) z_l) \end{aligned} \tag{2}$$

or in the compact form:

$$u_c(k) = \lambda f\left[z^T F(Wx)\right] \tag{3}$$

The output of the controller $u_c(k)$ is law control which is used as an input signal for the nonlinear plant. The used training is based on the descent gradient method in order to minimize a function cost ($E = \frac{1}{2}\sum_{k=1}^{N}(e(k))^2$) and the tuning of the synaptic weights of the neural controller is based on the standard delta rule defined as:

$$\Delta w_{lj} = -\eta \frac{\partial E}{\partial w_{lj}} \tag{4}$$

$$\Delta z_l = -\eta \frac{\partial E}{\partial z_l} \tag{5}$$

These all equations are used in the adaptive control strategy.

III. The proposed adaptation mechanism

The aim of the controller is to find the suitable control law which is given by the following equation:

$$\begin{aligned} u_c(k) = f\,[&u_c(k-1),\ldots,u_c(k-n_1), r(k), y(k-1), \\ &\ldots, y(k-n_2)] \end{aligned} \tag{6}$$

Although the changing of the parameters model, the control law must be suitable in order to let the plant follow the required trajectory of the model reference, i.e. the convergence of the error between the actual output of plant and the reference model is zero, this condition is given by the following equation.

$$\lim_{k\to\infty} e^{(k+1)} = \lim_{k\to\infty}(ym^{(k+1)} - y^{(k+1)}) \approx 0 \tag{7}$$

At time instant $(k+1)$, is introduced a new data $(u_c^{(k+1)}, y^{(k+1)}, r^{(k+1)})$, if

$$\left\| ym^{(k+1)} - y^{(k+1)} \right\| < \varepsilon \tag{8}$$

If the condition (8) is not satisfied, $\left\| e^{(k+1)} \right\| > \varepsilon$, the tuning of the synaptic weights of the neural controller is necessary in order to reduces the error. The updates of the synaptic weights are given by the equation (9) and (10) [19, 38].

$$w_{lj}^{(k+1)} = w_{lj}^{(k)} + \eta \Delta w_{lj}^{(k+1)} \tag{9}$$

$$z_l^{(k+1)} = z_l^{(k)} + \eta \Delta z_l^{(k+1)} \tag{10}$$

with:

$$\Delta w_{lj} = \eta \lambda f'(h_l) F'(Wx) z_l x^T e(k)$$

$$\Delta z_l = \eta \lambda f'(h_l) F(Wx) e(k)$$

$$\begin{aligned} \eta = 1/(\lambda^2 f'^2(h_l)\Big[&F^T(Wx)F(Wx) + \\ &z_l^T x^T F'(Wx) F'(Wx) z_l x^T x\Big]^T) \end{aligned}$$

It's clear that the proposed algorithm is simple to implement, but it requires an initialization phase. This step is necessary to find the initialization parameters neural controller like the number of neuron in each layer and the synaptic weights w_{lj} and z_l. This step proceeds in off-line training.

IV. Results and Discussion

In this section, a nonlinear time-varying system is used to study the performance of the proposed MRAC.

A. Example of time-varying system

The time-varying nonlinear system is described by the input-output model in the following equation.

$$y(k+1)=\frac{y(k)y(k-1)y(k-2)u(k-1)(y(k-2)-1)+u(k)}{1+a_0(k)y^2(k-1)+a_1(k)y^2(k-2)} \tag{11}$$

with:

$$a_0(k)=1+0.2\cos(k)$$
$$a_1(k)=1-0.2\sin(k) \tag{12}$$

The trajectory of $a_0(k)$ and $a_1(k)$ are given in the following figure.

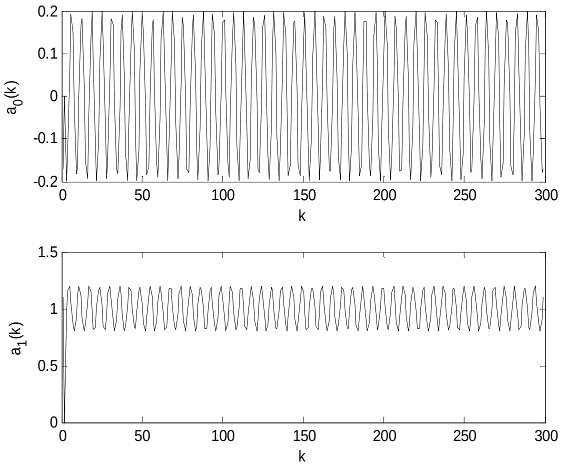

Fig. 2. $a_0(k)$ and $a_1(k)$ trajectories

The multilayer Perceptron network topology with sigmoid activation function was chosen. The variation of error with number of hidden neurons is shown in the following figure.

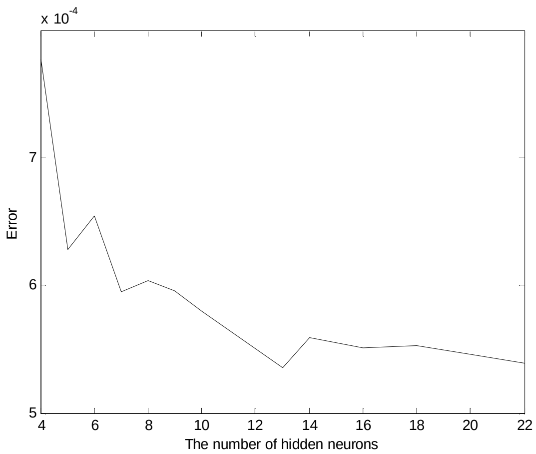

Fig. 3. Variation of error with hidden neurons

The lowest error corresponds to 13 neurons in the hidden layer. Hence it is selected as optimal architecture of RNN. The RNN selected here consists of five neurons in the input layer, 13 neurons in the hidden layer and one neuron in the output layer.

The neural model of the nonlinear time-varying time-delay system is presented in figure 4.

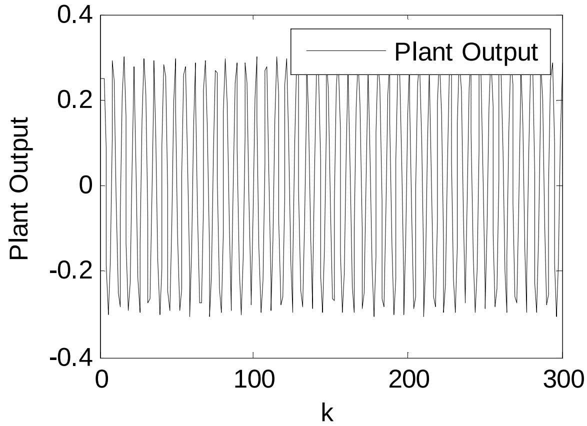

Fig. 4. The time-varying plant output

The model reference is given by the following equation.

$$y_r(k)=(1+\alpha_1+\alpha_2)y_c(k)-\alpha_1 y_r(k-1)$$
$$-\alpha_2 y_r(k-2) \tag{13}$$

with y_c is a setpoint sequence, $\alpha_1=0.0693$ and $\alpha_2=0.0286$.

The output of the reference model and the output of the nonlinear plant are presented in figure 5. The error between the plant output and the model reference output is showed in figure 6. The control law is presented in figure 7.

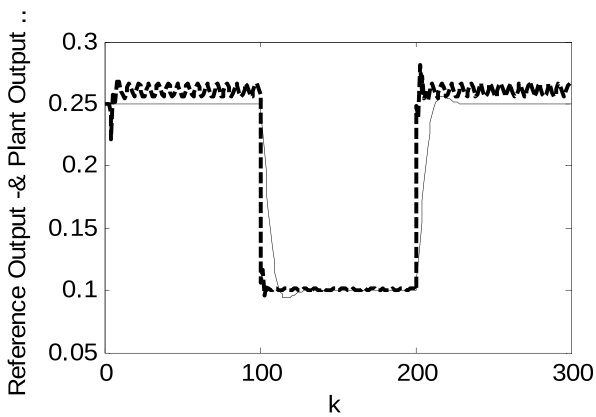

Fig. 5. The plant output and the reference model

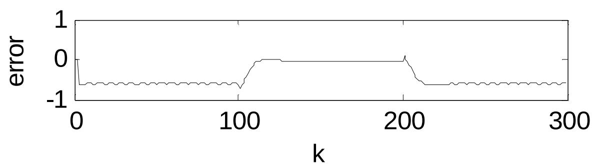

Fig. 6. The error estimation

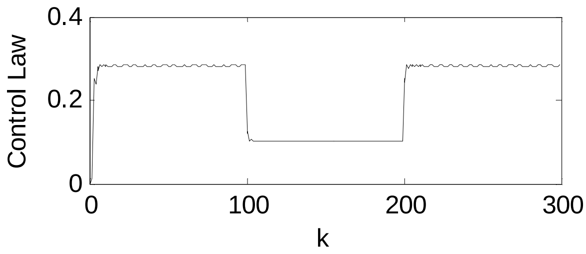

Fig. 7. The control law

B. Effect of disturbances

In this section a noise ξ is added to the output of the plant in order to test the effectiveness of the proposed algorithm.

To measure the correspondence between the system output and the estimated output, a Signal Noise Ratio (SNR) is taken by the following equation:

$$SNR = \frac{\sum_{k=0}^{N} (y(k) - \bar{y})}{\sum_{k=0}^{N} (\xi(k) - \bar{\xi})} \tag{14}$$

with $\xi(k)$ is noise of measurement of symmetric terminal δ, $\xi(k) \in [-\delta, \delta]$, $\bar{y}$ and $\bar{\xi}$ are an output average value and a noise average value respectively. In this paper, the taken SNR is 5%.

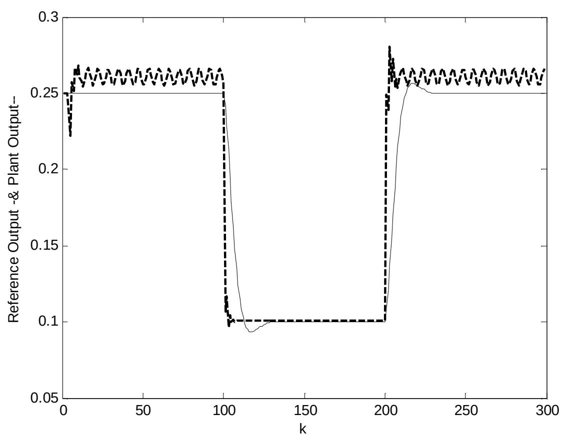

Fig. 8. The plant output and the reference model

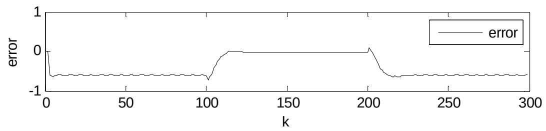

Fig. 9. The error estimation

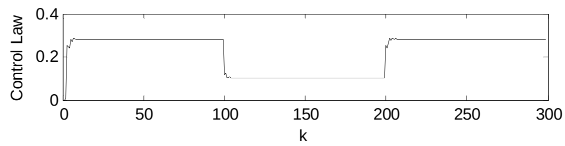

Fig. 10. The control law

The output of the reference model and the output of the nonlinear plant are presented in figure 8. The error between the plant output and the model reference output is showed in figure 9. The control law is presented in figure 10.

The used time-varying nonlinear system, with and without noise, it is clear that the plant output follows the reference model output although the time-varying parameters and the added noise. This simulation result shows the efficiency of the proposed algorithm, and its simplicity to treat complex nonlinearity.

V. CONCLUSION

This paper has presented a direct model reference neural network adaptive controller for time-varying nonlinear system. The proposed mechanism adaptation is based on the convergence of the error between the actual output of plant and the output of the model reference. The tuning of the synaptic weight depends on the variation of the parameter of the plant. The simulation results conforms the effectiveness and

REFERENCES

[1] G. Debbache and A. Bennia, "Neural network-based MRAC control of dynamic nonlinear systems". Int. J. Appl. Math. Compt. Sci., 6(2) : 219-232, 2006.

[2] G.L. Plett, "Adaptive inverse control cf linear and nonlinear systems using dynamic neural control networks". IEEE Trans. Neural Network, 14(2) : 360-376, 2003.

[3] K.S. Narendra and K. Parthasarthy, "Identification and control of dynamical systems using neural networks". IEEE Trans. on Neural Networks, 1(1) : 4-27, 1990.

[4] H.D. Patino and D. Liu, "Neural network-based model reference adaptive control system". IEEE Trans. Syst. Man Cybern., 30(1) : 198-204, 2000.

[5] M. Zhihong, H.R. Wu and M. Palaniswami, "An adaptive tracking controller using neural networks for a class cf nonlinear systems". IEEE Trans. on Neural Networks, 9(5) : 947-955, 1998.

[6] I. Rivals and L. Personnaz, "Nonlinear internal model control using neural using neural networks: application to processes with delay and design issues". IEEE Trans. Syst. Man. Cybern., 35(6) : 1311-1316, 2005.

[7] A. Yesildirek and F.L. Lewis, "Feedback linearization using neural networks". Automatica, 31(11) : 1659-1664, 1995.

[8] Y. Zhang, P.Y. Peng and and Z.P. Jiang, "Stable neural controller using design for unknown nonlinear systems". IEEE Trans. on Neural Networks, 11(6) : 1347-1359, 2000.

[9] Y-C. Chang and H-M. Yen, "Adaptive output feedback tracking control for a class cf uncertain nonlinear system using neural networks". IEEE Trans. on Neural Networks, 1: 4-26, 1990.

[10] J.C. Neidhoefer, C.J. Cox and R.E. Saeks, "Development and application of a Lyapunov synthesis based neural adaptive controller". IEEE Trans. Syst. Man. Cybern., 33(1) : 125-137, 2003.

[11] A.S. Poznyak, W. You, E.E. Sanchez and J.P. Perez, "Nonlinear adaptive trajectory tracking using dynamic neural networks". IEEE Trans. Syst. Man. Cybern., 35(6) : 1311-1316, 2005.

[12] S. Seshagiri and H. Khalil, "Output feedback control cf nonlinear systems using RBF neural networks". IEEE Trans. Neural Network. 11(1) : 69-79, 2005.

[13] S-H. Yu and A.M. Annaswamy, "Adaptive control cf nonlinear dynamic systems using adaptive neural networks". Automatica, 33(11) : 1975-1995. 1997.

[14] S.S. Ge, C.C. Hang and T. Zhang, "A direct method for robust adaptive nonlinear control with guaranteed transient performance". Syst. Contr. Lett., 37 : 275-284. 1999.

[15] S.N. Huang, K.K. Tan and T.H. Lee, "Nonlinear adaptive control cf interconnected systems using neural networks". IEEE Trans. Neural Network., 17(1) : 243-246. 2006.

[16] R.M. Sanner and J.E. Slotine, "Gaussian networks for direct adaptive control". IEEE Trans. Neural Network., 3(6) : 837-863. 1992.

[17] J.T. Spooner and K.M. Passino, "Stable adaptive control using fuzzy systems and neural networks". IEEE Trans. Neural Net. 4(3) : 339-359. 1996.

[18] P. Borne, M. Benrejeb et J. Haggège, "Les réseaux de neurones. Présentation et applications". Editions Technip, 2007.

[19] A. Errachdi, I. Saad and M. Benrejeb, "Neural modeling of multivariable nonlinear system. Variable learning rate case". 18th Mediterranean Conference on Control and Automation, 557-562, 2010.

[20] M. Karadeniz, I. Iskender and S. Yuncu, "Adaptive neural network control of a DC motor". Gazi University, Faculty of Engineering & Architecture, Department of Electrical & Electronics Engineering, 06570 Maltepe, Ankara Turkiye.

[21] Y.K. Choi, S.K. Lee and Y.C. Kay, "Design and implementation of an adaptive neural network compensator for control systems". IEEE Trans. Industrial Elect. 48(2). 2001.

[22] N. Magnus, "Neural networks for modeling and control of dynamic systems". Springer, Berlin. New Yor 2000.

[23] R.D. Braatz and M. Morari, "On the stability of systems with mixed time-varying parameters". Int. J. of Robust and Nonlinear Control, 7 : 105-112. 1997.

[24] J-X. Xu, Y-J. Pan and T-H. Lee, "VSS identification schemes for time-varying parameters". The 15th Triennial World Congress, IFAC 2002.

[25] W-S. Chen, R-H. Li and J. Li, "Observer-based adaptive iterative learning control for nonlinear systems with time-varying delays". Int. J. Automation and Computing. 2009.

[26] R-H. Chi, S-L. Sui and Z-S. Hou, "A new discrete-time adaptive ILC for nonlinear systems with time-varying parametric uncertainties". ACTA Automatica Sinica, 34(7), 2008.

[27] M.M. Arefi and M.R. Jahed-Motlagh, "Adaptive robust synchronization of rossler systems in the presence of unknown matched time-varying parameters". Commmun Nonlinear Sci Numer Simulat 15: 4149-4157. 2010.

[28] S.S. Ge and J. Wang, "Robust adaptive tracking for time-varying uncertain nonlinear systems with unknown control coefficients". IEEE Trans. Automatic control, 48(8) : 1463-1469. 2003.

[29] Y. Tan, "Time-varying time-delay estimation for nonlinear systems using neural networks". Int. J. Appl. Math. Comput. Sci., 14(1) : 63-68. 2004.

[30] J. Wang and Z. Qu, "Robust adaptive control of a class of nonlinearly parameterized time-varying uncertain systems". IET Control Theory and Applications. 2008.

[31] Y. Zhang, B. Fidan and P.A. Ioannou, "Backstepping control of linear time-varying systems with known and unknown parameters". IEEE Trans. Automatic Control, 48(11). 2003.

[32] Y-W. Cho, K-S. Seo and H-J. Lee, "A direct adaptive fuzzy control of nonlinear systems with application to robot manipulator tracking control". I. Journal of Control, Automation and Systems, 5(6) : 630-642. 2007.

[33] Y.D. Landau, "Adaptive Control: the model reference approach". New York : Marcel Dekker. 1979.

[34] H. Husain, M. Khalid and R. Yusof, "Direct model reference adaptive controller based on neural fuzzy techniques for nonlinear dynamical systems". American Journal of Applied Sciences 5(7) : 769-776, 2008.

[35] J.M. Skowronski, "Adaptive nonlinear model following and avoidance under uncertainty". IEEE Trans. Circuits and system, 35 : 1082-1088, 1988.

[36] J. Lu and T. Yahagi, "Applications of neural networks to nonlinear adaptive control systems". Proceeding of ICSP200 : 252-257, 2000.

[37] H.K. Lam and F.HF. Leung, "On design of a switching controller for nonlinear systems with unknown parameters based on a model reference approach" . IEEE Int. Conference on Fuzzy systems, 1263-1266. 2001.

[38] B. Minaoui, "Contrôle du convertisseur monophasé par réseau de neurones". Afrique Science, 03(1) : 24-36, 2007.