Efficient Neural and Fuzzy Models for the Identification and Control of Nonlinear Systems

AOUICHE Abdelaziz[1*], SOUDANI Mouhamed Salah[2], AOUICHE El Moundher[3]

[1]Department of Electrical Engineering, University Laarbi Tebessi of Tebessa, Algeria LABGET Laboratory, Faculty of Sciences and Technology

[2]Mining engineering Institute, University Laarbi Tebessi of Tebessa, Algeria Laboratory of Development and Valorisation of Renewable Energy

[3]School of Electrical and Electronic Engineering, Hebei University of Technology, China

*Corresponding author's e-mail: abdelaziz.aouiche@univ-tebessa.dz

ABSTRACT

The purpose of this study is to identify and control nonlinear dynamical systems under some ambiguity by fuzzy inference systems (FISs) and artificial neural networks (ANNs). Due to the basic ability of FISs and ANNs to approximate unknown functions and to update different inputs and parameters, they are able to control systems which are complicated for linear controllers. The results indicate the FISs and ANNs (Back Propagation Algorithm) used were very efficient with better performance and good durability in modeling and control of nonlinear systems.

Keywords: Non-linear systems, Fuzzy set Models, Neural network

1 Introduction

In recent years, the artificial intelligence methods have been successfully used as building blocks in the design of practically feasible identifiers and controllers for non-linear dynamical systems [l]- [2]. Gaoua *et al.* have created reliable fuzzy-neural and neural based modeling methods for field-effect transistors (FETs) and hetero junction bipolar transistors in [3]. Artificial Neural Networks (ANNs) are information processing systems whose design was inspired by the studies of the ability of the human brain to learn from observations and to generalize by abstraction [4]. This work is organized as follows. In Section I, the FISs and ANNs structures are developed and studied. The training architectures for identification and control and the learning algorithm are presented either. Simulation results are discussed in Section II. The last section gives the conclusion of this paper.

2 Description and Analysis of FISs And ANNs

2.1 Artificial Neural Networks

There are many types of neural networks for various applications [5]. The Multi-Layered Perceptron Neural Network (MLP NN) structure is used in this paper to identify the unknown function [6].

2.2 Fuzzy Systems

The main part of the fuzzy systems is consisting of fuzzy IF-THEN rules. We have to obtain fuzzy rules (IF-THEN) from person specialists or area expertise before constructing fuzzy systems [7], [8]. In this paper for all results, we applied the TSK fuzzy model of order 0 (single design) for identification and modeling of our suggested nonlinear systems [9], [10].

3 Systems Description

3.1 System 1

The system to be modeled is governed by the difference equation

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$$y(k+1) = 0.3y(k) + 0.6y(k-1) + f[u(k)] \quad (1)$$

3.2 System 2

The system to be modeled is described by the second-order difference equation:

$$y(k+1) = f[y(k), y(k-1)] + u(k) \quad (2)$$

3.3 System 3

The following difference equation presents the system to be modeled:

$$y(k+1) = F[y(k)] + G[u(k)] \quad (3)$$

3.4 System 4

The system MISO to be modeled is described by the recurrent equation:

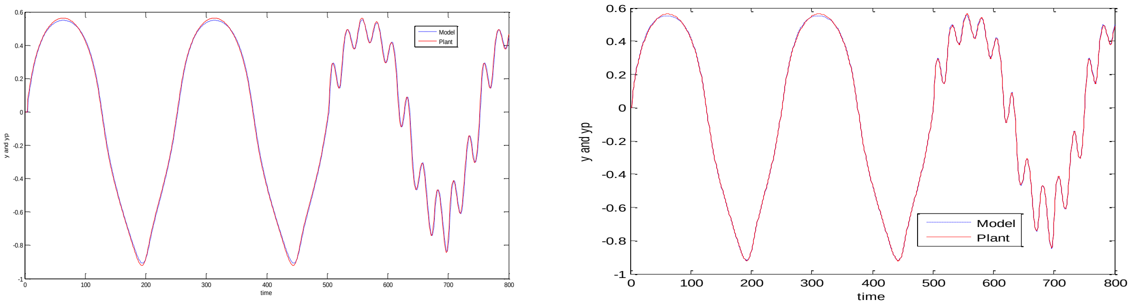
$$y(k+1) = f[y(k), y(k-1), y(k-2), u(k), u(k-1)]$$

Where the undefined function f has the form:

$$f(x_1, x_2, x_3, x_4, x_5) = \frac{x_1 x_2 x_3 x_5 (x_3 - 1) + x_4}{1 + x_3^2 + x_2^2} \quad (4)$$

4 The Simulation Results

4.1 System 4



(a) (b)

Figure 1:(*a) Neural identification, (b) Fuzzy identification*

5 Results

The outputs of Neural and Fuzzy models of system 4 are presented in Figure 1. Based always on the numerical values of MSE, the FIS identifier achieved better performance than the ANN identifier. We believe that having a very effective initial parameter selection approach is the primary factor contributing to the FIS identifier's excellent performance.

6 Conclusion

In this work, fuzzy and neural Back-Propagation algorithms were used as trainers for nonlinear systems. The ANNs and FISs were demonstrated to be able to approximate any nonlinear real continuous function on a compact set with arbitrary precision. Finally in all the systems, the results of the ANNs and FISs trained with their respective algorithms for the identification and control of non-linear systems are in very good agreement with the desired results.

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