FUZZY AND NEURO-FUZZY MODELLING AND CONTROL OF NONLINEAR SYSTEMS

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ABSTRACT

The fuzzy logic provides a means of converting a linguistic control strategy based on expert knowledge into an automatic control strategy. The ability of fuzzy logic to handle imprecise and inconsistent real-world problems has made it suitable for a wide variety of applications. The present work is concerned with modeling and control of nonlinear systems using fuzzy and neuro-fuzzy techniques. Design of controllers using conventional methods for nonlinear systems is difficult due to absence of a systematic theory behind it. In such cases, an approach based on the use of neural network for identifying the requirements of the controller and the system from the input output data have been shown to be attractive. But identification using a neuro-fuzzy approach will help in reducing the arbitrariness in the choice of the type pf membership functions and the ranges of variables in the universe of discourse. This paper presents two methods based on fuzzy logic for the control of nonlinear systems, one using PID like fuzzy control and another using a neuro-fuzzy approach. Simulation results are attractive.

I. INTRODUCTION

The fuzzy logic provides a means of converting a linguistic control strategy based on expert knowledge into an automatic control strategy.[1] The ability of fuzzy logic to handle imprecise and inconsistent real-world data made it suitable for a wide variety of applications. In particular, the methodology of the fuzzy logic controller (FLC) appears very useful when the processes are too complex for analysis by conventional quantitative techniques or when the available sources of information are qualitative, inexact, or uncertain.[2] Thus fuzzy logic control may be viewed as a step toward a rapprochement between conventional precise mathematical control and human – like decision making.

One of the major problems in the not so widespread use of the fuzzy logic control is the difficulty of choice and design of membership functions to suit a given problem. A systematic procedure for choosing the type of membership function and the ranges of variables in the universe of discourse is still not available. Tuning of the fuzzy controller by trial and error is often necessary to get a satisfactory performance. However, the neural networks have the capability of identification of a system by which the characteristic features of a system can be extracted from the input output data. This learning capability of the neural network can be combined with the control capabilities of a fuzzy logic system resulting in a neuro-fuzzy inference system. Recently an adaptive neuro-fuzzy inference system (ANFIS) has been proposed which has been shown to have very good data prediction capabilities [3] .

Control of nonlinear systems is difficult in the absence of a systematic procedure as available for linear systems. Many techniques are limited in their application to special class of systems. Here again, more commonly available methods are heuristic in nature and the fuzzy logic and neuro-fuzzy technique can reduce the arbitrariness in the design of a controller to a great extent.

This paper reports some results on the fuzzy control of nonlinear systems and the application of the adaptive neuro-fuzzy modeling technique for the control of nonlinear systems. A comparison of the performance of these with conventional control is also made.

II. CONTROL OF NONLINEAR SYSTEMS

A nonlinear system can be controlled in many ways to make it act like a linear system in its overall performance. Making a nonlinear system act like a linear system has many advantages, since linear systems are much easier to work with and are better understood. However, even if a model of the nonlinear system is available, no systematic and generally applicable control theory is available for the design of controllers for nonlinear systems. The best-known controllers used in industrial control processes are proportional-integral-derivative (PID) controllers because of their simple structure and robust performance in a wide range of operating conditions. Attempts have been made to use feed forward and recurrent neural networks for the control of nonlinear plants. The work reported in [4] makes use of two neural networks, one for representing the requirements on the controller and the other representing the system from the input output data if the plant model is not known in a mathematical form.

A. PID-LIKE FUZZY CONTROLLER

A typical nonlinear system can be represented as shown in Fig.1., with a linear plant and a nonlinear element in the forward path. Common nonlinear elements like saturation, relay, saturation with dead-zone, dead-zone and relay with dead-zone can be considered . Initially a conventional PID controller can be designed for the system followed by tuning of the PID controller parameters, in such a way that the performance of the nonlinear system is as good as that of the linear system with conventional PID control. The same PID parameters can be utilized for the design of a fuzzy PID controller.

B. ADAPTIVE NEURO- FUZZY CONTROL

System modelling based on conventional mathematical tools is not well suited for dealing with ill – defined and uncertain systems. By contrast, a fuzzy inference system employing fuzzy ' if – then' rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. Takagi and Sugeno were the first to systematically explore fuzzy modeling or fuzzy identification [2]. However, even today, no standard methods exist for transforming human knowledge or experience into the rule base and database of a fuzzy inference system. There is a need for effective methods for tuning the membership functions (MF's) so as to minimize the output error measure or maximize performance index. Recently, it was suggested by Roger Jang et al. [3] that an architecture called Adaptive – Network – based Fuzzy Inference System or Adaptive Neuro – Fuzzy Inference system can be used effectively for tuning the membership functions. ANFIS can serve as a basis for constructing a set of fuzzy 'if – then' rules with appropriate membership functions to generate the stipulated input-output pairs. Fundamentally, ANFIS is about taking an initial fuzzy inference (FIS) system and tuning it with a back propagation algorithm based on the collection of input-output data. In principle, if the size of available input-output data is large enough, then the fine-tuning of the membership functions are applicable (or even necessary). Since the human-determined membership functions are subject to the differences from person to person and from time to time; they are rarely optimal in terms of reproducing desired outputs. However, if the data set is too small, then it probably does not contain enough information of the system under consideration. In this situation, the human-determined membership functions represent important knowledge obtained through human experts experiences and it might not be reflected in the data set; therefore the membership functions should be kept fixed throughout the learning process. Interestingly enough, if the membership functions are fixed and only the consequent part is adjusted, the ANFIS can be viewed as a functional-link network, where the "enhanced representation" of the input variables are achieved by the membership functions. This "enhanced representation" which takes advantage of human knowledge are apparently more insight-revealing than the functional expansion and the tensor (outerproduct) models. By fine-tuning the membership functions, we actually make this "enhanced representation" also adaptive.[3]

ANFIS FOR CONTROL APPLICATIONS

Fuzzy control is by far the most successful applications of the fuzzy set theory and fuzzy, inference systems. Due to the adaptive capability of ANFIS, its applications to adaptive control and learning control are immediate. Most of all, it can replace almost any neural networks in control systems to serve the some purposes. For a controller to be designed, a model of the system is required. The design can be done using conventional methods or ANFIS. In the former case, a mathematical model will be required, while the latter will be convenient if an identified ANFIS model of the system is available. The structure of the controller using ANFIS can take the schematic shown in Fig.2. Two ANFIS networks are used. The first one, called Controller ANFIS (CANFIS) is trained using the input output data of the controller as per the design specifications. If the mathematical model of the plant is not available, a second ANFIS can be trained from the experimental input output data from the plant and the trained ANFIS can be used in place of the model.

III. SIMULATION RESULTS

For the purpose of simulation, a linear plant with second order model with very poor damping is chosen which has a continuous transfer function :

$$G(s) = \frac{10^6}{s(s+400)} \tag{1}$$

For a sampling time Ts=0.0001 seconds, the discrete transfer function becomes:

$$\frac{Y(z)}{U(z)} = \frac{0.00493\, z^{-1} + 0.00487\, z^{-2}}{1 - 1.961\, z^{-1} + 0.961\, z^{-2}} \tag{2}$$

On reverting to time domain:

$$y(k) = 1.961\, y(k-1) - 0.961\, y(k-2) + 0.00493\, u(k-1) + 0.00487\, u(k-2) \quad (3)$$

Results on Fuzzy PID Control

A conventional PID controller is designed for this system. Tuning of the conventional PID controller parameters is then performed, in such a way that the performance of the nonlinear system is as good as that of the linear system with conventional PID controller. After tuning the conventional PID controller, the parameters are :$k_p = 0.03$, $k_d = 0.45$, $k_i = 0.0008$. Using the same parameters a fuzzy PID controller is designed for this system. The inputs to the fuzzy controller are the error 'e', the change in error 'ce' and the sum of the errors 'se'. The ranges for 'e',' se' , ' ce' and u are chosen to be [-0.8 0.8], [-0.05 0.05], [-1 1], and [-5 5] respectively.

In Fig.3. is shown the comparison of the step response of the system without controller, with PID controller using conventional method and with PID like fuzzy controller. Results with two typical nonlinear elements are given. The nonlinear elements chosen are the saturation with and without dead zone. Keeping the linear plant as it is, different types of nonlinear elements have been included in the forward path and the variation of performance, if any, observed. It is seen that in most of the cases, the performance of the system with fuzzy PID controller compares favorably with those with conventional PID controller. The choice of PID parameters for the nonlinear system is more difficult than in the case of linear systems. However, designing a fuzzy controller is seen to be less difficult. Once an FLC is designed for a particular set of parameters of the nonlinear element, it will yield satisfactory performance for a range of these parameters. However, in some cases, retuning of the controller parameters may be required if the parameters of the non-linear element is significantly different.

Results on ANFIS Control

The input-output data pairs for training the CANFIS and SANFIS were generated using the conventional PID controller as discussed earlier. The plant transfer functions are the same as given in eqn (1) – (3). The parameters of the ANFIS network are as follows: No. of training data pairs : 500, Type of membership function: generalized bell , No. of membership functions: 20, and No. of epochs for training : 500

The change in the membership functions for the ANFIS while identifying the system from the input output data is shown in Fig.4. Typical plots of the training data for the nonlinear system and the step response of the closed loop control system are shown in Fig. 5. Here again, it is seen that the step response of the system with the proposed ANFIS controller is nearer to the ideal one. However, the output appears to be scaled down due to the normalization involved in the ANFIS network and hence additional gain may be required on the amplifier for practical implementation of the scheme. Performance-wise, ANFIS configuration is far superior to the conventional PID and fuzzy controllers discussed in [4]. Obviously the penalty is the additional computational effort in training the two ANFIS networks.

IV.CONCLUSIONS

It has been shown by simulation that fuzzy logic control can be used to design a controller for typical nonlinear plants. The difficulty in tuning of the PID like controllers by several trials can be overcome if we choose a recently proposed adaptive neuro-fuzzy network for identifying the controller requirements and the model for representing a plant which does not have a proper mathematical description or it is difficult to get one. The data available in the form of input output data pairs for the controller based on the specifications and the system from the experimental observations can be used in the ANFIS with relative ease. Of course, the practical implementation requires more studies as some of the normalization methods used in the ANFIS may have to be compensated for in scaling out the output level.

V.REFERENCES.

[1] Zadeh.L.A. Fuzzy Sets, Information and Control, Vol.8. 1965, pp 338-353

[2] Takagi.T. sugeno.M: Application of fuzzy algorithms for control of simple dynamic plant, IEE Proceedings, Vol. 12, December , 1974, pp 1585-1588.

[3]. Rojer Jang J S: ANFIS: Adaptive Network=based Fuzzy Inference System, IEEE Transactions on Systems, Man and Cybernetics, Vol.23, No.3, May 1993., pp 665-684.

[4] Mohandas K P, Deepthy A: Partial Recurrent Networks for identification and Control of Nonlinear Systems, IASTED International Conference on Control and Applications, Honolulu, USA, 12-15 Aug, 1998.

[5] MathWorks Inc. MATLAB User Manual for MATLAB and Fuzzy Logic Tool box.

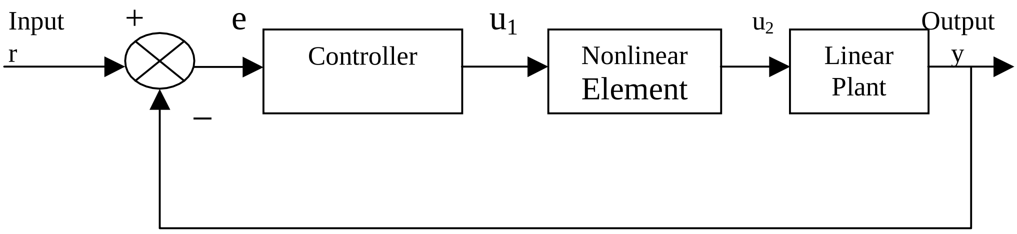

Fig. 1. Control of nonlinear system

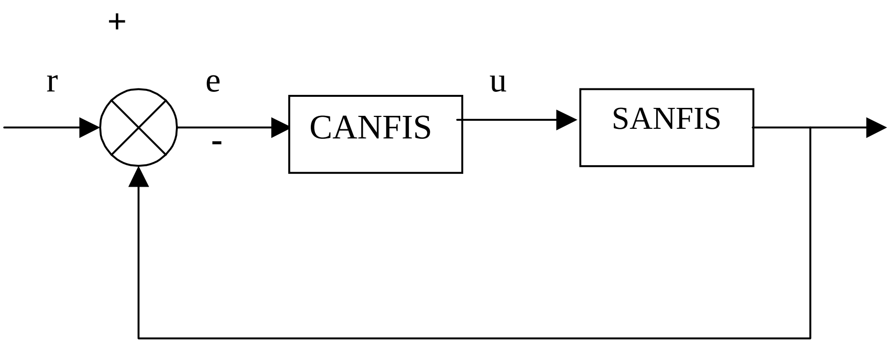

Fig.2. Controlled system using ANFIS

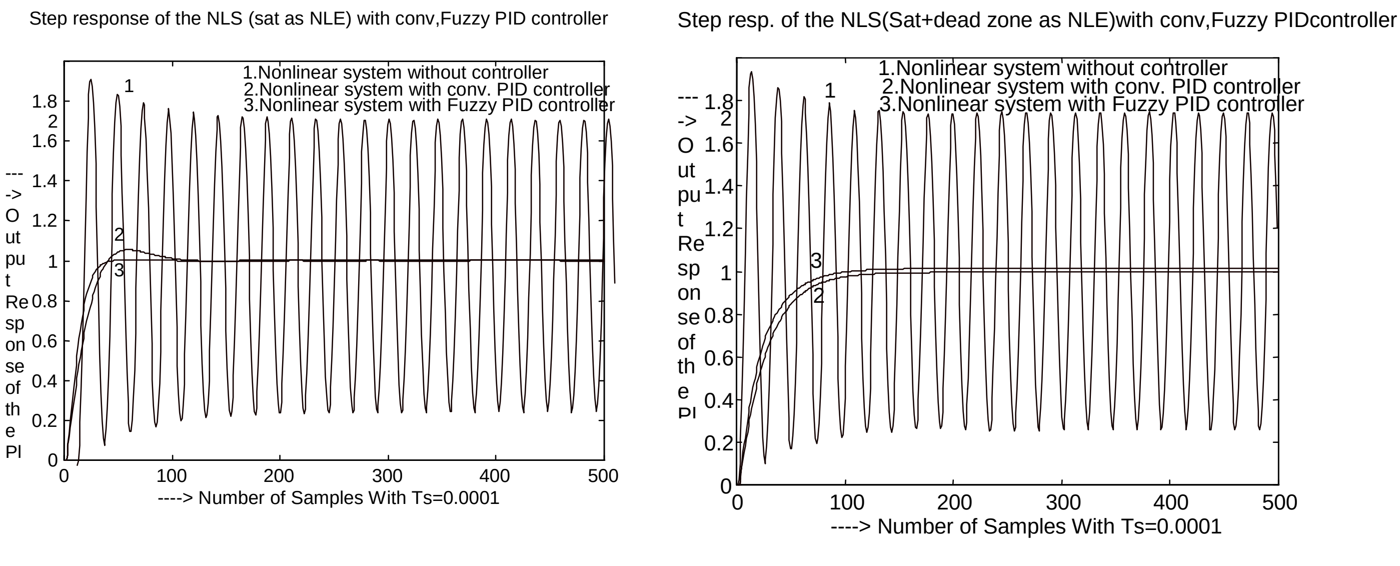

Fig. 3. Comparison of step responses , uncontrolled, conv. PID and fuzzy PID

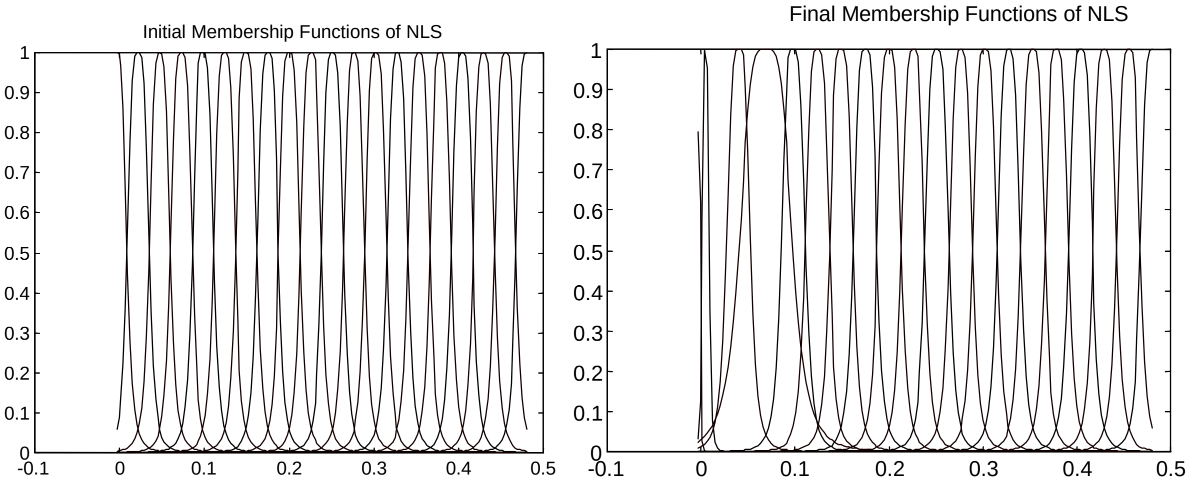

Fig. 4. Initial and final membership functions for nonlinear system identification

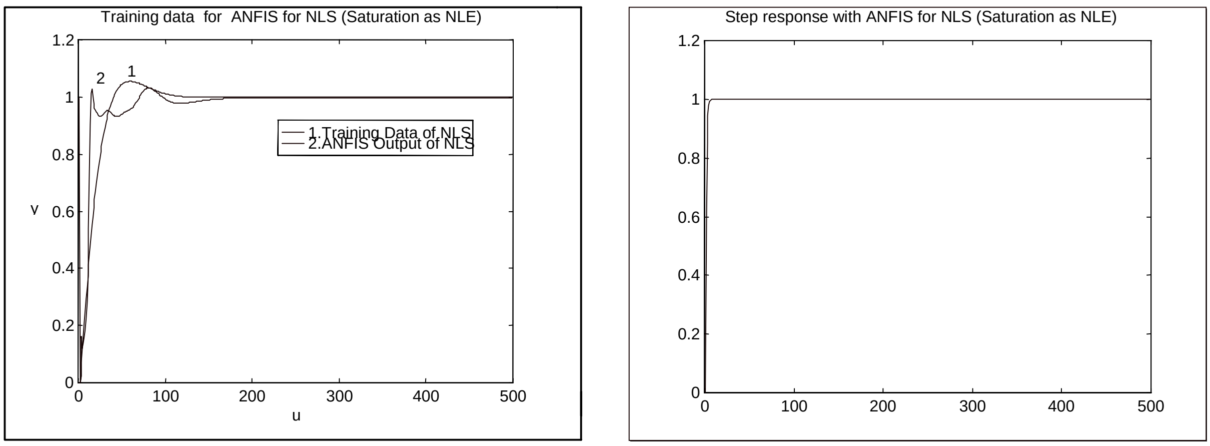

Fig.5. Training data and Step Response of ANFIS Control of Nonlinear Systems.