Comparison of intelligent techniques for a case study in control systems

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Abstract.*Intelligent systems are more and more used in society and industry. Diverse techniques have appeared over the last few decades. It is not an easy task to choose technique to solve a specific problem. This paper describes a methodology to help to choose intelligent techniques to solve a control problem. We use three techniques: Artificial Neural Network, Fuzzy Logic and NARX Models in control application. The results have shown that the techniques have been adequate. However each one has characteristics that become it more inclined to be applied depending on the available resources. Finally, we conclude that this work contributed for the generation of a methodology to choose techniques of Artificial Intelligence.*

Keywords: *Artificial Intelligence, Soft Computing, Control, Artificial Neural Network, Fuzzy Logic, NARX Model*

1. Introduction

After a long period of discredit in the scientific community, Artificial Intelligence (AI) has become an important scientific field (Nascimento and Yoneyama, 2000; Russel and Norvig, 2003). Its objectives have been changed and efforts have been started to solve specific problems, rather than construct robots or machines with human-like intelligence. In this way, it was created the Soft Computing (SC) (Jang et al., 1997). It is considered by someone such a branch of AI and by others such a new science field. The SC objective is to study and to apply computational techniques and systems that imitate nature and human aspects, for example: reasoning, perception, learning, evolution and adaptation.

There are many techniques that present SC characteristics, such as: Artificial Neural Networks (Haykin, 2001), Fuzzy Logic (Jang et al., 1997), Genetic Programming (Koza, 1992), Ant Colony Optimization (Dorigo and Stutzle, 2004), NARX models (Aguirre, 2004). Many research groups have produced thousands of articles about new techniques for many applications. These techniques are applied in several areas, as for example: medicine, education, energy, finances, industry, business, telecommunications, and others (Jang et al., 1997). Generally in engineering it has been applied in process optimization, specialist systems, control and automation.

Control is one of the main application of SC and has been used in many devices. In industry, process control is important to reach quality and lower cost. Although about *90%* of controllers used on industry are based on PID algorithm (Astrom and Hagglund, 2001), there are cases that the PID algorithm is not efficient. In these situations it is usually feasible the application of the SC based controllers (Dote and Ovaska, 2001; Pereira et al., 2005). In this context, a question arises: which technique should be used. There is no general answer for this question mainly due to: i) the intrinsic complexity of the issue - there are innumerable techniques and each technique by itself presents a considerable amount of knowledge; ii) protectionism of the research groups iii) unconcern of the scientific community in develop a methodology to solve it.

In this work, three techniques were compared in an control application. These techniques are: Artificial Neural Network (ANN), Fuzzy Logic (FL) and NARX Model. They have been used in many control and automation problems (Nascimento and Yoneyama, 2000). The model used for this case study was a generic fifth order linear model. A generic model was chosen because the main objective of this paper is the comparison of SC techniques used in a control case. The metodology applied in this work only needs a set of input and output data for identification of the controller structure.

This work can be divided in three parts. First, the input and output data have been obtained by means of model simulation. These data were used to identify controller models through of the reverse engineering. Each SC technique is used to build a model of $u = f(y, u)$. Second, the system compound by model and controller was simulated to obtain its performance index. Third, the results were analyzed and a comparison among techniques is explained.

2. Preliminary Concepts

In this section a brief overview of the three techniques is presented.

2.1 NARX Polynomial Models

Consider the NARX (Leontaritis and Billings, 1985) model described by:

$$y(k) = F^{\ell}\left[\begin{array}{l} y(k-1), ..., y(k-n_y), \\ u(k-d), ..., u(k-d-n_u+1) \end{array}\right], \quad (1)$$

where n_y and n_u are the maximum lags considered for the process and input, respectively, and d is the delay measured in sampling intervals, $T_{\rm s}$. Moreover, $y(k)$ is the time series of the output and $u(k)$ is the time series of the input. $F^{\ell}[\cdot]$ is some nonlinear function of $y(k)$ and $u(k)$. In this paper $F^{\ell}[\cdot]$ is taken to be a nonlinear polynomial of degree $\ell \in \mathbb{Z}^{+}$. To estimate the parameters of such a polynomial (1) can be expressed in:

$$y(k) = \psi^{\rm T}(k-1)\hat{\boldsymbol{\theta}} + \xi(k), \quad (2)$$

where $\psi(k-1)$ is the vector of regressors (independent variables)) that contains linear and nonlinear combinations of output and input up to and including time $k-1$. The parameters corresponding to each term in such matrices are the elements of the vector $\hat{\theta}$. Finally, $\xi(k)$ is the *residual* or *prediction errors* at time k which is the difference between the measured data $y(k)$ and the one-step-ahead prediction $\psi^{\rm T}(k-1)\hat{\boldsymbol{\theta}}$.

A dynamical model as in (2) taken over a set of data, furnishes constraints which can be presented by a matrix equation represented in:

$$\mathbf{y} = \Psi\hat{\boldsymbol{\theta}} + \xi. \quad (3)$$

The parameter vector $\hat{\theta}$ that minimizes the inner product of the residual vector can be estimated by orthogonal least-squares techniques that minimize the cost function:

$$J_{\rm LS}(\hat{\boldsymbol{\theta}}) = (\mathbf{y} - \Psi\hat{\boldsymbol{\theta}})^{\rm T}(\mathbf{y} - \Psi\hat{\boldsymbol{\theta}}). \quad (4)$$

One of several advantages of such algorithms are that the error reduction ratio (ERR) can be easily obtained as a by-product (Billings et al., 1989). This criterion provides an indication of which terms to include in the model by ordering all the candidate terms according to a hierarchy that depends on the relative importance of each term. After the terms have been ordered by the ERR, information criteria help deciding a good cut-off point.

2.2 Feed-Foward backpropagation Neural Network

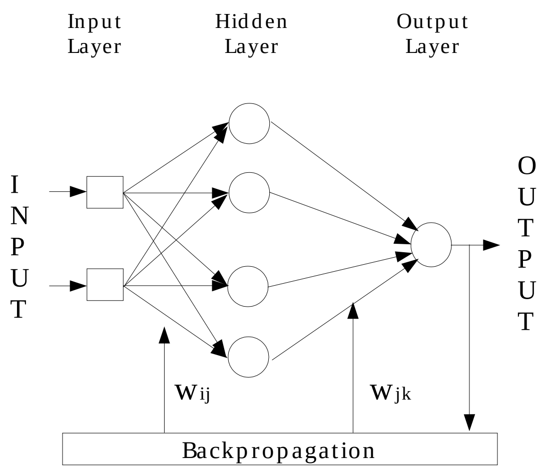

Figure 1. Basic structure of a neural network.

According to Haykin (2001), a neural network is a consisting processor highly distributed of units of simple processing, that has the natural function to store experimental knowledge and to become it available for use. With these characteristics a ANN allows the function approximation through training.

Considering the topology, a neural network can be classified as feedfoward or feedback (Nascimento and Yoneyama, 2000). A unit or neuron of a feedfoward neural network (FFNN) send its output to a neuron that it does not receive an input. Therefore, there are not feedbacks or loops in a FFNN. This topology was used here.

Figure 1, shows a basic structure of a ANN. The nodes (□) and neurons (◯) were connected to each other by weighted links, w_{ij}, over which signal can pass. The inputs into a neuron are multiplied by their corresponding connection weights (w_{ij}) and summed together. The outputs were calculated taking as inputs the corresponding output values of the previous hidden layer neurons and multiplying then by the connection weights w_{jk}.

2.3 Fuzzy Logic

The concept of Fuzzy Logic was conceived by Lotfi Zadeh, a professor at University of California at Berkley. FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. FL aims at solving a person would make decisions (Zadeh et al., 1993). This technique allows to incorporate the human thinking way in controllers (Shaw and G., 1999).

As described for Jang and co-workers (1997), the Fuzzy inference System (FIS) is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning. Fuzzy inference is the process of formulating the mapping from a given input to an output using FL. The ANFIS is a class of adaptive network that are functionally equivalent to FIS and its implemented by Sugeno model (Jang et al., 1997; Shaw and G., 1999). The Fuzzy Matlab Toolbox contains the ANFIS formulation and is used in this work. Figure 2 shows a basic FIS structure.

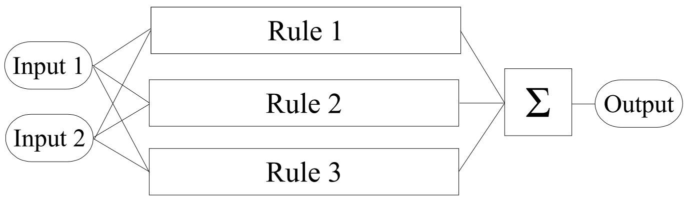

Figure 2. Basic structure of a FIS.

3. Controller Identification

A physical system model can be obtained when the laws that conduct this system is knew (Aguirre, 2004). But in many situations, this knowledge is not available. In these cases, a set of input and output data obtained of the systems can be used to model itself (Giannakis and Serpedin, 2001). This also can be used to identify a model for the controller based on reverse engineering. In this strategy, the system input becomes the desired output of the controller and the system output becomes the applied input of the controller. In other words, a SC technique should obtain a model of $u = f(y, u)$.

Output and input data are used to estimate the parameters of the controllers. The appropriated method was used with each technique and its presented in the Tab. 1 . The controller identification consists all created models and its diagram is shown in Fig. 3.

The Root Mean Square Error (RMSE) was used to choose the best model. The RMSE makes a comparison between the data obtained with the identified model and temporal average of originally signal (Aguirre, 2004). The RMSE is represented by:

$$\text{RMSE} = \frac{\sqrt{\sum_{k=1}^{N} \big(y(k) - \hat{y}(k)\big)^2}}{\sqrt{\sum_{k=1}^{N} \big(y(k) - \bar{y}\big)^2}}, \tag{5}$$

where $\hat{y}(k)$ is the simulated signal, $\bar{y}$ is the average of original signal $y(k)$.

3.1 Model simulation

As introduced in section 2, the model simulation was necessary to obtain the controller identification data. The input used was a random signal (Aguirre, 2004) and the function *lsim* was used to simulate the model transfer function. This function is available in Matlab. The transfer function presented in Eq. 6 represent the relationship between input $R(s)$ and output $C(s)$ of the model. The input and output variables have not physical meaning, because this is a generic model.

$$\frac{C(s)}{R(s)} = \frac{25s^2 + 150s + 118}{s^5 + 15s^4 + 85s^3 + 225s^2 + 274s + 120}. \tag{6}$$

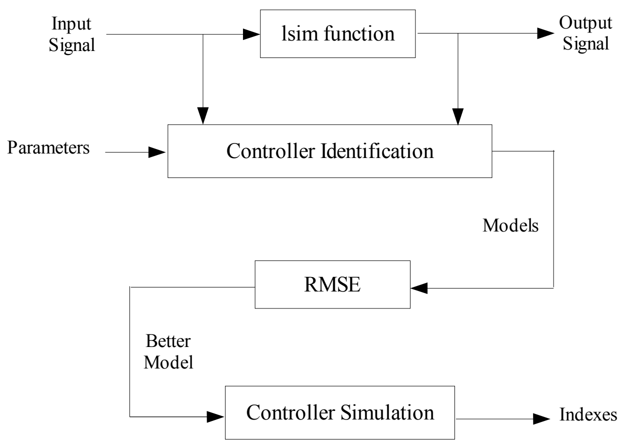

Figure 3. Diagram of controller identification.

The data set has been divided in two subgroups. The first set was used on the identification of controller model and the second one was used on its validation.

3.2 Determination of the models

The controller identification can be started after data has been obtained. The determination of structure can be carried out by different forms. Tab. 1 shows a brief description of procedures to yields the models for the three techniques studied.

Table 1. SC controllers implementation characteristics

Characteristic	NARX	Fuzzy Logic	Neural Network
Structure development	It is necessary to inform: degree of nonlinearity, maximum number of polynomial terms, maximum input lag and maximum output lag.	It is necessary to inform: membership function (MF) type, number of MFs, number of epochs and training algorithm.	It is necessary to inform: number of hidden layers, number of neurons by layer, input range, number of epochs, training algorithm and TF type.
Parameter estimation	Minimum square method as it is linear in the parameters	It usually needs a nonlinear optimization method	
Parameter optimization data	It is necessary: training data and checking data	It is necessary training data	
Obtaining candidates models	It is necessary to develop a function to vary parameters and compare obtained models using RMSE, or other validation technique.		
Obtained model structure	A function given with a data set	A function set given with a data set	

4. Controller simulation

A unit step response is used to measure performance of controllers. After the selection of the best model of each technique, the step response are compared. The indexes evaluated are: dead time, overshoot, offset error, rising time and settling time (Ogata, 2003). The step input was applied on each SC controller that each one were connected to the model. Figure 4 shows the simulation diagram. The step response obtained for NARX controller, FL controller and ANN controller is shown in Fig. 5 to 7, respectively. The indexes obtained on simulation was given on Tab. 2.

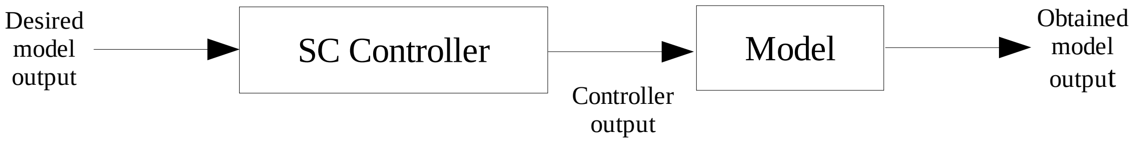

Figure 4. Diagram of model control system

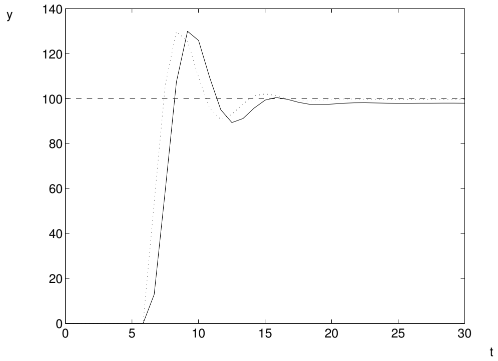

Figure 5. Step response for a NARX controller
Input is the dashed line, controller output is the dotted line and model output is the continuous line.

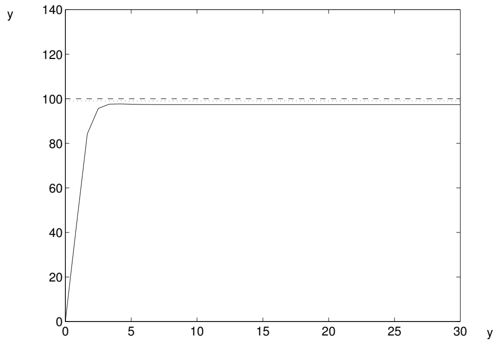

Figure 6. Step response for a Neural Network controller
Input is the dashed line, controller output is the dotted line and model output is the continuous line.

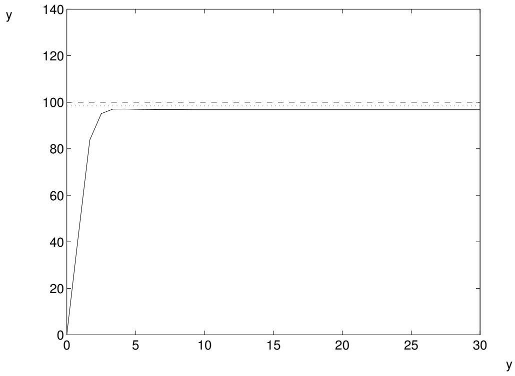

Figure 7. Step response for a Fuzzy controller
Input is the dashed line, controller output is the dotted line and model output is the continuous line.

Table 2. Step response indexes to SC controllers

SC controller	dead time (s)	overshoot (%)	offset error (%)	rising time (s)	settling time (s)
NARX	5.8382	29.9650	2.019	6.6722	43.3700
ANN	0	-	2.6224	2.0020	15.0150
FL	0	-	3.2085	1.6681	13.3445

5. Final Remarks

The results show the adequacy of each technique for solving this specific problem. This can be verified through indexes on Tab. 2 . Analyzing this particular results it can be observed that the FL controller presents the smallest rise and settling time, but the biggest offset. In this case study, the NARX controller presented the poorest result.

Beyond the results analysis it is also necessary the analysis of implementation characteristics that closed any technique. Basing on the tools used to controllers implementation some characteristics can be considered. These considerations will be made in a beginner-user perspective.

Considering the structure development, it is facilitated due to use of available tools for all used techniques. No advanced knowledge was needed for implementation of the SC controllers when someone use Matlab Toolboxes.

Real implementation is an important issue that should be taken in account. In industry, control algorithms are usually implemented on Programmable Logic Controller (PLC) or Distributed Control System (DCS) Gupta and Sharma (2005). Electronic devices were applied in situations that PLCs and DCSs costs are high or in simpler applications. The FL and ANN controllers implementation are facilitated when it is using PLCs and DCSs with block logic. These devices generally has FL an ANN routines available to use, but in some devices these routines are not available. In these cases, the implantation of NARX polynomial controller is easier due its structure.

Parameters adjustments are necessary after the controller has been implemented. In this situation, the FL becomes more interesting because it allows adjusts on specific range through MF parameters. Adjusting NARX and ANN controllers when they are operating at industry is more complicated because in these cases, their parameters do not represent a specific condition of the input and output range, as it can be the case of the Fuzzy membership function.

SC techniques are powerful tools to solve problems that it become complex to traditional control theory. The choice of which technique to use to solve a specific problem is a hard task. The objective of this work was to facilitate the choice by means of the comparison of SC techniques characteristics. Important aspects that should be considered are: how many information are necessary to know to development of the controller structure described in Tab. 1 ; how much work will spend to use a SC tool; what kind of device are available for controller algorithm implementation and the facilitate for adjustment of controllers parameters. The case study presented in this paper shows the efficiency of each technique and it helps the choice of the appropriate technique by analysis of the topics previous cited.

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