Journal of Information Systems Engineering and Management
2025, 10(62s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Inverse Neuro-Fuzzy Control of Nonlinear Systems

Fatima Zohra DAIKH[1], Mohamed Amine HAMADOUCHE[2]
[1] University Mustapha Stambouli of Mascara, Algeria, fatima_daikh@yahoo.fr
[2] University Mustapha Stambouli of Mascara, Algeria, Ham1879@ yahoo.fr.

ARTICLE INFO

Received: 30 Dec 2024

Revised: 12 Feb 2025

Accepted: 26 Feb 2025

ABSTRACT

This article, we addressed the use of Artificial Intelligence techniques in the field of control engineering. Our work focuses on the use of neuro-fuzzy networks, specifically ANFIS (Adaptive Neuro-Fuzzy Inference System), for the identification of inverse models required for implementing the control laws of a nonlinear dynamic system. In the first approach, the identified model is used as an open-loop controller with the system (Direct Inverse Control) for regulation purposes. In the second approach, Internal Model Control (IMC) is applied to improve the performance of the neuro-fuzzy model when the system is subject to a constant disturbance. The final section presents an application of these control structures to a nonlinear system. The results are validated through simulations carried out in the MATLAB environment.

Keywords: Neuro-fuzzy networks, ANFIS, Neuro-fuzzy control, Nonlinear system, Artificial intelligence, Inverse model.

INTRODUCTION

In the control of real-world dynamic systems, the availability of an accurate mathematical model is essential for the design and implementation of any control structure. However, obtaining such a model through analytical methods is often difficult or nearly impossible. Even when a model is available, it is frequently affected by uncertainties and modeling errors. As a result, the use of Artificial Intelligence (AI) techniques for identifying the mathematical model becomes an absolute necessity [1].

A significant body of research has explored the application of AI in the control of nonlinear systems.

Among AI-based approaches, neuro-fuzzy networks stand out due to their ability to combine the global reasoning and adaptability of fuzzy logic with the powerful learning and generalization capabilities of neural networks [2]. Various hybridizations of these two paradigms have led to the development of neuro-fuzzy systems, which are particularly well-suited for the control of complex and multivariable systems [3].

Several researchers have sought to leverage the strengths of neuro-fuzzy networks for controlling dynamic systems, especially in areas such as robotics and asynchronous motor control [4].

This work emphasizes the capability of neuro-fuzzy networks to approximate the inverse dynamics of nonlinear systems, and employs the resulting inverse neuro-fuzzy model (ANFIS) in the design of neuro-fuzzy control strategies for a nonlinear dynamic system.

The first section addresses the development of the inverse neuro-fuzzy (ANFIS) model. In the second section, two control structures are presented: the first utilizes the inverse model directly as the controller (Direct Inverse Control), while the second integrates both the inverse model and the internal (direct) model within an Internal Model Control (IMC) framework.

Finally, the last section applies these control approaches to a nonlinear system. The performance of the proposed methods is assessed and validated through MATLAB simulations.

NEURO-FUZZY

Neuro-fuzzy is a term used to describe systems or methods that combine neural networks and fuzzy logic

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Techniques [2]. These systems utilize the learning capabilities of neural networks along with the human-like reasoning style of fuzzy logic to address complex problems, particularly in areas involving uncertainty, imprecision, and incomplete information [4]

The structure of a neuro-fuzzy network is inspired by the similarity in organization between a fuzzy inference system and a multilayer neural network. This analogy can be summarized as follows:

- The reasoning process in a fuzzy inference system is carried out in three main stages—fuzzification, rule inference, and defuzzification—regardless of the number of rules involved, which reflects a form of massive parallelism.
- This reasoning process exhibits a structure that can be described as *pre-neuronal*, meaning that it is organized in layers, with each layer representing a specific component of the inference system. The controller parameters correspond to the network weights, while the fuzzy rules are generated from the network structure itself.

There are four main categories of combinations between neural networks and fuzzy logic: neural fuzzy networks, simultaneous neural/fuzzy systems, cooperative neuro-fuzzy models, and hybrid neuro-fuzzy models. The modern neuro-fuzzy approaches belong to this latter category. In such systems, a neural network and a fuzzy system are integrated within a unified architecture. The resulting structure can be interpreted either as a specialized neural network with fuzzy parameters or as a fuzzy system implemented in a distributed parallel form [5].

- **Adaptive Neuro Fuzzy Inference System (ANFIS)**

The ANFIS method is an optimization technique for Takagi–Sugeno type fuzzy inference systems, proposed by Jang [6]. It is used to adjust the parameters of the system by combining the least-squares method with gradient descent. This approach is based on the structure of multilayer networks.

Let us assume that the fuzzy inference system has two inputs, x and y, and one output f (Figure 1). The fuzzy rule base is expressed using *if–then* Takagi–Sugeno type rules:

rule i: if *x is Ai* and *y is Bi* then $f_i = p_i x + q_i y + r_i$

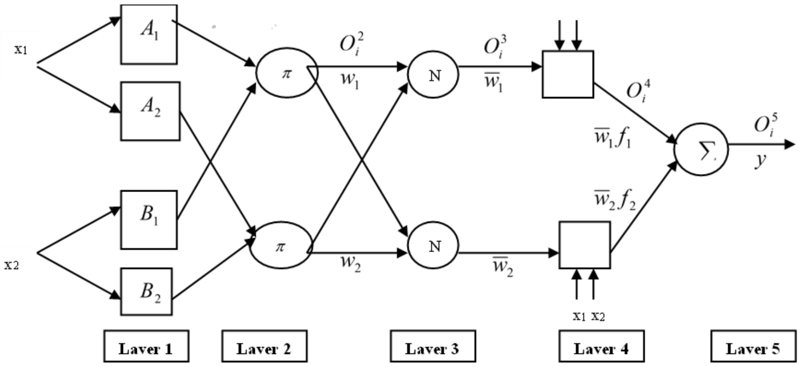

Figure 1: ANFIS Architecture.

The network consists of five layers, each performing a specific function (Figure 1):

- Layer1: fuzzification

Each node i in this layer is a square node that represents a membership function.

$$O_i^1 = U_{Ai}(x) \tag{1}$$

With x: the input of node i, Ai: the linguistic label associated with the function node. In other words, it is the membership function of Ai, and it specifies the degree of membership with which x satisfies it. The function is chosen in the form of [7]:

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- bell-shaped form

$$U_{Ai}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{\alpha_i}\right)^2\right]^b} \qquad (2)$$

Or a Gaussian function

$$U_{Ai}(x) = exp\left[-\left(\frac{x-c_i}{\alpha_i}\right)^2\right] \qquad (3)$$

Or $\{\alpha_i, b_i, c_i\}$ These are parameters that refer to the premise parameters. Their values change according to different representations of the membership function.

- Layer 2: Rule Strength

Each node multiplies the incoming signals:

$$w_i = U_{Ai}(x) \times U_{Bi}(x) \qquad (3)$$

- Layer 3: Normalization

Each node computes the normalized firing strength:

$$\overline{w_i} = \frac{w_i}{w_1+w_2}, i = 1,2(x) \qquad (4)$$

- Layer 4 – Consequent Parameters

Each node computes the output of the rule based on the first-order Sugeno function:

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \qquad (5)$$

- Layer 5 – Output

A single node that sums all incoming signals to produce the final output:

$$O_i^5 = \sum_i \overline{w_i}\, f_i \qquad (6)$$

- **Inverse Model**

Although the inverse model of a system plays an important role in control theory, obtaining its analytical form is often quite difficult. Several system modeling methods have been presented in the literature [8]. A dynamic system can be described by Equation (8), which relates its inputs to its outputs:

$$y(k+1) = f(y(k),\ldots,y(k-n+1),u(k),\ldots,u(k-m+1)) \qquad (7)$$

Where the system output *y(k+1)* depends on the previous n output values and the past m input values. In general, the inverse model of this system can be expressed in the following form (9):

$$u(k) = f^{-1}(y(k+1),y(k)\ldots,y(k-n+1),u(k-1),\ldots,u(k-m)) \qquad (8)$$

Neuro-fuzzy networks can be used to develop the inverse model of the system [5], however, representing the dynamic aspect of the system remains a challenge. Applying delays to the input layer of this type of network may offer a solution to address this shortcoming.

The corresponding network is:

$$\hat{u}(k) = g(x(k), w) \qquad (9)$$

The function g will be approximated by an ANFIS by adjusting its weights w. The network has an input vector x(k) composed of the output k+1 and past values of outputs and inputs, with the output being the signal û, which will be used to control the system.

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The identification of the inverse model begins with the determination of the input vector, namely the number of output and input delays, which is related to the system's order [9].

- ***ANFIS control***

As the name suggests, the inverse neuro-fuzzy model, placed in front of the system, is used as a controller to operate the system in open-loop mode (Figure 2).

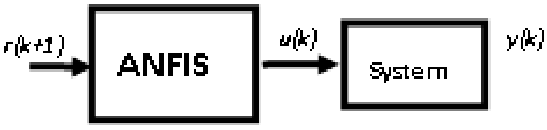

Figure 2: Direct control by inverse model.

The value of *y(k+1)* in equation (9) is replaced by the desired output *r(k+1)*. The network is fed with the delayed values of *u(k)*and *y(k)* [10]. If the ANFIS model is an exact inverse of the system, it drives the output to follow the reference signal.

- ***Internal Model Control (IMC)***

In a classical Internal Model Control (IMC) strategy, a model of the process is placed in parallel with the real system. The difference between the output of the process and that of the model provides an error signal, which is then used to adjust the control input. One of the main advantages of IMC is that it provides good performance even in the presence of constant disturbances or system variations.

In our approach, the IMC structure consists of an ANFIS controller, a direct ANFIS model, and a filter (Figure 3). The ANFIS controller is trained to represent the inverse model of the system. The error between the output of the direct ANFIS model and the output of the real process is fed back and processed through the filter, whose output is then applied to the ANFIS controller. In this way, the controller adjusts the control signal to reduce the error and compensate for disturbances.

The ANFIS models (direct and inverse) are obtained through offline training, which ensures their stability and accuracy before being integrated into the IMC structure [11]

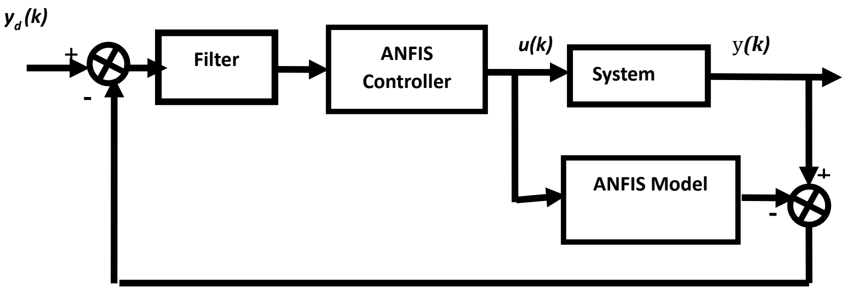

Figure 3: Internal Model Control (IMC).

The simulations were carried out on a didactic model of a single-degree-of-freedom manipulator robot, whose model (11) is given by Berghuis [12]:

$$u = y'' + 2y' - 10\,sin(y) \tag{11}$$

First, we developed the inverse model of the system, and then we used it in the two control structures, with and without noise. To generate the training and validation data, the system (11) was excited by an input signal $u(k)$, which is a random sequence with a uniformly distributed amplitude in the interval $[-5,5]$, in order to ensure a sufficiently rich excitation.

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The ANFIS model has the inputs $\{y(k), y(k-1), y(k-2)\}$and uses two bell-shaped membership functions for each input.

The error between the two signals, the actual system input $u(k)$and the output of the inverse ANFIS $\hat{u}(k)$, is shown in Fig. 4, with a corresponding cost of 10^{-3}.

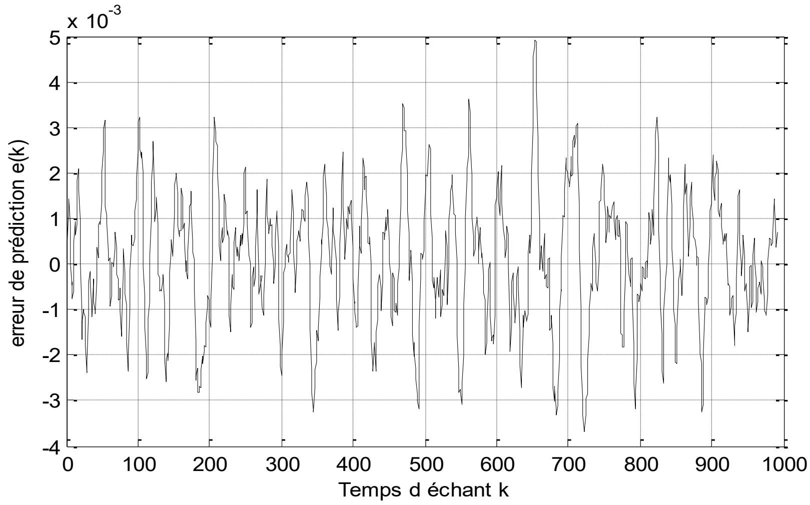

Figure 4: Inverse Model Prediction Error.

For the application of the inverse model in direct control (§ 4.1), we tested the model using two reference signals: the first one is a random signal y_d, and the second is a sinusoidal reference signal y_{d1}.

The error between the reference $y_d$and the output of the system controlled by the inverse model is shown in Figure 5, while the error between the sinusoidal reference $y_{d1}$and the system output is presented in Figure 6.

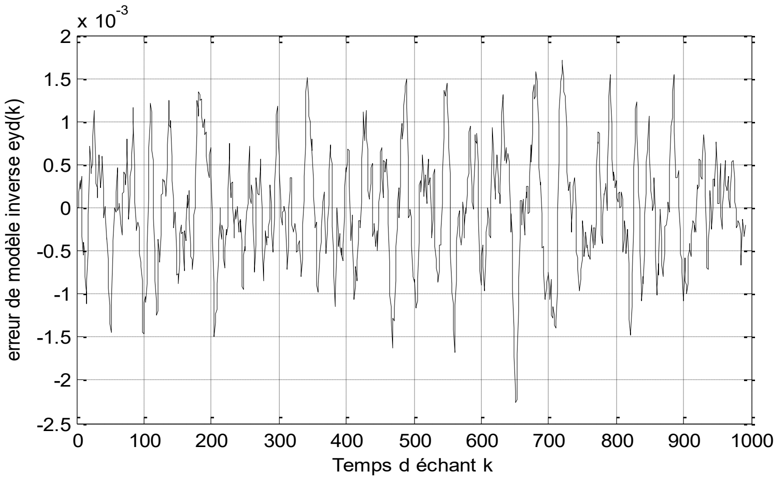

Figure 5: Tracking error for direct inverse control with reference y_d.

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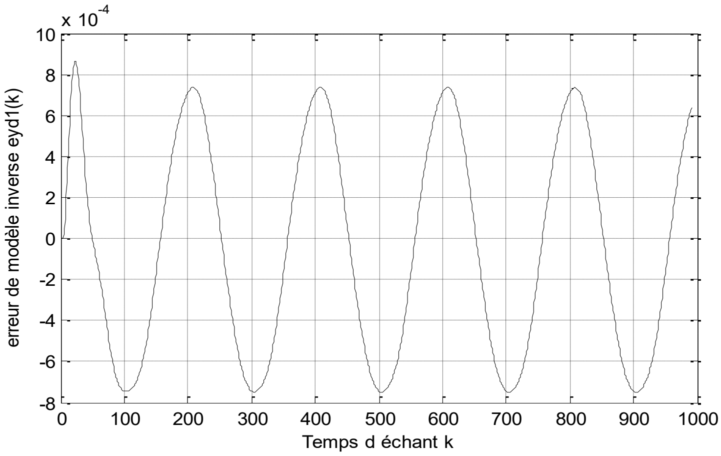

Figure 6: Tracking error for direct inverse control with reference y_{d1}.

The obtained tracking error is very small for both reference signals (y_d and y_{d1}). For the Internal Model Control (IMC) approach, the error between the output of the system (11) and the output of the ANFIS model is shown in Figure 7.

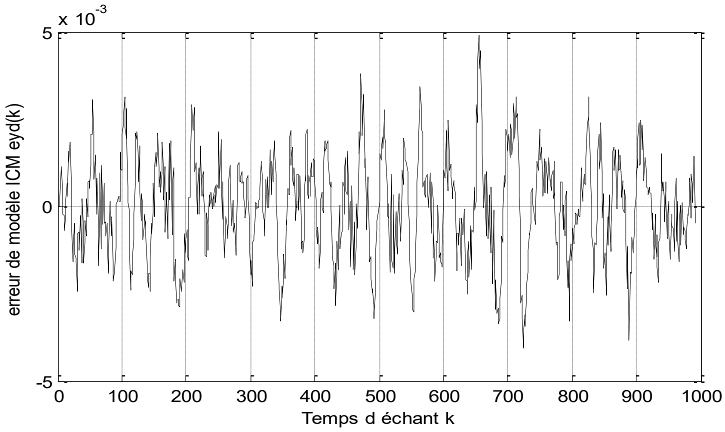

Figure 7: Tracking error for the IMC control strategy.

Finally, noise was added to the output of the system, and Figure 8 shows the error obtained with the Internal Model Control in the presence of noise. It can be observed that the error remains very small, even in the presence of disturbances.

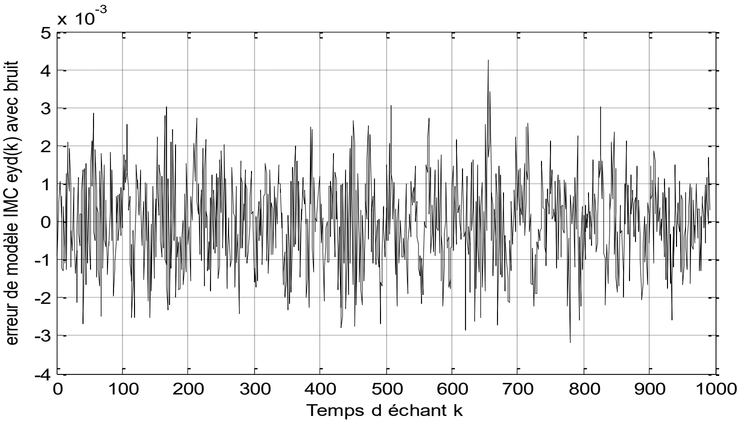

Figure 8: Tracking error for the IMC control strategy in the presence of noise.

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CONCLUSION

In this paper, we presented two neuro-fuzzy control structures based on an inverse ANFIS model. The training of this model was carried out in order to achieve an optimal architecture while minimizing the number of parameters. The selected ANFIS architecture consists of three inputs and two bell-shaped membership functions. The resulting prediction error is very small.

The obtained inverse model was then used in a direct open-loop control scheme; however, this approach assumes that the inverse model is nearly perfect and that the system is noise-free, which is unrealistic in practice. To address this limitation, the inverse model was subsequently integrated within an Internal Model Control (IMC) structure, leading to highly satisfactory results.

To further validate the IMC structure, noise was injected into the system. The control performance remained stable and only slightly affected by the disturbances. The results demonstrate that an ANFIS model with proper training can effectively adapt to the system dynamics and ensure robust disturbance rejection.

CONFLICT OF INTEREST

There was no conflict of interest declared by the authors.

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