

implemented an optimization technique allowing an on-line adjustment of the fuzzy controller parameters. The descent gradient algorithm, with its capacities to adapt to unknown situations by the means of its faculties of optimization, and the fuzzy logic, with its capacities of empirical knowledge modeling, are combined to control. Indeed, we have obtained an on - line optimized Takagi-Sugeno type FIS of zero order STFIS.

The feasibility of STFIS control for inverted pendulum has been proved and illustrated by simulation. The STFIS controller presented very interesting tracking features and was able to respond to different dynamic conditions.

5 References

- A. Abraham "Neuro Fuzzy Systems: State-of-the-art Modeling Techniques", School of Computing & Information Technology, Monash University, Australia, 2001.
- M.I. Jordan, D. Rumelhart "Internal word models and supervised learning" *Proceeding of the 8th International Workshop on Machine learning*, pp 70-74, 1991.
- H. Maaref, C. Barret, " Progressive Optimization of a Fuzzy Inference System ", *IFSA-NAFIPS'2001*, Vancouver, pp.665-679, 2001.
- D.Nauck, R. Kruse, " What are Neuro-Fuzzy Classifiers?", *Seventh International Fuzzy Systems Association World Congress IFSA'97*, Vol. IV, pp. 228-233, Academie de Prague, 1997.
- A. Yazici, A. Karamancioglu, R. N. Gasimov " Nonlinear Programming Based Sliding Mode Control of an Inverted Pendulum " Osmangazi University, Meselik, Eskisehir TURKEY, 2006.
- W. Wang "Adaptive Fuzzy Sliding Mode Control for Inverted Pendulum" *Proceedings of the Second Symposium International Computer Science and Computational Technology(ISCST '09)Huangshan*, P. R. China, 26, pp. 231-234, Dec, 2009.
- K. Zemalache Meguenni "Commande d'un système sous- actionne: Application a un drone a Quatre Helices " Université d'Evry Val d'Essonne, Dec 2006.
- K. Zemalache, L. Beji, H. Maaref " Control of Drone: Study and Analysis of the Robustness " *Journal of Automation, Mobile Robotics and Intelligent Systems*, 2008.

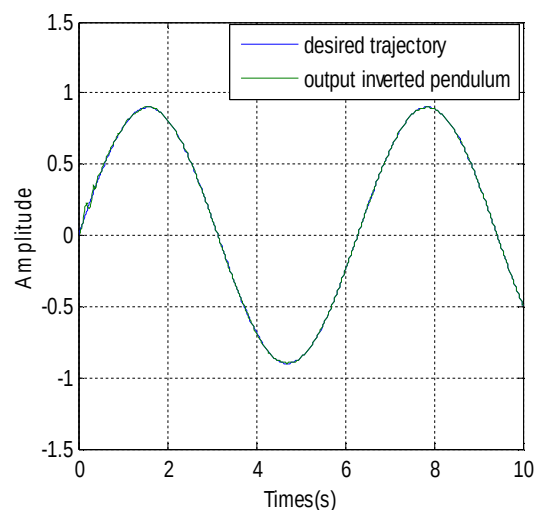


Fig. 4. Trajectory designed and Trajectory tracking of inverted pendulum with STFIS controller for angle.

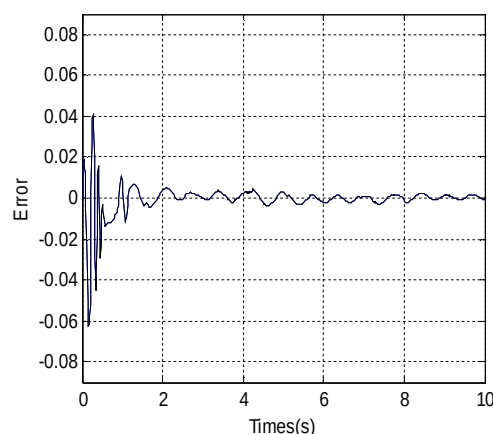


Fig. 5. Tracking error for inverted pendulum.

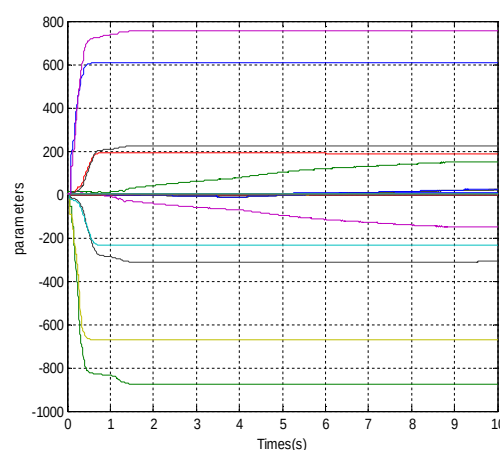


Fig. 6. The parameters (weights).

4 4. conclusion

In this paper, we studied a new configuration of control inverted pendulum. We considered in this work the stabilizing tracking control problem for nonlinear system. We have presented and

inverted pendulum dynamic model is constructed using MATLAB Simulink software.

A Fuzzy controller based on an on-line optimization of a zero order Takagi-Sugeno inference system is successfully applied. It is used to minimize the cost function that is made up of a quadratic error term. We use the architecture know as (mini-JEAN)"Fig.2 b".

The Memberships functions are normalized and shared in five subsets for all displacement "Fig.3". The linguistic labels are defined follows: NB: Negative Big, NS: Negative Small, Z approximately Zero, PS: positive Small and PB: Positive Big.

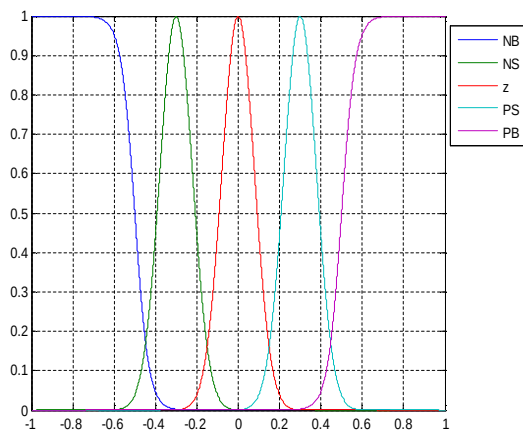


Fig. 3. Memberships function.

For the STFIS network parameters, there were five memberships functions of type sigmoid and gaussians "Fig. 3" and $\beta = 0.0001$, $\eta = 0.3$ and $b = 0.9$.

The "Fig. 4" shows the STFIS controller response of the inverted pendulum for the given desired point angle trajectory. It is found that actual trajectories of the inverted pendulum is almost merged with the desired rectory, with the presence of the perturbations.

Form this inference, it is concluded that STFIS training is completely satisfied and inverted pendulum tracking error is almost nearly zero "Fig.5".

"Fig.6" represents the convergence of the parameters (weights) of the last layer.

$$w(t+1) = w(t) + \eta \left(-\frac{\partial E}{\partial w} \right) - \beta w(t) \quad (6)$$

Since a fuzzy inference system is concerned, we adapt this formula by multiplying β by the firing term of the rule, namely $\alpha_i / \sum \alpha_i$, α_i is the truth value of the premise part of the triggered rule.

If we limit the optimization only on the conclusions parameters w_{1j}^4 then we get

$$\Delta w_{1j}^4(t) = -\eta \delta_1^4 \alpha_j^3 + b \Delta w_{1j}^4(t-1) - \alpha_j^3 \beta w_{1j}^4(t-1) / \sum \alpha_j^3 \quad (7)$$

With

$$\delta_1^4 = y_1 - y / \sum_j \alpha_j^3 \quad (8)$$

Where:

y_1 : effective output value.

y : desired output.

3 3. simulation results

In this section we apply the theoretical results presented in the preceding section to an inverted pendulum stabilization problem. The stabilization problem is to design a controller to keep the pendulum in its unstable equilibrium point in the presence of disturbances. Because of its dynamically rich structure, inverted pendulum system is widely used in the literature to check validity of control strategies [5].

The dynamic equation of inverted pendulum can be given [6]:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \frac{g \sin x_1 - m l x_2^2 \cos x_1 \sin x_1 / (m_c + m)}{l(4/3 - m \cos^2 x_1 / (m_c + m))} + \frac{\cos x_1 / (m_c + m)}{l(4/3 - m \cos^2 x_1 / (m_c + m))} u(t) + d(t) \end{cases} \quad (9)$$

Where x_1 is angular position and x_2 is the velocity of the pole respectively, $g = 9.8 \text{ m/s}^2$, m_c is the mass of cart and $m_c = 1 \text{ kg}$, m is the mass of pole and $m = 0.1 \text{ kg}$, here $l = 0.5 \text{ m}$ is half lengthen of pole, u is control input, $d(t)$ is external disturbance and here are sine function $d(t) = 0.2 \sin(t)$. This

$w_{ij}^n(t)$: i^{th} parameter between i of layer n

and j^{st} unit of layer n-1.

η : learning gain.

t : training iteration.

b : moment parameter.

$$\delta_i^n$$
 : error term(i^{th} neuron of layer n).
$$\alpha_j^{n-1} : \text{output of } j^{st} \text{ unit of layer n-1.}$$

The quality of solution obtained using this algorithm depends on input learning signals, algorithm control parameters and learning duration (number of iterations).

<i>D.</i>	<i>Algorithm</i>	<i>Modification</i>	<i>Weight</i>
	<i>Regression</i>		

The procedure is entirely done on-line on the engine. The table of rules (weights w_i) can be initially empty or filled with an a priori knowledge. The engine acquires by its systems output measures, calculates the error to back-propagated, updates the triggered rules on-line. The weights of the table of decision are then adjusted locally and progressively. The cost function is given by [8]:

$$J = E + \lambda \sum w_i^2 \quad (4)$$

Where E is the classic quadratic error, w are the parameters (weights) to optimize parameters and λ is a constant that controls the growth parameters. The second term in J is known as weight decay and used usually in the context of classification problems. This technique has been analyzed in the framework of leaning theory and it was shown that is a very simple manner to implement a regularization method in a neural network in order to optimize the compromise between the learning error and the generalization error. Thanks to the classic back-propagation algorithm, the parameters are modify as:

$$w(t+1) = w(t) + \eta \left(\frac{-\partial J}{\partial w} \right) \quad (5)$$

This algorithm easily includes the effect of the second term of the cost function J and by taking $\beta = 2\lambda\eta$ (regression coefficient) we obtain:

1. A first network to identify the system (Model).
2. A second network to control the system (Controller).

For the control of the inverted pendulum, we have used the architecture known as the "mini-JEAN" as illustrated in the "Fig.2.b". This architecture doesn't require an emulator net-work. It uses only one network as a controller, the learning of which is done directly by the back propagation of the output error [3].

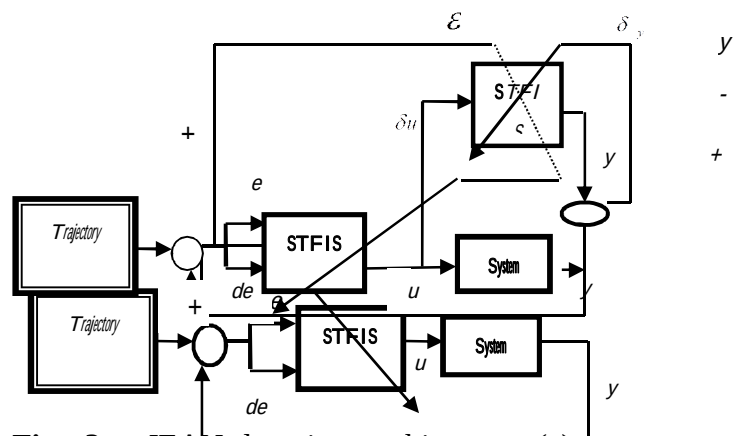


Fig. 2. JEAN learning architecture (a), control

architecture mini-JEAN (b).

Compared to the architecture JEAN, some equivalent performances are obtained for the mean error in generalization. On the other hand, the computing time favors clearly mini-JEAN. Optimization of adjustable parameter is accomplished with a version of the classic gradient retro-propagation algorithm adapted to net structure of "Fig.2". The aim is to minimize cost function E:

$$E = \frac{1}{2} \varepsilon^2 \quad (1)$$

Where ε is the difference between set point process output. The basic equations of the algorithm are:

$$w_{ij}^n(t) = w_{ij}^n(t-1) + \Delta w_{ij}^n(t) \quad (2)$$

$$\Delta w_{ij}^n(t) = -\eta \delta_i^n \alpha_j^{n-1} + b \Delta w_{ij}^n(t-1) \quad (3)$$

Where

- A truth value degree α_i is obtained, associated to the premises of each rule R_i :

IF x_1 is X_1 AND x_2 is X_2 THEN u is w_i .

- An aggregation stage to take in to account all rules by $u = \sum \alpha_i w_i / \sum \alpha_i$ permit to obtain a crisp value u .

These operations can be traduced by the layer structure shown in "Fig. 1". Each layer, connected with others by adjustable parameters, having a specific function.

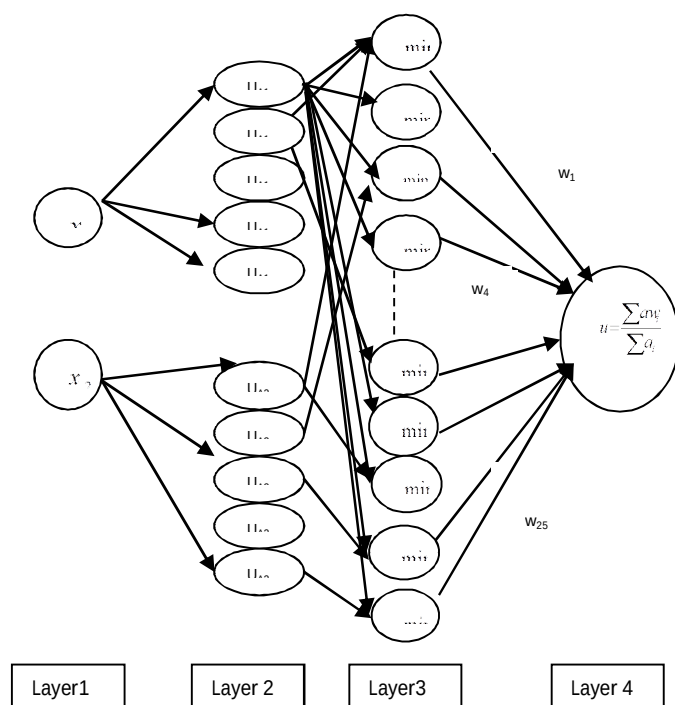


Fig. 1. Self Tuning Fuzzy Inference System.

C. Architecture and learning Algorithm Architecture

In this work, we propose to generate the fuzzy control rules by an optimization method, which is done entirely on-line. Jordan [2] proposes the distal control method, which is used under the name of JEAN (Jordan method Extended for Adaptive Neurocontrol). This architecture "Fig. 2" needs the used of two STFIS networks:

Finally, conclusions are summarized in Section 4.

2.2. NEURO-fuzzy

In Neuro-Fuzzy architecture, ANN learning algorithms are used to determine the parameters of FIS. NF systems share data structures and knowledge representations. A common way to apply a learning algorithm to a fuzzy system is to represent it in a special ANN like architecture. However, the conventional ANN learning algorithms (gradient descent) cannot be applied directly to such a system as the functions used in the inference process are usually non differentiable [4]. This problem can be tackled by using differentiable functions in the inference system or by not using the standard neural learning algorithm.

We broadly classify the integration of ANN and FIS into four categories namely, neuronal fuzzy network, concurrent model, cooperative model and neuro-fuzzy hybrid model. The modern approaches neuro-fuzzy are of this last forms. A neural network and fuzzy system are combined in a homogeneous architecture. The system can be interpreted like a special neural network with vague parameters or like a vague system application in a parallel distributed form [7].

A. Self tuning Fuzzy Inference System STFIS

The formal analogy between a fuzzy inference system and a multilayer neural network associated with optimization algorithms is used from the retro-propagation gradient algorithm have winded up in what is called a STFIS network [8].

B. presentation of STFIS

A sugeno type fuzzy system is determined in three stagers:

- Given an input x a membership degree u is obtained from the antecedent part of rules.

1 1. Introduction

The common methods of the automatic that were largely implemented have many problems of industrial regulation. However, the majority of the physical systems have nonlinearities and their parameters are often little known about and/or variable in time. For the control of such classes of systems, the conventional methods of the automatic have shown their limits in terms of stabilization and performances. With the considerable development of the digital computers, the automation experts have adopted more new approaches such as the predictive control, the robust control, as well as the techniques based on the artificial intelligence.

Among these approaches; the “control by Neuro-Fuzzy”, this control is currently one of the concerns of the researchers in the world.

Fusion of Artificial Neural Networks ANN and Fuzzy Inference Systems FIS have attracted the growing interest of researchers in various scientific and engineering areas due to the growing need of adaptive intelligent systems to solve the real world problems. ANN learns from scratch by adjusting the interconnections between layers. FIS is a popular computing framework based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The advantages of a combination of ANN and FIS are obvious [1]. The use of the theory of neuro-fuzzy in modeling and the control of the complex systems knew a considerable development.

The work presented in this article relates to the implementation of this technique of control with neuro- fuzzy and specially STFIS with the physical system: “inverted pendulum”.

The present paper is organized in the following manner: Section 2 describes the neuro-fuzzy and proposes self tuning fuzzy inference system (STFIS) then STFIS architecture and learning algorithm, section 3 presents the application of STFIS controller to the inverted pendulum.

Abstract-- This work deals with application of Neuro-Fuzzy network control approach to inverted pendulum, which motivated the researchers to use it to validate and test the control laws developed in theory. At the beginning Neuro-fuzzy network and especially Self Tuning Fuzzy Inference System (STFIS) is presented. Then STFIS controller is synthesized. At the end, we present the application of this control law dedicated to inverted pendulum. Some simulations with robustness tests are performed, which demonstrates the feasibility of the proposed control strategy. Results of simulations containing tests of robustness are presented and realized in MATLAB environment.

Index Terms-- Inverted Pendulum, Neuro-Fuzzy, Self Tuning Fuzzy Inference System (STFIS), STFIS controller.

ملخص الدراسة

يتناول هذا العمل تطبيق نهج التحكم في الشبكات العصبية المبهمة على البندول المقلوب ، والذي حفز الباحثين على استخدامه للتحقق من صحة واختبار قوانين التحكم المطورة نظرياً. في البداية يتم تقديم شبكة غامضة عصبية وخاصة نظام ضبط النفس الغامض.

(STFIS). ثم يتم تصنيعها STFIS تحكم. في النهاية ، نقدم تطبيق قانون الرقابة هذا المخصص للبندول المقلوب. مع إجراء بعض عمليات المحاكاة مع اختبارات الصلابة ، مما يوضح جدوى استراتيجية التحكم المقترحة. هذا مع تقديم نتائج المحاكاة التي تحتوي على اختبارات المتانة وتحقيقها في بيئة MATLAB.

الكلمات المفتاحية -- بندول المقلوب ، الغموض العصبي ، نظام الاستدلال الذاتي الغامض المضبوط (STFIS) ، وحدة تحكم STFIS

Fuzzy Neural Network Control for Inverted Pendulum

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