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New Trends in Neuro-Fuzzy System Identification and Control

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Abstract

A new definition of Neuro-Fuzzy Dynamical Systems is introduced, using the concept of Fuzzy Dynamical Systems (FDS) in conjunction with High Order Neural Network Functions (F-HONNFs). The dynamical System is assumed nonlinear and totally unknown. Its approximation by a special form of a fuzzy dynamical system (FDS) is first proposed and in the sequel the fuzzy rules are approximated by appropriate HONNF's. Thus the identification scheme leads to a Recurrent High Order Neural Network, which however, takes into account the fuzzy output partitions of the initial FDS. The proposed scheme does not require a priori experts' information on the number and type of input variable membership functions, making it less vulnerable to initial design assumptions. After the identification process the system can be adaptively controlled either directly or indirectly. The indirect control case is considered in this paper. By doing so, weight updating laws for the involved HONNs are presented. With rigorous proofs it is guaranteed that the errors converge to zero exponentially fast, or at least become uniformly ultimately bounded. At the same time the stability is guaranteed by proving that all signals in the closed loop remain bounded. During both the identification and control process it is assumed that the centers and shapes of membership functions are known, and the HONN parameters are identified, in which case a directional variation is obtained. In order to guarantee existence of the control law, a new method is defined, which is termed parameter hopping, replacing the well known projection. Thus, the existence of the control law it is rigorously proved, guaranteeing stability properties.

Key words: *neural networks, fuzzy systems, adaptive control, parameter hopping.*

Introduction

Nonlinear dynamical systems can be represented by general nonlinear dynamical equations of the form

$$\dot{x} = f(x,u)\,. \tag{1}$$

The mathematical description of the system is required, so that we are able to control it. Unfortunately, the exact mathematical model of the plant, especially when this is highly nonlinear and complex, is rarely known and thus appropriate identification schemes have to be applied which will provide us with an approximate model of the plant.

It has been established that neural networks and fuzzy inference systems are universal approximators [1, 2, 3], i.e., they can approximate any nonlinear function to any prescribed accuracy provided that sufficient hidden neurons and training data or fuzzy rules are available.

Recently, the combination of these two different technologies has given rise to fuzzy neural or neuro fuzzy approaches, that are intended to capture the advantages of both fuzzy logic and neural networks. Numerous works have shown the viability of this approach for system modeling [4 - 12].

The neural and fuzzy approaches are most of the time equivalent, differing between each other mainly in the structure of the approximator chosen. Indeed, in order to bridge the gap between the neural and fuzzy approaches several researchers introduce adaptive schemes using a class of parameterized functions that include both neural networks and fuzzy systems [6 - 12]. Regarding the approximator structure, linear in the parameters approximators are used in [10], [13], and nonlinear in [14, 15, 16].

Adaptive control theory has been an active area of research over the past years [13 - 30]. The identification procedure is an essential part in any control procedure. In the neuro or neuro fuzzy adaptive control two main approaches are followed. In the indirect adaptive control schemes [13 - 19], first the dynamics of the system are identified and then a control input is generated according to the certainty equivalence principle. In the direct adaptive control schemes [20] - [26] the controller is directly estimated and the control input is generated to guarantee stability without knowledge of the system dynamics. Also, many researchers focus on robust adaptive control that guarantees signal boundness in the presence of modeling errors and bounded disturbances [27]. In [28] both direct and indirect approaches are presented, while in [29],[30] a combined direct and indirect control scheme is used.

Recently, [31, 32] and [33], high order neural network function approximators (HONNFs) have been used in a new neuro-fuzzy representation of unknown dynamical systems. This approximation depends on the fact that fuzzy rules could be identified with the help of HONNFs.

In adaptive fuzzy control, the identification phase usually consists of two categories: structure identification and parameter identification. Structure identification involves finding the main input variables out of all possible, specifying the membership functions, the partition of the input space and determining the number of fuzzy rules which is often based on a substantial amount of heuristic observation to express proper strategy's knowledge. Most of structure identification methods are based on data clustering, such as fuzzy Cmeans clustering [9], mountain clustering [11], and subtractive clustering [12]. These approaches require that all input-output data are ready before we start to identify the plant. So these structure identification approaches are off-line.

This paper is based on [31] and [33]. HONNFs are used for the neuro fuzzy identification of unknown nonlinear dynamical systems. Regarding the underlying Fuzzy system description of the method, the required a-priori information obtained by linguistic information or data is obtained also off-line but is very limited. The only required information is an estimate of the centers of the output fuzzy membership functions. Information on the input variable membership functions and on the underlying fuzzy rules is not necessary because this is automatically estimated by the HONNFs. This way the proposed method is less vulnerable to initial design assumptions. The parameter identification is then easily addressed by HONNFs, based on the linguistic information regarding the structural identification of the output part and from the numerical data obtained from the actual system to be modeled. So, the parameters of identification model are updated on - line in such a way that the error between the actual system output and the model output reaches zero exponentially fast.

It is assumed that the nonlinear system is affine in the control and could be approximated with the help of two independent fuzzy subsystems. Every fuzzy subsystem is approximated from a family of HONNFs, each one being related with a group of fuzzy rules. Weight updating laws are given and we prove that when the structural identification is appropriate then the error converges very fast to zero.

The paper is organized as follows. Section II presents preliminaries related to the concept of adaptive fuzzy systems (AFS) and the terminology used in the remaining paper, while Section III reports on the ability of HONNFs to act as fuzzy rule approximators. The new neuro fuzzy representation and the indirect control of affine in the control dynamical systems is introduced in Section IV, where the associated weight adaptation laws are given and the method of parameter hopping is briefly explained. Simulation results on the identification of well known benchmark problems are given in Section V and the performance of the proposed scheme is compared to another well known approach of the literature. Finally, Section VI concludes the work.

Preliminaries

In this section we briefly present the notion of adaptive fuzzy systems and their conventional representation. We are also introducing the representation of fuzzy systems using the rule firing indicator functions (RFIF), simply called indicator functions (IF), which is used for the development of the proposed method.

A. Adaptive Fuzzy Systems

The performance, complexity, and adaptive law of an adaptive fuzzy system representation can be quite different depending upon the type of the fuzzy system (Mamdani or Takagi-Sugeno). It also depends upon whether the representation is linear or nonlinear in its adjustable parameters. Suppose that the adaptive fuzzy system is intended to approximate the nonlinear function f(x). In the Mamdani type, linear in the parameters form, the following fuzzy logic representation is used [2, 3]:

$$f(x) = \sum_{l=1}^{M} \theta_l \xi_l(x) = \theta^T \xi(x), \tag{2}$$

where M is the number of fuzzy rules, $\theta(\theta_1,...,\theta_M)^T$, $\xi(x) = (\xi_1(x),...,\xi_M(x))^T$ and $\xi_l(x)$ is the fuzzy basis function defined by

$$\xi_l = \frac{\prod_{i=1}^{n} \mu_{F_i^l}(x_i)}{\sum_{l=1}^{M} \prod_{i=1}^{n} \mu_{F_i^l}(x_i)}. \tag{3}$$

θ_l are adjustable parameters, and $\mu_{F_i^l}$ are given membership functions of the input variables (can be Gaussian, triangular, or any other type of membership functions).

In Tagaki-Sugeno formulation $f(x)$ is given by

$$f(x) = \sum_{l=1}^{M} g_l(x) \xi_l(x), \tag{4}$$

where $g_l(x) = a_{l,0} + a_{l,1}x_1 + ... + a_{l,n}x_n$, with x_i, $i = 1...n$ being the elements of vector x and $\xi_l(x)$ being defined in (3). According to [3], (4) can also be written in the linear to

the parameters form, where the adjustable parameters are all $a_{l,1}, l = 1...M, i = 1...n$.

From the above definitions it is apparent in both, Mamdani and Tagaki-Sugeno forms that the success of the adaptive fuzzy system representations in approximating the nonlinear function $f(x)$ depends on the careful selection of the fuzzy partitions of input and output variables. Also,

the selected type of the membership functions and the proper number of fuzzy rules contribute to the success of the adaptive fuzzy system. This way, any adaptive fuzzy or neuro-fuzzy approach, following a linear in the adjustable parameters formulation becomes vulnerable to initial design assumptions related to the fuzzy partitions and the membership functions chosen. In this paper this drawback is largely overcome by using the concept of rule indicator functions, which are in the sequel approximated by High order Neural Network function approximators (HONNFs). This way there is not any need for initial design assumptions related to the membership values and the fuzzy partitions of the if part.

B. Fuzzy system description using rule indicator functions

Let us consider the system with input space $x \subset R^m$ and state - space $x \subset R^n$, with its i/o relation being governed by the following equation

$$z(k) = f(x(k), u(k)), \tag{5}$$

where $f(\cdot)$ is a continuous function and k denotes the temporal variable. In case the system is dynamic the above equation could be replaced by the following differential equation

$$\dot{x}(k) = f(x(k), u(k)). \tag{6}$$

By setting $y(k) = [x(k), u(k)]$, Eq. (5) may be rewritten as follows

$$z(k) = f(y(k)), \tag{7}$$

with $y \subset R^{m+n}$.

In case f in (7) is unknown we may wish to approximate it by using a fuzzy representation. In this case both $y(k) = [x(k), u(k)]$ and $z(k)$ are initially replaced by fuzzy linguistic variables. Experts or data depended techniques may determine the form of the membership functions of the fuzzy variables and fuzzy rules will determine the fuzzy relations between $y(k)$ and $u(k)$. Sensor input data, possibly noisy and imprecise, enter the fuzzy system, are fuzzified, are processed by the fuzzy rules and the fuzzy implication engine and are in the sequel defuzzified to produce the estimated $z(k)$ [2, 3]. We assume here that a Mamdani type fuzzy system is used.

Let now $\Omega^{l_1,l_2,\ldots,l_n}_{j_1,j_2,\ldots,j_{n+m}}$ be defined as the subset of (x,u) pairs, belonging to the $(j_1, j_2, \ldots, j_{n+m})^{th}$ input fuzzy patch and pointing - through the vector field $f(\cdot)$ - to the subset of $z(k)$, which belong to the $(j_1, j_2, \ldots, j_{n+m})^{th}$ output fuzzy patch. In other words, $\Omega^{l_1,l_2,\ldots,l_n}_{j_1,j_2,\ldots,j_{n+m}}$ contains input value pairs that are associated through a fuzzy rule with output values.

In order to present the lemma of Section III, we define the Indicator function (IF) $I^{l_1,l_2,\ldots,l_n}_{j_1,j_2,\ldots,j_{n+m}}$ of the subset $\Omega^{l_1,l_2,\ldots,l_n}_{j_1,j_2,\ldots,j_{n+m}}$, that is,

$$I^{l_1,l_2,\ldots,l_n}_{j_1,j_2,\ldots,j_{n+m}}(x(k),u(k)) = \begin{cases} \alpha & if\,(x(k),u(k)) \in \Omega^{l_1,\ldots,l_n}_{j_1,\ldots,j_{n+m}} \\ 0 & otherwise \end{cases} \tag{8}$$

where α denotes the firing strength of the rule.

Define now the following system

$$z(k) = \sum \bar{z}_{j_1,\ldots,j_{n+m}}^{l_1,\ldots,l_n} \times I_{j_1,j_2,\ldots,j_{n+m}}^{l_1,l_2,\ldots,l_n}(\mathrm{x(k),u(k)}), \tag{9}$$

where $\bar{z}_{j_1,\ldots,j_{n+m}}^{l_1,\ldots,l_n} \in R^n$ be any constant vector consisting of the centers of the membership functions of each output variable z_i and $I_{j_1,\ldots,j_{n+m}}^{l_1,\ldots,l_n}(x(k),u(k))$ is the IF of (8) normalized by the sum of all IF participating in the summation of (9). Then, the system in (9) represents the fuzzy system (FS). It is obvious that Eq. (9) can be also valid for dynamic systems. In its dynamical form it becomes

$$\dot{x}(k) = \sum \bar{z}_{j_1,\ldots,j_{n+m}}^{l_1,\ldots,l_n} \times I_{j_1,j_2,\ldots,j_{n+m}}^{l_1,l_2,\ldots,l_n}(\mathrm{x(k),u(k)}), \tag{10}$$

where $\bar{x}_{j_1,\ldots,j_{n+m}}^{l_1,\ldots,l_n} \in R^n$ be again any constant vector consisting of the centers of fuzzy partitions of every variable x_i and $I_{j_1,\ldots,j_{n+m}}^{l_1,\ldots,l_n}(x(k),u(k))$ is the IF.

The HONNF's as fuzzy rule approximators

The main idea in presenting the main result of this section lies on the fact that functions of high order neurons are capable of approximating discontinuous functions; thus, we use high order neural network functions in order to approximate the indicator functions $I_{j_1,\ldots,j_{n+m}}^{l_1,\ldots,l_n}$. The relevant assumptions and proofs that make this approximation valid can be found in [31]. Here, only the definitions of HONNFs are given.

Let us define the following high order neural network functions (HONNFs).

$$N(x,u;w,L) = \sum_{k=1}^{L} w_k \prod_{j \in I_k} \Phi_j^{d_j(k)}, \tag{11}$$

where $\{I_1, I_2, \ldots, I_L\}$ is a collection of L not-ordered subsets of $\{1,2,\ldots,m+n\}$, $d_j(k)$ are non-negative integers, Φ_j are sigmoid functions of the state or the input and $w := [w_1 \ldots w_L]^T$ are the HONNF weights. Eq. (11) can also be written

$$N(x,u;w,L) = \sum_{k=1}^{L} w_k s_k(x,u), \tag{12}$$

where $s_k(x,u)$ are high order terms of sigmoid functions of the state and/or input.

It has been proved [31] that a HONNF of the form in Eq. (12) can approximate the indicator function $I_{j_1,\ldots,j_{n+m}}^{l_1,\ldots,l_n}$.

Indirect adaptive neuro-fuzzy control

A. Neuro fuzzy representation and identification

We consider affine in the control, nonlinear dynamical systems of the form

$$\dot{x} = f(x) + G(x) \cdot u, \tag{13}$$

where the state $x \in R^n$ is assumed to be completely measured, the control u is in R^n, f is an unknown smooth vector field called the drift term and G is a matrix with columns the unknown

smooth controlled vector fields $g_i, i=1,2,...,n$ and $G=[g_1, g_2,...,g_n]$. The above class of continuous-time nonlinear systems are called affine, because in (13) the control input appears linear with respect to G. The main reason for considering this class of nonlinear systems is that most of the systems encountered in engineering, are by nature or design, affine. Furthermore, we note that non affine systems of the form given in (1) can be converted into affine, by passing the input through integrators, a procedure known as dynamic extension.

In our approach, referred to as *indirect adaptive fuzzy-HONNF control*, the plant parameters are estimated on-line except of the state fuzzy partitions, which are used to calculate the controller parameters. The basic structure of the *indirect adaptive fuzzy-RHONN controller* is shown in Figure 1.

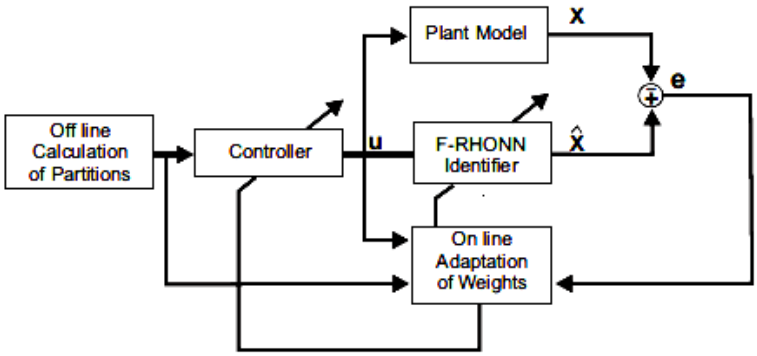

Fig. 1. Overall scheme of the proposed indirect adaptive neuro-fuzzy control system.

The following mild assumptions are also imposed on (13), to guarantee the existence and uniqueness of solution for any finite initial condition and $u \in U$.

Proposition 1: Given a class U of admissible inputs, then for any $u \in U$ and any finite initial condition, the state trajectories are uniformly bounded for any finite $T > 0$. Hence, $|x(T)| < \infty$.

Proposition 2: The vector fields $f, g_i, i=1,2,...,n$ are continuous with respect to their arguments and satisfy a local Lipchitz condition so that the solution $x(t)$ of (13) is unique for any finite initial condition and $u \in U$.

We are using an affine in the control fuzzy dynamical system, which approximates the system in (13) and uses two fuzzy subsystem blocks for the description of $f(x)$ and $G(x)$ as follows

$$f(\chi) = A\chi + \sum \bar{f}_{j_1,...,j_n}^{l_1,...,l_n} \times I_{j_1,...,j_n}^{l_1,...,l_n}(\chi), \tag{14}$$

$$g_i(\chi) = \sum (\bar{g}_i)_{j_1,...,j_n}^{l_1,...,l_n} \times I_{1\,j_1,...,j_n}^{l_1,...,l_n}(\chi), \tag{15}$$

where the summation is carried out over the number of all available fuzzy rules, I, I_1 are appropriate fuzzy rule indicator functions and the meaning of indices $\bullet_{j_1,...,j_n}^{l_1,...,l_n}$ has already been described in *Preliminaries*.

According to [31], every indicator function can be approximated with the help of a suitable HONNF. Therefore, every I, I_1 can be replaced with a corresponding HONNF as follows

$$f(\chi) = A\chi + \sum \bar{f}_{j_1,...,j_n}^{l_1,...,l_n} \times N_{j_1,...,j_n}^{l_1,...,l_n}(\chi), \tag{14}$$

$$\bar{g}_i(\chi) = \sum(\bar{g}_i)_{j_1,\ldots,j_n}^{l_1,\ldots,l_n} \times N_{1\,j_1,\ldots,j_n}^{l_1,\ldots,l_n}(\chi)\,, \tag{15}$$

where N, N_1 are appropriate HONNFs.

In order to simplify the model structure, since some rules result to the same output partition, we could replace the NNs associated to the rules having the same output with one NN and therefore the summations in (16),(17) are carried out over the number of the corresponding output partitions. Therefore, the affine in the control fuzzy dynamical system in (14), (15) is replaced by the following equivalent affine Recurrent High Order Neural Network (RHONN), which depends on the centers of the fuzzy output partitions $\bar{f}_l$ and $\bar{g}_{i,l}$

$$\dot{\hat{\chi}} = A\hat{\chi} + \sum_{l=1}^{Npf} \bar{f} \times N_l(\chi) + \sum_{i=1}^{n}\Big(\sum_{l=1}^{Npg_i}(\bar{g}_i)_l \times N_{1l}(\chi)\Big)u_i\,, \tag{18}$$

or in a more compact form

$$\dot{\hat{\chi}} = A\hat{\chi} + XWS(\chi) + X_1W_1S_1(\chi)u\,, \tag{19}$$

where A is a $n \times n$ stable matrix which for simplicity can be taken to be diagonal as $A = diag[a_1, a_2, \ldots, a_n], X, X_1$ are matrices containing the centres of the partitions of every fuzzy output variable of $f(x)$ and $g(x)$ respectively, $S(\chi), S_1(\chi)$ are matrices containing high order combinations of sigmoid functions of the state χ and W, W_1 are matrices containing respective neural weights according to (18) and (12). The dimensions and the contents of all the above matrices are chosen so that $XWS(\chi)$ is a $n \times l$ vector and $X_1W_1S_1(\chi)$ is a $n \times n$ matrix. Without compromising the generality of the model we assume that the vector fields in (15) are such that the matrix G is diagonal. For notational simplicity we assume that all output fuzzy variables are partitioned to the same number, m, of partitions. Under these specifications X is a $n \times n \cdot m$ block diagonal matrix of the form $X = diag(X^1, X^2, \ldots, X^n)$ with each X^i being an m-dimensional raw vector of the form

$$X^i = [\bar{f}_1^i \;\; \bar{f}_2^i \ldots \bar{f}_m^i],$$

where $\bar{f}_p^i$ denotes the centre of the p-th partition of f_i. Also, $S(\chi) = [s_1(\chi) .. s_k(\chi)]^T$, where each $s_i(\chi)$ with $i = \{1,2,\ldots,k\}$, is a high order combination of sigmoid functions of the state variables and W is a $n \cdot m \times k$ matrix with neural weights. W assumes the form $W = [W^1 ... W^n]^T$, where each W^i is a matrix $[w_{jl}^i]_{m \times k}$. X_1 is a $n \times n \cdot m$ block diagonal matrix $X_1 = diag({}^1X^1, {}^1X^2, \ldots, {}^1X^n)$ with each ${}^1X^i$ being an m-dimensional raw vector of the form

$${}^1X^i = [\bar{g}_1^{i,i} \;\; \bar{g}_2^{i,i} \ldots \bar{g}_m^{i,i}],$$

where $\bar{g}_k^{ii}$ denotes the center of the k-th partition of g_{ii}. W_1 is a $m \cdot n \times n$ block diagonal matrix $W_1 = diag({}^1W^1, {}^1W^2, \ldots, {}^1W^n)$, where each ${}^1W^i$ is a column vector $[{}^1w_{jl}^i]_{m \times 1}$ of neural weights. Finally, $S_1(\chi)$ is a $n \times n$ diagonal matrix with each diagonal element $s_i(\chi)$ being a high order combination of sigmoid functions of the state variables.

It has to be mentioned here that the proposed neurofuzzy representation, finally given by (19), offers some advantages over other fuzzy or neural adaptive representations. Considering the proposed approach from the adaptive fuzzy system (AFS) point of view, the main advantage is that the proposed approach is much less vulnerable in initial AFS design assumptions because there is no need for apriori information related to the IF part of the rules (type and centers of

membership functions, number of rules). This information is replaced by the existence of HONNFs. Considering the proposed approach from the NN point of view, the final representation of the dynamic equations is actually a combination of High Order Neural Networks, each one being specialized in approximating a function related to a corresponding center of output state membership function. This way, instead of having one large HONNF trying to approximate ”everything” we have many, probably smaller, specialized HONNFs. Conceptually, this strategy is expected to present better approximation results; this is also verified in the simulations section. Moreover, as it will be seen in section IV-C, due to the particular bond of each HONNF with one center of an output state membership function, the existence of the control law is assured by introducing a novel technique of parameter ”hopping” in the corresponding weight updating laws.

B. Parametric uncertainty

We assume the existence of only parameter uncertainty, so, we can take into account that the actual system (13) can be modeled by the following neural form

$$\dot{\chi} = A\chi + XW * S(\chi) + X_1 W_1 * S_1(\chi)u \,. \tag{20}$$

Define now, the error between the identifier states and the real states as

$$e = \hat{\chi} - \chi \,. \tag{21}$$

Then from (19) and (21) we obtain the error equation

$$\dot{e} = Ae + X\tilde{W}S(\chi) + X_1\tilde{W}_1 S_1(\chi)u \,, \tag{22}$$

where $\tilde{W} = W - W*$ and $\tilde{W}_1 = W_1 - W_1^*$.

Our objective is to find suitable control and learning laws to drive both e and χ to zero, while all other signals in the closed loop remain bounded. Taking u to be equal to

$$u = -[X_1 W_1 S_1(\chi)]^{-1} XWS(\chi) \,, \tag{23}$$

and substituting it into (19) we finally obtain

$$\dot{\hat{\chi}} = A\hat{\chi} \tag{24}$$

In the next theorem the weight updating laws are given, which can serve both the identification and the control objectives provided that the updating of the weights of matrix W_1 is performed so that the existence of $[X_1 W_1 S_1(\chi)]^{-1}$ is assured.

Theorem 1: Consider the identification scheme given by (22). Provided that $[X_1 W_1 S_1(\chi)]^{-1}$ exists the learning law

a) For the elements of W^i

$$\dot{w}_{jl}^i = -\bar{f}_j^i p_i e_i s_l(\chi) \,; \tag{25}$$

b) For the elements of ${}^1W^i$

$${}^1\dot{w}_{j1}^i = -\bar{g}_j^{ii} p_i e_i u_i s_i(\chi) \,; \tag{26}$$

or equivalently ${}^1\dot{W}^i = -({}^1X^i)^T p_i e_i u_i s_i(\chi)$ with $i = 1,\ldots,n$, $j = 1,\ldots,m$, $l = 1,\ldots,k$ guarantees the following properties.

- $e, \hat{\chi}, \tilde{W}, \tilde{W}_1 \in L_\infty$, $\quad e, \hat{\chi} \in L_2$;
- $\lim_{t\to\infty} e(t) = 0$, $\lim_{t\to\infty} \hat{\chi}(t) = 0$;
- $\lim_{t\to\infty} \dot{\tilde{W}}(t) = 0$, $\lim_{t\to\infty} \dot{\tilde{W}}_1(t) = 0$.

Proof: Consider the Lyapunov function candidate

$$V(e, \hat{\chi}, \tilde{W}, \tilde{W}_1) = \frac{1}{2} e^T P e + \frac{1}{2} \hat{\chi}^T P \hat{\chi} + \frac{1}{2} tr\{\tilde{W}^T \tilde{W}\} + \frac{1}{2} tr\{\tilde{W}_1^T \tilde{W}_1\},$$

where $P > 0$ is chosen to satisfy the Lyapunov equation

$$PA + A^T P = -I .$$

Taking the derivative of the Lyapunov function candidate and taking into account (24) we get

$$\dot{V} = \frac{1}{2} e^T \left(A^T P + PA\right) e + \frac{1}{2} \hat{\chi}^T \left(A^T P + PA\right) \hat{\chi} + \left(\frac{1}{2} e^T PX\tilde{W}S + \frac{1}{2} e^T PX\tilde{W}S\right) +$$

$$+ \left(\frac{1}{2} e^T PX_1 \tilde{W}_1 S_1 u + \frac{1}{2} e^T PX_1 \tilde{W}_1 S_1 u\right) + tr\{\dot{\tilde{W}}_1^T \tilde{W}\} + tr\{\dot{\tilde{W}}_1^T \tilde{W}_1\} \Rightarrow$$

$$\Rightarrow \dot{V} = -\frac{1}{2} e^T e - \frac{1}{2} \hat{\chi}^T \hat{\chi} + e^T PX\tilde{W}S + e^T PX_1 \tilde{W}_1 S_1 u + tr\{\dot{\tilde{W}}^T \tilde{W}\} + tr\{\dot{\tilde{W}}_1^T \tilde{W}_1\} \Rightarrow$$

$$\Rightarrow \dot{V} = -\frac{1}{2} e^T e - \frac{1}{2} \hat{\chi}^T \hat{\chi} \le 0$$

when

$$tr\{\dot{\tilde{W}}^T \tilde{W}\} = -e^T PX\tilde{W}S ,$$

$$tr\{\dot{\tilde{W}}_1^T \tilde{W}_1\} = -e^T PX_1 \tilde{W}_1 S_1 u .$$

Then, taking into account the form of W and W_1 the above equations result in the element wise learning laws given in (25),(26). These laws can also be written in the following compact form

$$\dot{W} = -X^T PeS^T , \tag{27}$$

$$\dot{W}_1 = -X_1^T PEUS_1^T , \tag{28}$$

where E and U are diagonal matrices such that $E = diag(e_1, ..., e_n)$ and $U = diag(u_1, ..., u_n)$.

Using the above Lyapunov function candidate V and proving that $V \le 0$ all properties of the theorem are assured [23].

Remark 1: The control law (23) can be also extended to the following form

$$u = -[X_1 W_1 S_1(\chi)]^{-1} [XWS(\chi) + kx], \tag{29}$$

where k is appropriate positive definite diagonal gain matrix. It can be easily verified that with this control law the negativeness of the derivative of the Lyapunov function is further enhanced. Therefore, term kx is actually acting as a robustifying term.

Proof: Indeed, by using the extended control law (29) the state estimate dynamics become

$$\dot{\hat{\chi}} = A\hat{\chi} - kx . \tag{30}$$

Then, using the weight updating laws given in theorem 1 the derivative of the Lyapunov function becomes

$$\dot{V} = -\frac{1}{2}e^T e - \frac{1}{2}\hat{\chi}^T \hat{\chi} - xKP\hat{\chi} \Rightarrow \dot{V} = -\frac{1}{2}\|e\|^2 - \frac{1}{2}\|\hat{x}\|^2 - \hat{x}^T KP\hat{\chi} + e^T KP\hat{x}$$

$$\Rightarrow \dot{V} \le -\frac{1}{2}\|e\|^2 - \frac{1}{2}\|\hat{x}\|^2 - \lambda_{\min}(KP)\|\hat{x}\|^2 + \|e\|\,\|KP\|\,\|\hat{\chi}\|$$

$$= -[\|e\|\,\|\hat{\chi}\|]\begin{bmatrix} 1/2 & -\|KP\| \\ 0 & 1/2 + \lambda_{\min}(KP) \end{bmatrix}\begin{bmatrix} \|e\| \\ \|\hat{\chi}\| \end{bmatrix} < 0$$

C. Introduction to the parameter hopping

The weight updating laws presented previously in subsection B are valid when the control law signal in (23) exists. Therefore, the existence of $[X_1 W_1 S_1(\chi)]^{-1}$ has to be assured. Since $S_1(\chi)$ is diagonal with its elements $s_i(\chi) \neq 0$ and X_1, W_1 are block diagonal the existence of the inverse is assured when ${}^1X^i \cdot {}^1W^i \neq 0, \forall \mathrm{i} = 1,...,\mathrm{n}$. Therefore, W_1 has to be confined such that $\left|{}^1X^i \cdot {}^1W^i\right| \ge \theta_i > 0$, with θ_i being a design parameter. In case the boundary defined by the above confinement is nonlinear the updating W_1 can be modified by using a projection algorithm [23]. However, in our case the boundary surface is linear and the direction of updating is normal to it because $\nabla[{}^1X^i \cdot {}^1W^i] = {}^1X^i$. Therefore, the projection of the updating vector on the boundary surface is of no use. Instead, using concepts from multidimensional vector geometry we modify the updating law such that, when the weight vector approaches (within a safe distance θ_i) the forbidden hyper-plane ${}^1X^i \cdot {}^1W^i = 0$ and the direction of updating is toward the forbidden hyper-plane, it introduces a hopping which drives the weights in the direction of the updating but on the other side of the space, where here the weight space is divided into two sides by the forbidden hyper-plane. This procedure is depicted in Figure 2, where a simplified 2-dimensional representation is given. Theorem 2 below introduces this hopping in the updating law.

Theorem 2: Consider the control scheme (22), (23), (24).

The updating law:

a) For the elements of W^i given by (25)

b) For the elements of ${}^1W^i$ given by the modified form:

$${}^1\dot{W}^i = -({}^1X^i)^T p_i e_i u_i s_i(\chi) \quad if \left|{}^1X^i \cdot {}^1W^i\right| > \theta_i > 0,$$

$$or \left|{}^1X^i \cdot {}^1W^i\right| = \theta_i \; and \; {}^1X^i \cdot {}^1W^i \le 0,$$

$${}^1\dot{W}^i = -({}^1X^i)^T p_i e_i u_i s_i(\chi) - \frac{2}{tr\{({}^1X^i)^T\,{}^1X^i\}}\,{}^1X^i\,{}^1W^i\,({}^1X^i)^T,$$

otherwise guarantees the properties of theorem 1 and assures the existence of the control signal.

Proof: In order the properties of theorem 1 to be valid it suffices to show that by using the modified updating law for ${}^1W^i$ the negativeness of the Lyapunov function is not compromised.

Indeed the ***if*** part of the modified form of ${}^1W^i$ is exactly the same with (26) and therefore according to theorem 1 the negativeness of V is in effect. The ***if*** part is used when the weights are at a certain distance (condition if $\left|{}^1X^i \cdot {}^1W^i\right| > \theta_i$) from the forbidden plane or at the safe limit (condition $\left|{}^1X^i \cdot {}^1W^i\right| = \theta_i$) but with the direction of updating moving the weights far from the forbidden plane (condition ${}^1X^i \cdot {}^1W^i \le 0$).

In the ***otherwise*** part of ${}^1W^i$, term $-\dfrac{2}{tr\{({}^1X^i)^T\ {}^1X^i\}}\ {}^1X^i\ {}^1W^i\ ({}^1X^i)^T$ determines the magnitude of weight hopping, which as explained later and is depicted in Figure 3 has to be two times the distance of the current weight vector to the forbidden hyper-plane. Therefore the ***existence*** of the control signal is assured because the weights never reach the forbidden plane. Regarding the ***negativeness*** of $\dot{V}$ we proceed as follows.

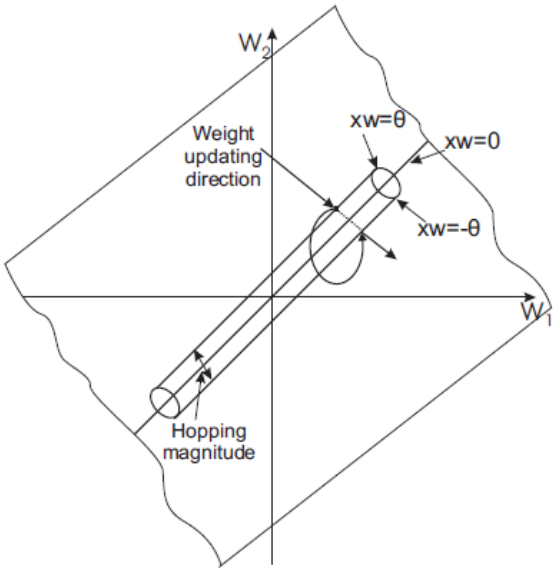

Fig. 2. Pictorial representation of parameter hopping.

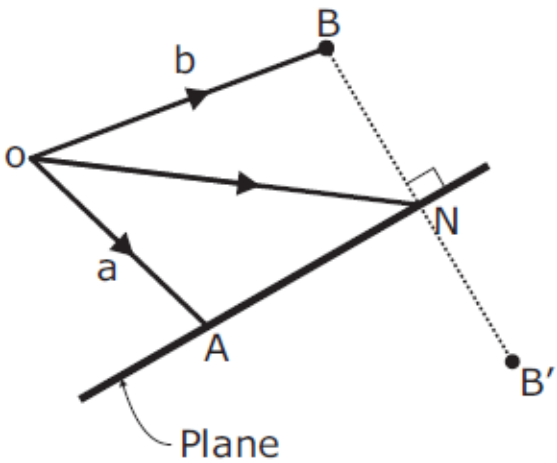

Fig. 3. Vector explanation of parameter hopping.

Let that ${}^1W^{*i}$ contains the initial values of ${}^1W^i$ provided from the identification part such that $\left|{}^1X^i \cdot {}^1W^{*i}\right| >> \theta_i$ and that ${}^1\tilde{W}^i = {}^1W^i - {}^1W^{*i}$. Then, the weight hopping can be equivalently written with respect to ${}^1\tilde{W}^i$ $as - 2\theta_i\, {}^1\tilde{W}^i / \left\|{}^1\tilde{W}^i\right\|$. Under this consideration the modified updating law is rewritten as ${}^1\dot{W}^i = -({}^1X^i)^T p_i e_i u_i s_i(\chi) - 2\theta_i\, {}^1\tilde{W}^i / \left\|{}^1\tilde{W}^i\right\|$. With this updating law it can be easily verified that $\dot{V} = -\frac{1}{2}e^T e - \frac{1}{2}\hat{\chi}^T \hat{\chi} - \Theta$, with Θ being a positive constant expressed as $\Theta = \sum 2\theta_i \left(({}^1\tilde{W}^i)^T ({}^1\tilde{W}^i)\right) / \left\|{}^1\tilde{W}^i\right\|$, where the summation includes all weight vectors which require hopping. Therefore, the negativeness of $\dot{V}$ is actually enhanced.

1) Vectorial proof of parameter hopping: In selecting the terms involved in parameter hopping we start from the vector definition of a line, of a plane and the distance of a point to a plane. The equation of a line in vector form is given by $r = a + \lambda t$, where a is the position vector of a given point of the line, t is a vector in the direction of the line and λ is a real scalar. By giving different numbers to λ we get different points of the line each one represented by the corresponding position vector r. The vector equation of a plane can be defined by using one

point of the plane and a vector normal to it. In this case $r \cdot n = a \cdot n = d$ is the equation of the plane, where a is the position vector of a given point on the plane, n is a vector normal to the plane and d is a scalar. When the plane passes through zero, then apparently $d = 0$. To determine the distance of a point B with position vector b from a given plane we consider Figure 3 and combine the above definitions as follows. Line BN is perpendicular to the plane and is described by vector equation $r = b + \lambda n$, where n is the normal to the plane vector. However, point N also lies on the plane and in case the plane passes through zero

$$r \cdot n = 0 \Rightarrow (b + \lambda n) \cdot n = 0 \Rightarrow \lambda = \frac{-b \cdot n}{\|n\|}.$$

Apparently, if one wants to get the position vector of B' (the symmetrical of B in respect to the plane), this is given by

$$r = b - 2\frac{b \cdot n}{\|n\|} n.$$

In our problem $b = {}^1W^i$, our plane is described by the equation ${}^1X^i \cdot {}^1W^i = 0$ and as it has already been mentioned the normal to it is the vector ${}^1X^i$.

Simulation results

To demonstrate the potency of the proposed scheme some simulations are presented. First, the function approximation abilities of the proposed technique are compared with those of a well established approach of adaptive fuzzy system definition for function approximation (see Eq. (2)). The simulations are carried out on the approximation of a nonlinear function appearing in the inverted pendulum benchmark problem. The full potential of the method in both approximation and control is demonstrated in the next simulation, where the proposed method is compared with the well known RHONN approach [35] in approximating and regulating a DC Motor described by nonlinear equations. In this case both modeling approaches assume a generic affine in the control form.

A. Comparison of function approximation abilities

Let $f(x)$ the function to be approximated, which assumes the following form

$$f(x_1, x_2) = \frac{g \sin x_1 - \dfrac{m l x_2^2 \cos x_1 \sin x_1}{m_C + m}}{l\left(\dfrac{4}{3} - \dfrac{m \cos^2 x_1}{m_C + m}\right)}. \tag{31}$$

This function appears in the well known problem of the control of an inverted pendulum [34]. $x_1 = \theta$ and $x_2 = \dot{\theta}$ are the angle from the vertical position and the angular velocity respectively of the pole. Also, $g = 9.8 m/s^2$ is the acceleration due to gravity, m_c is the mass of the cart, m is the mass of the pole, and l is the half-length of the pole. We choose $m_c = 1kg$, $m = 0.1kg$, and $l = 0.5m$ in the following simulation. In this case we also have that $|x_1| \le \pi/6$ and $|x_2| \le \pi/6$.

It is our intention to compare the approximation abilities of the proposed Neuro-Fuzzy approach with Wang [2] adaptive Fuzzy approach. To this end we assume that $f(x)$ can be approximated

using Wang's approach and Eq. (2) or alternatively by the XWS term of Eq. (19) in the proposed approach. The weight updating laws are chosen to be: For the Wang approach ([2], page 115)

$$\dot{\theta}_f = -\gamma_1 e^T P b_c \xi(x), \tag{32}$$

where only the simplified approach, without parameter projection case was necessary to be used.

For the proposed F-HONNF approach the following adaptive law is used:

$$\dot{W} = -X^T P e S^T \tag{33}$$

The experimental data were obtained as follows: Based on Wang's input variables limits and fuzzy partition we created an artificial stair-like signal shown in Figure 5. Input variables x_1 and x_2 assume values in the interval $[-\pi/6, \pi/6]$.

Taking 5 samples from x_1 and 100 samples from x_2 we obtain 500 samples of $f(x_1, x_2)$ presenting the stair discontinuities when x_1 changes values. For the construction of ξ_i functions used in Eq. (2) and given in Eq. (3) we used the fuzzy membership partitions and the final rules characterizing $f(x_1, x_2)$ and shown in Figure 4, which comprises 25 fuzzy rules carefully chosen and given by Wang in [2] (page 129). Under these design specifications Eq. (2) assumes 25 adjustable weights.

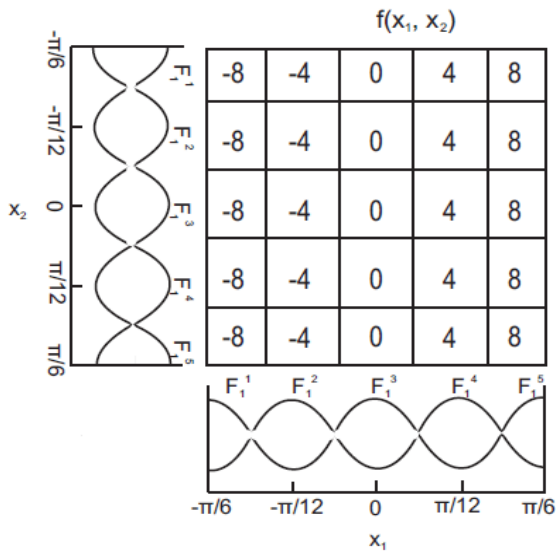

Fig. 4. Linguistic fuzzy rules for $f(x_1,x_2)$.

In order our model to be equivalent with regard to adjustable parameters we have chosen 5 centers for the fuzzy output variables partition (-8, -4, 0, 4, 8) and 5 high order sigmoidal terms $(s(x_1), s(x_2), s(x_1)\cdot s(x_2), s^2(x_1), s^2(x_2))$ in each HONNF. This configuration also assumes 25 adjustable weights. Terms $\gamma_1 P b_c$ in Eq. (32) and P (the updating learning rates) in Eq. (33) were chosen to have the same values. Figure 5 shows the approximation abilities of (2) with the updating law of (32) while Figure 6 shows the performance of the proposed approach with the updating law of (33). The mean squared error (MSE) for Wang's approach was measured to be $6.24\cdot 10^{-4}$, while for the proposed approach was $1.25\cdot 10^{-5}$, demonstrating a significant (order of magnitude) increase in the approximation performance, although in our approach no a-priori information regarding the inputs were used.

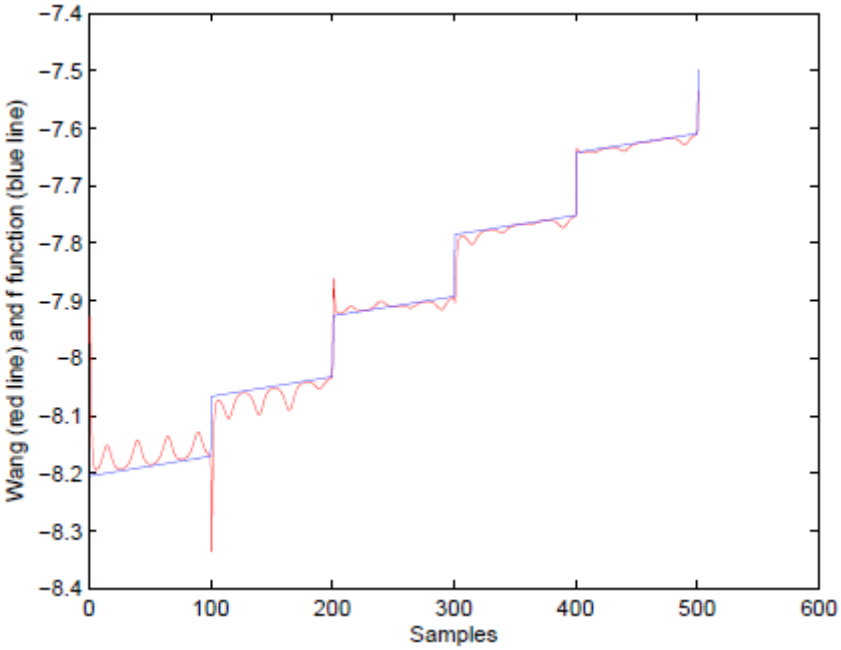

Fig. 5. Approximation of the f function with Eq. (2).

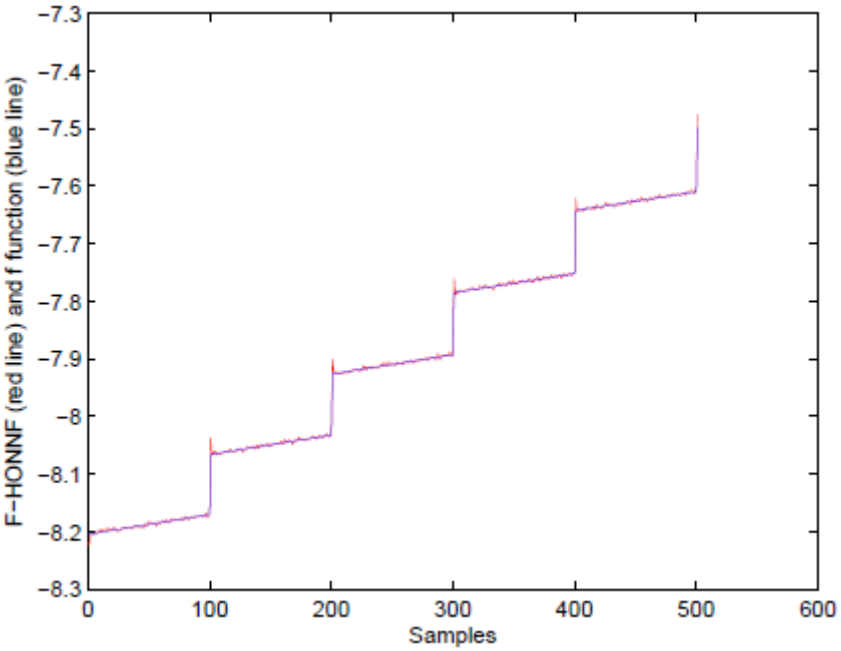

Fig. 6. Approximation of the f function with the proposed approach.

B. DC Motor Identification and Control

In this section we present simulations, where the proposed approach is applied to solve the problem of controlling the speed of a 1 KW DC motor with a normalized model described by the following dynamical equations [35].

Table 1. Parameter values for the DC motor

Parameter	Value
$1/T_a$	148.88
$1/T_m$	42.91
K_0/T_m	0.0129
T_f	31.88
T_L	0.0
α	2.6
β	1.6

$$
\begin{aligned}
T_a \frac{dI_a}{dt} &= -I_a - \Phi\Omega + V_a, \\
T_m \frac{d\Omega}{dt} &= \Phi I_a - K_0\Omega - mL, \\
T_f \frac{d\Phi}{dt} &= -I_f + V_f, \\
\Phi &= \frac{a I_f}{1 + b I_f}.
\end{aligned}
\tag{34}
$$

The states are chosen to be the armature current, the angular speed and the stator flux $x = [I_a \;\; \Omega \;\; \Phi]^T$. As control inputs the armature and the field voltages $x = [V_a \;\; V_f]^T$ are used.

With this choice, we have

$$
\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} -\frac{1}{T_a} x_1 - \frac{1}{T_a} x_2 x_3 \\ \frac{1}{T_m} x_1 x_3 - \frac{K_0}{T_m} x_2 - \frac{m_L}{T_m} \\ -\frac{1}{T_f} \frac{x_3}{a - \beta x_3} \end{bmatrix} + \begin{bmatrix} \frac{1}{T_a} & 0 \\ 0 & 0 \\ 0 & \frac{1}{T_f} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix},
\tag{35}
$$

which is of a nonlinear, affine in the control form. The regulation problem of a DC motor is translated as follows: Find a state feedback to force the angular velocity and the armature current to go to zero, while the magnetic flux varies.

When Φ is considered constant, the above nonlinear 3rd order system can be linearized and reduced to a second order form having 2 states ($x_1 = I_a$ and $x_2 = \Omega$), with the value Φ being included as a constant parameter. Inspired by that, we first assume that the system is described, within a degree of accuracy, by a 2nd order (n = 2) nonlinear neuro-fuzzy system of the form (19), where $x_1 = I_a$ and $x_2 = \Omega$. Coefficients a_i in matrix A of (19) were chosen to be $a_i = 15$. The number of fuzzy partitions in X was chosen to be $m = 5$ and the range of $f_1[-182.5667, 0]$, $f_2[-19.3627, 30.0566]$. The depth of high order terms was $k = 2$ (only first order sigmoidal terms $S(x_1), S(x_2)$ were used). The number of fuzzy partitions of each

g_{ii} in X_1 is $m=1$ and the range of g_{11} is $[148,150]$ and of g_{22} is $[42,44]$. The parameters of the sigmoidals that have been used are $\alpha_1=0.4$, $\alpha_2=5$, $\beta_1=\beta_2=1$ and $\gamma_1=\gamma_2=0$. In the simulations carried out, the actual system is simulated by using the complete set of equations (35). The produced control law (23) is applied on this system, which in turn produces states x_1, x_2, which in the sequel are used for the computation of the estimation errors that are employed by the updating laws.

We simulated a 1KW DC motor with parameter values that can be seen in Table 1. Our two stage algorithm was applied.

For comparison purposes we test the identification abilities of the proposed F-HONNF model against the conventional RHONN approximator presented in [35] using equivalent parameters regarding learning rate and number of high order terms used. Figure 7 shows the performance of the proposed scheme (blue line) against the corresponding performance of RHONN (red line). In the embedded figure a detailed comparison between the two methods for the first iterations is presented, where the graph is adjusted to the scale of the lower error values (those of the F-HONNF model). The mean square error (MSE) was measured to be $5.87*10^{-5}$ for the proposed scheme and $1.18*10^{-2}$ for RHONN showing that the proposed scheme performs much better.

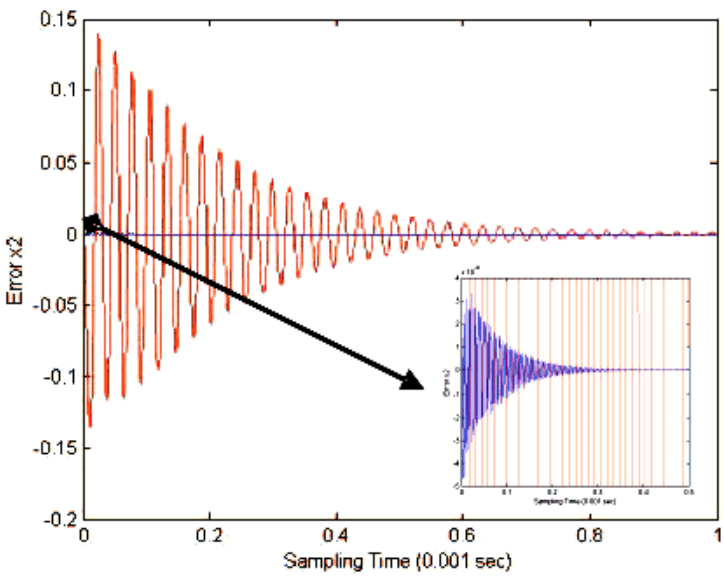

Fig. 7. Evolution of e_2.

In the control phase, we assumed that the system variables have the initial values $\Omega=0.1$, $I_a=0.1$, $\Phi=0.98$. The proposed feedback control law and the corresponding control law of [35] were applied, with the corresponding initial weight values resulted from the identification phase. Figures 8, 9 give the evolution of the angular velocity and armature current respectively, for F-HONNF (blue line) and RHONN (red line). As can be seen, both Ω and I_a converge to zero very fast as desired and the corresponding mean squared errors are 0.0017 and 0.0135 for x_1 (F-HONNF Vs RHONN approach) and 0.0013 and 0.0094 for x_2 (F-HONNF Vs RHONN approach), demonstrating a significant improvement when the proposed method is used.

Conclusion

A new neuro-fuzzy approach for the identification and control of unknown non linear plants was presented in this paper. The approach uses the concept of Adaptive Fuzzy Systems (AFS) operating in conjunction with High Order Neural Network Functions (F-HONNFs). Compared to other neuro-fuzzy approaches of the literature, the proposed scheme does not require a-priori experts' information on the number and type of input variable membership functions making it less vulnerable to initial design assumptions. Weight updating laws for the involved HONNFs were provided, which guarantee that both the identification error and the system states reach zero exponentially fast, while keeping all signals in the closed loop bounded. A method of parameter hopping assures the existence of the control signal and is incorporated in the weight updating law.

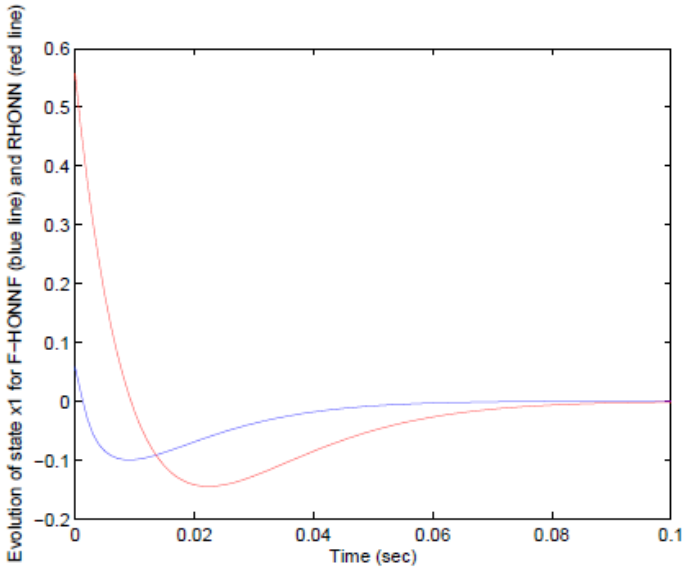

Fig. 8. Convergence of the angular velocity to zero from 0.1 initially.

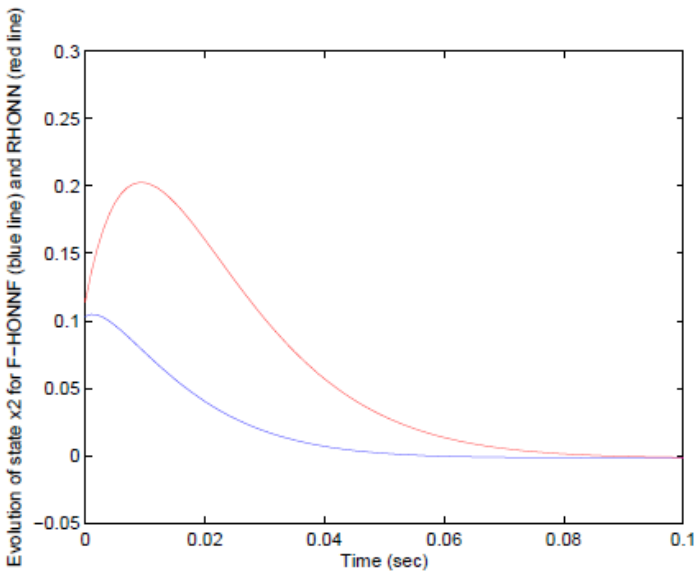

Fig. 9. Convergence of the armature current to zero from 0.1 initially.

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Noi tendinţe în identificarea şi conducerea sistemelor neuro-fuzzy

Rezumat

În acest articol se introduce o definiţie nouă a sistemelor dinamice neuro-fuzzy, folosind conceptul de sistem fuzzy dinamic (FDS) în conjuncţie cu noţiunea de funcţii neuronale de ordin superior (F-HONNF). Se presupune că sistemul dinamic este neliniar şi în întregime necunoscut. Se propune mai întâi aproximarea lui cu ajutorul unei forme speciale de sistem fuzzy dinamic (FDS) iar regulile fuzzy sunt aproximate prin HONNF potrivite. Astfel, schema de identificare conduce la o reţea neuronală recurentă de ordin superior care, totuşi, ia în considerare partiţiile ieşirii fuzzy a sistemului FDS initial. Schema propusă nu necesită informaţie apriori despre numărul şi tipul funcţiilor de apartenenţă pentru variabilele de intrare, fiind mai puţin vulnerabilă la presupunerile iniţiale de proiectare. După procesul de identificare sistemul poate fi controlat în mod adaptiv direct sau indirect. În articol este luat în considerare controlul indirect şi sunt prezentate regulile folosite la actualizarea ponderilor HONN. Demonstraţiile riguroase garantează faptul că erorile converg rapid la zero în mod exponenţial sau, cel puţin sunt uniform mărginite. În acelaşi timp, stabilitatea este garantată prin faptul că toate semnalele din sistemul închis rămân mărginite. Pe durata proceselor de identificare şi de control se presupune că centrele şi formele funcţiilor de apartenenţă sunt cunoscute, iar parametri HONN sunt identificaţi, caz în care se obţine o variaţie direcţională. Pentru a garanta existenţa legii de reglare se defineşte o nouă metodă, numită comutarea parametrilor, care înlocuieşte proiecţia cunoscută. În acest mod este riguros demonstrată existenţa legii de control, garantând proprietăţile de stabilitate.

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