Decoupled Adaptive Neuro-Fuzzy Sliding Mode Control Applied in a 3D Crane System

Belkheir BENHELLAL
Department of Electrical Engineering, University of Ouargla, Algeria.
Electrical Engineering Laboratory LAGE
ge.bbenhellal@gmail.com

Mustapha Hamerlain
Centre for Development of Advanced Technologies
mhamerlain@cdta.dz

Rachid Ouiguini
r_ouiguini@yahoo.fr

Yacine Rahmani
Department of Electrical Engineering, University of Ouargla, Algeria.
r.yacine1991@gmail.com

Abstract *– This paper presents the control of 3D crane system by using a decoupled adaptive neuro-fuzzy controller based on the sliding mode theory. The considered 3D crane involves a planar motion in conjunction with a hoisting motion. The control inputs are three (trolley and hoisting forces), whereas the variables to be controlled are five (the trolley position in the XOY plane, the length of the lifting cable, and the two angles of swing). The interactions between each control subsystem are not taken account explicitly, but are considered to be disturbances in control of each individual subsystem. In the proposed approach, a conventional controller (PD) is used in parallel with the neuro-fuzzy controller, the PD controller ensures the asymptotic stability in compact space, the parameter update rules of the fuzzy neural network are derived, and the proof of the online learning algorithm is verified by using the Lyapunov stability method. Experimental results are given to solve the crane position control problem of 3D crane system laboratory equipment.*

Keywords*:adaptive neuro-fuzzy control, sliding-mode learning algorithm, 3DCrane system.*

I. Introduction

The gantry crane systems are used mainly for lifting heavy and moving loads beyond the normal capability of a man, For this reason, the control of these systems, which is not a simple task because of the complexity of their model (MIMO systems, strongly coupled and nonlinear), play an important role in industrial applications because of the good performance they must offer. During the past decades, many approaches regarding crane control have been developed and reported in the literature, A. Nowacka-Leverton, et al [1] proposed a sliding mode control strategies for the point-to-point motion control, C.Vazquez, et al [2] present the sliding mode control design based on the Super-Twisting Algorithm (STA), Sun, N., et al [3] have applied an energy coupling-based output feedback (OFB) control scheme, neural and fuzzy logic compensators are introduced in anti-swing control schemes as shown in [4-9], time-optimal control and visual feedback are applied by Yoshida Y., Tabata, H in [10] to solve position and anti-swing control problems, genetic algorithms are employed in [11] to obtain the parameters in simple models of 3D crane systems, Sam Chau Duong et all [12] are used a recurrent neural network (RNN) which is evolved by an evolutionary algorithm to control of an underactuated three-dimensional tower crane system. An adaptive sliding mode fuzzy control approach is proposed in [13] for a two-dimensional overhead crane, in [14-15] adaptive control schemes are used. D. Chwa proposed in [16] a nonlinear control method for trajectory tracking of 3-D crane systems robust towards the load variation and initial swing angle, a three-dimensional generalization of an anti-swing control law based on the second-order sliding -mode approach was proposed by A. Pisano in [17], previously proposed for the 2-D model of crane. The authors in [18] have introduced a methodology to design controllers that can cope with different load conditions on an Ethernet network. And have used an interpolated, delay-dependent gain scheduling law to deal with time-varying delays between measurement and control. M.-B. Radac and all developed a Previous and Current Cycle Learning (PCCL) approach to the position control of a 3D crane system in the framework of a new Iterative Learning Control (ILC) structure [19].

The severely nonlinear dynamic properties as well as lack of actual control input for the sway motion might bring about undesired significant sway oscillations, especially at take off and arrival phases, In addition, the gantry crane systems have the characteristic of having a limited number of input to control more output. In this case, the uncontrollable oscillations may cause severe security problems and stability, and would severely limit the effectiveness of the operation. However these undesirable phenomena would also make the conventional control strategies fail to achieve the goal.

In most control engineering applications the performance of controller is directly related to the accuracy of the mathematical model obtained for the controlled system. During the last decades, intelligent computing techniques using either fuzzy logic or neural networks have been studied in order to overcome the difficulties existing modeling. The concept of incorporating fuzzy logic in the neural network has emerged and has become a popular research area [20]. Fuzzy neural networks (FNNs) combine the advantages of both techniques. Like the fuzzy systems and neural networks, FNNs have been proven to be universal approximators too [21].

The present paper addresses the design of an adaptive neuro-fuzzy controller, used for each input variable of the 3D crane system to control the position in three direction xyz plan with a minimum swing of the carried load. The proposed controller uses a new variable structure systems-based on-line learning algorithm for parameter adaptation. It controls the error dynamics. It is defined as the control signal produced by a conventional controller connected in parallel and is described using a differential equation. Learning parameters are tuned by the proposed algorithm in a way to enforce the error to satisfy this stable equation.

The present work consists of four sections. Section 2 presents the Mathematical model of the 3DCrane systems, and continues with the proposed neuro-fuzzy structure. Then, the developed new variable structure systems-based method for parametric adaptation of fuzzy rule-based neural networks is presented in section 3, and finally in section 4 we present the experimental results with interpretation obtained by the proposed method with discussion.

II. Mathematical model of the 3DCrane

The schematic diagram of 3DCrane is given in Fig .1. [22]. the forces acting on this system and relevant variables, needed for the model development, are presented. An important element in the construction of the mathematical model is the appropriate choice of the system of coordinates. The Cartesian system, although simple in interpretation and determining the position in space in a unique way in both directions, it is not convenient for the description of the rotational motion dynamics, so we choose the spherical system. The position of the payload is described by two angles, α and β, shown in Fig.1.

The shortcoming of the spherical system of coordinates is that for every point on the *y*-axis, the corresponding value of β is not uniquely determined. However, this is not valid in the case of the real crane systems, so it can be neglected. The position of the payload is described by the following equations.

The position of the payload is described by the equalities:

$$x_c = x_w + R\ sin\alpha\ sin\beta \tag{1}$$
$$y_c = y_w + R\ cos\alpha \tag{2}$$
$$z_c = -R\ sin\alpha\ cos\beta. \tag{3}$$

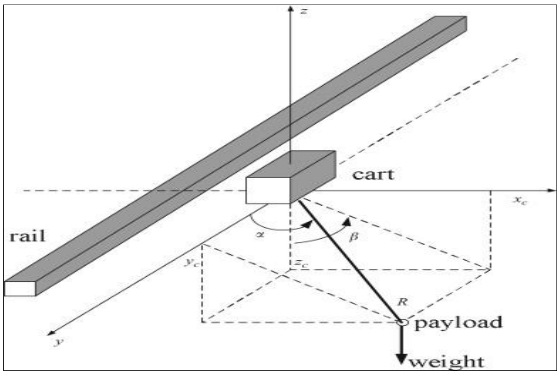

Fig.1. 3D crane system: coordinates and forces.

Where x_w represents the distance of the rail with the cart from the center of the construction frame, and y_w is the distance of the cart from the center of the rail. The 3dcrane parameters are shown in *Table1.*

In similar manner, the dynamics of the crane can be obtained as:

$$m_c\ddot{x}_c = -S_x \tag{4}$$
$$m_c\ \ddot{y}_c = -S_y \tag{5}$$
$$m_c\ \ddot{z}_c = -S_z - m_c g \tag{6}$$
$$(m_w + m_s)\ \ddot{x}_w = F_x - T_x + S_x \tag{7}$$
$$m_w\ \ddot{y}_w = F_y + T_y + S_y \tag{8}$$

WhereS_x, S_y and S_z are the components of vector S

$$S_x = S\ sin\alpha\ sin\beta \tag{9}$$
$$S_y = S\ cos\alpha \tag{10}$$
$$S_z = -S\ sin\alpha\ cos\beta \tag{11}$$

Table.1. Parameters of 3DCrane model

Symbol	***Description***
$\boldsymbol{R}$	length of the lift-line.
$\boldsymbol{\alpha}$	angle between the *y*-axis and the lift line.
β	angle between the negative direction on the *z*-axis and the projection of the lift line onto the *x z* plane.
$\boldsymbol{m_c}$	mass of the payload.
$\boldsymbol{m_w}$	mass of the cart.
$\boldsymbol{m_s}$	mass of the moving rail.
$\boldsymbol{x_c, y_c, z_c}$	coordinates of the payload.
S	reaction force in the lift-line acting on the cart.
$\boldsymbol{F_x}$	force driving the rail with cart.
$\boldsymbol{F_y}$	force driving the cart along the rail.
$\boldsymbol{T_x, T_y}$	friction forces.

The complete nonlinear model with varying pendulum length and three control forces of 3D crane system is completely determined by these equations.

III. Controller design

III.1. The Control Scheme and the Neuro-Fuzzy Structure

The conventional proportional plus derivative (PD) controller is provided both as an ordinary feedback controller to guarantee global asymptotic stability in compact space and as an inverse reference model of the response of the system under control. The PD control law is described as follows [23, 24, 25, 26]:

$$\tau_c = k_D\,\dot{e} + k_P\,e \tag{12}$$

Where e is the vector of the feedback error

$$e = (e_x\; e_y\; e_z) \tag{13}$$

$$e = (x_d - x,\; y_d - y,\; z_d - z)$$

$(x_d,\; y_d,\; z_d)$ are the desired positions axis.

$k_D = (\,k_{Dx}\; k_{Dy}\; k_{Dz}\,)$ and $k_p = (\,k_{px}\; k_{py}\; k_{pz}\,)$ are the vectors of the controller gains.

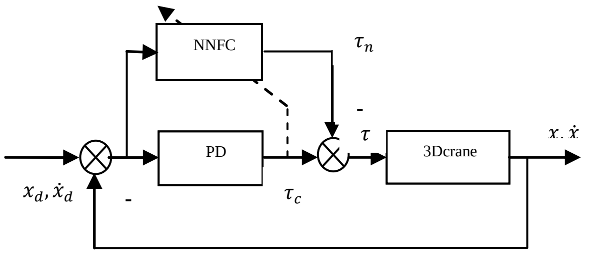

Fig.2. Adaptive Neuro-Fuzzy Sliding Mode Control scheme.

We assumed that the system to be controlled is decoupled, therefore the developed controller is applied to each of the three axis individually, in the following section to simplify, the design of the controller is developed for one axis of 3d crane systems.

The structure of fuzzy neural networks used for the three axes of 3dcrane system is presented in Fig.2. This structure with two inputs $x_1(t) = e(t)$, $x_2(t) = \dot{e}(t)$ and one output is implemented as a feedback controller in the control law Fig.3.

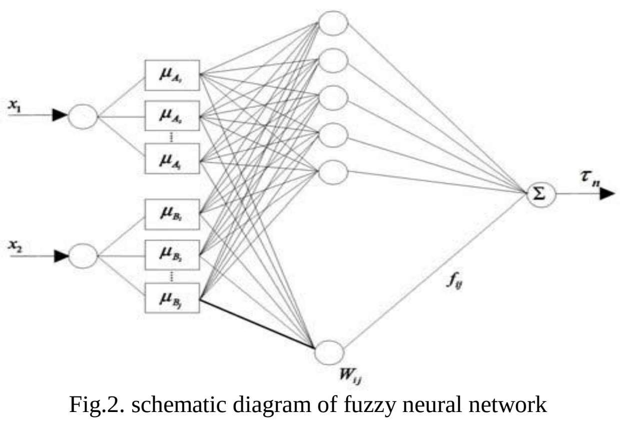

Fig.2. schematic diagram of fuzzy neural network

In the first layer signals x1 and x2 are fuzzified using Gaussian membership functions, which are defined by their corresponding membership functions $\mu_{1i}(x_1)$ and $\mu_{2j}(x_2)$ for i=1,…I and j=1,…J.

Each Gaussian membership function is defined by two parameters: its center c and the distribution σ which are among the tunable parameters of the fuzzy-neural structure.

The takagi sugeno type of fuzzy rule base is used, when each rule R_{ij} can be expressed by:

R_{ij} : if x_1 is A_i and x_2 is B_j then f_{ij}=$a_i\,x_1 + b_j x_2 + d_{ij}$

Where $i = 1, \dots I$ and $j = 1 \dots J$.

For simplification we suppose that the two parameters a_i and b_j are zero.

The output signal of the neuro-fuzzy feedback controller can be determined as follows:

$$\tau_n\,(t) = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}(W_{ij}f_{ij})}{\sum_{i=1}^{I}\sum_{j=1}^{J}(W_{ij})} \tag{14}$$

Where the strong W_{ij} of the rule R_{ij} is obtained as a T-norm of membership functions in the premise part:

$$W_{ij} = \mu_{1i}(x_1).\,\mu_{2j}(x_2) \tag{15}$$

The normalized value of W_{ij} is obtained by the following equation:

$$\bar{W}_{ij} = \frac{W_{ij}}{\sum_{k=1}^{kmax}\sum_{l=1}^{lmax}W_{kl}} = \frac{\mu_{1i}(x_1).\mu_{2j}(x_2)}{\sum_{k=1}^{kmax}\sum_{l=1}^{lmax}\mu_{1k}(x_1).\mu_{2l}(x_2)} \tag{16}$$

Therefore τ_n is written as follow:

$$\tau_n\,(t) = \sum_{i=1}^{I}\sum_{j=1}^{J}\big(\bar{W}_{ij}f_{ij}\big) \tag{17}$$

The following assumptions have been used:

The input signals $x_1(t)$ and $x_2(t)$, and their time derivatives can be considered bounded :

$$|x_1(t)| \le B_x,\; |x_2(t)| \le B_x \qquad \forall t \tag{18}$$

$$|\dot{x}_1(t)| \le B_{\dot{x}},\; |\dot{x}_2(t)| \le B_{\dot{x}} \qquad \forall t \tag{19}$$

Where B_x and $B_{\dot{x}}$ are assumed to be known positive constants.

The vectors defining the tuning parameters σ and c of the Gaussian membership functions are considered bounded as follows:

$$\|\sigma_1(t)\| \le B_\sigma,\; \|\sigma_2(t)\| \le B_\sigma \tag{20}$$

$$\|c_1\| \le B_c,\; \|c_2(t)\| \le B_c \tag{21}$$

Where B_σ and B_c are assumed to be known positive constants.

It will be assumed also that, due to physical constraints, the time-varying weight coefficients of the connections between the neurons from the second hidden layer and the output neuron of the neuro-fuzzy network are bounded:

$$|f_{ij}(t)| \leq B_f \quad \forall t \tag{22}$$

For some positive constant B_f .
From (18) to (22) it follows that τ and $\dot{\tau}$ will be bounded signals too,

$$|\tau(t)| \leq B_\tau,\ |\dot{\tau}(t)| \leq B_{\dot{\tau}} \qquad \forall t \tag{23}$$

Where B_τ and $B_{\dot{\tau}}$ are some known positive constants.

III.2. The Sliding Mode Learning Algorithm

Based on the principles of the sliding mode control theory [11] we defined the zero value of the learning error coordinate τc (t) as time-varying sliding surface, i.e.,

$$S_c(\tau_n, \tau) = \tau_c(t) = \tau_n(t) + \tau(t) = 0 \tag{24}$$

Which present the condition that the neuro-fuzzy network is trained to become a nonlinear regulator to obtain the desired response during the tracking-error convergence movement by compensation for the nonlinearity of the controlled plant.
The sliding surface for the nonlinear system under control $S_p(e, \dot{e})$ is defined as:

$$S_p(e, \dot{e}) = e + \gamma\, \dot{e} \tag{25}$$

With γ being a constant determining the slope of the sliding surface.

Definition: *A sliding motion will have place on a sliding manifold $S_c(\tau_n, \tau) = \tau_c(t) = 0$ after a time t_h, if the condition $S_c(\tau_n,\tau)\dot{S}_c(\tau_n,\tau) = \tau_c(t)\dot{\tau}_c(t) < 0$ is satisfied for all t in some nontrivial semi-open subinterval of time of the form $[t, t_h) \subset (-\infty, t_h)$.*

It is desired to devise a dynamical feedback adaptation mechanism or online learning algorithm for the neuro-fuzzy network parameters such that the sliding mode condition of the above definition is enforced.

Theorem 1: *If the adaptation law for the parameters of the considered neuro-fuzzy network is chosen respectively as:*

$$\dot{c}_{A_i} = \dot{x}_1 - \frac{\alpha}{s_A \delta_{A_i}} sign(\tau_c) \tag{26}$$

$$\dot{c}_{B_j} = \dot{x}_2 - \frac{\alpha}{s_B \delta_{B_j}} sign(\tau_c) \tag{27}$$

$$\dot{\delta}_{A_i} = \frac{\alpha}{s_A^T s_A} sign(\tau_c) \tag{28}$$

$$\dot{\delta}_{B_j} = \frac{\alpha}{s_B^T s_B} sign(\tau_c) \tag{29}$$

$$\dot{f}_{ij} = -\frac{\overline{W}_{ij}}{\overline{W}^T\overline{W}} \alpha\, sign(\tau_c) \tag{30}$$

Where $s_A = [s_{A_1}\ s_{A_2} \ldots s_{A_I}]^T$, $s_B = [s_{B_1}\ s_{B_2} \ldots s_{B_I}]^T$

$$s_{A_i} = x_1 - c_{A_i},\ s_{B_j} = x_1 - c_{B_j}$$

and α is a sufficiently large positive design constant satisfying the inequality:

$$\alpha > B_{\dot{\tau}} \tag{31}$$

Then given an arbitrary initial condition $\tau_c(0)$, the learning error $\tau_c(t)$ converges to zero during a finite time t_h, and a sliding motion sustained on $\tau_c(t) = 0$ for all $t > t_h$.

Proof:

Consider the following Lyapunov function candidate:

$$V_c = \frac{1}{2}\tau_c^2(t) \tag{32}$$

The time derivative of V_c is given by:

$$\dot{V}_c = \tau_c\dot{\tau}_c = \tau_c(\dot{\tau}_n + \dot{\tau}) \tag{33}$$

$$\dot{V}_c = \tau_c\left(\sum_i^I\sum_j^J\left(\dot{f}_{ij}\,\overline{W}_{ij} + f_{ij}\dot{\overline{W}}_{ij}\right) + \dot{\tau}\right) \tag{34}$$

$$\dot{\overline{W}}_{ij} = -\overline{W}_{ij}\dot{K}_{ij} + \overline{W}_{ij}\sum_i^I\sum_j^J \overline{W}_{ij}\,\dot{K}_{ij} \tag{35}$$

$$\dot{K}_{ij} = 2\left(A\dot{A} + B\dot{B}\right) \tag{36}$$

$$A = \frac{x_1 - c_{A_i}}{\delta_{A_i}}\ ;\ B = \frac{x_2 - c_{B_j}}{\delta_{B_j}} \tag{37}$$

$$\dot{A} = \frac{\left(\dot{x}_1 - \dot{c}_{A_i}\right)\delta_{A_i} - \dot{\delta}_{A_i}\left(x_1 - c_{A_i}\right)}{\delta_{A_i}^2} \tag{38}$$

$$\dot{B} = \frac{\left(\dot{x}_2 - \dot{c}_{B_j}\right)\delta_{B_j} - \dot{\delta}_{B_j}\left(x_2 - c_{B_j}\right)}{\delta_{B_j}^2} \tag{39}$$

$$A\dot{A} = 0 = \frac{\left(x_1 - c_{A_i}\right)\left(\dot{x}_1 - \dot{c}_{A_i}\right)\delta_{A_i} - \dot{\delta}_{A_i}\left(x_1 - c_{A_i}\right)^2}{\delta_{A_i}^3} \tag{40}$$

$$B\dot{B} = 0 = \frac{\left(x_2 - c_{B_j}\right)\left(\dot{x}_2 - \dot{c}_{B_j}\right)\delta_{B_j} - \dot{\delta}_{B_j}\left(x_2 - c_{B_j}\right)^2}{\delta_{B_j}^3} \tag{41}$$

$$\dot{V} = \tau_c\left(\sum_i^I\sum_j^J \dot{f}_{ij}\,\overline{W}_{ij} + \dot{\tau}\right) = \tau_c(-\alpha\, sign(\tau_c) + \dot{\tau}) \tag{42}$$

$$= (-\alpha\,|\tau_c| + \dot{\tau}|\tau_c|) \leq \tag{43}$$

$$\leq (-\alpha\,|\tau_c| + B_{\dot{\tau}}|\tau_c|) < 0 \tag{44}$$

The inequality (44) shows that the controlled trajectories of the learning error $\tau_c(t)$ converge to zero in a stable manner.
The relation between the sliding line Sp and the zero adaptive learning error level S_c, if γ is taken as
$\gamma = \frac{k_P}{k_D}$, is determined by the following equation:

$$S_c = \tau_c = k_D\,\dot{e} + k_P\,e = k_D\left(\dot{e} + \frac{k_P}{k_D}\right) = k_D S_p \qquad (45)$$

The tracking performance of the position control system in 3D crane is analyzed by the following Lyapunov function candidate:

$$V_p = \frac{1}{2} S_p^2 \qquad (46)$$

Theorem 2: If the adaptation strategy for the adjustable parameters of the NNFC is chosen as in (26-30), then the negative definiteness of the time derivative of the Lyapunov function in (46) is ensured.

Proof:
Evaluating the time derivative of the Lyapunov function in (46) yields:

$$\dot{V}_p = \dot{S}_p S_p = \frac{1}{k_D^2}\dot{S}_c S_c = \frac{1}{k_D^2}\tau_c\dot{\tau}_c \qquad (47)$$

$$= \frac{1}{k_D^2}\dot{V}_c \quad < 0 \quad \forall\, S_c,\ S_p \neq 0 \qquad (48)$$

The obtained result means that, assuming the sliding mode control task is achievable, using τ_c as a learning error for the NNFC together with the adaptation laws (26)-(30) enforces the desired reaching mode followed by a sliding regime for the system under control.

IV. Experimental Results

In this section, the practical verification of the proposed adaptive neuro-fuzzy controller based on the sliding mode theory is performed on the experimental 3D crane setup presented in Figure 4, commercially available from Inteco Ltd.The control algorithms are implemented in a Matlab/Simulink.

Fig.4. 3D Crane System made by Inteco.

The initial parameters used to obtain the experimental results are:

x axis parameters:
$k_{px} = 3 \quad k_{dx} = 2$

$$c_{Ax} = \begin{pmatrix} 2,99 \\ 3,99 \\ 4,99 \end{pmatrix};\ c_{Bx} = \begin{pmatrix} 2,34 \\ 4,34 \\ 6,34 \end{pmatrix};\ \delta_{Ax} = \begin{pmatrix} 1,95 \\ 23,14 \\ 2,18 \end{pmatrix};\ \delta_{Bx} = \begin{pmatrix} 1,92 \\ 49,89 \\ 2,05 \end{pmatrix};$$

$$f_x = \begin{pmatrix} -0,384 & -0,247 & -0,12 \\ -0,022 & 0,078 & 0,173 \\ -0,117 & 0,216 & -0,101 \end{pmatrix};$$

y axis parameters:
$k_{py} = 3 \quad k_{dy} = 2$

$$c_{Ay} = \begin{pmatrix} 2,39 \\ 3,39 \\ 4,39 \end{pmatrix};\ c_{By} = \begin{pmatrix} 1,67 \\ 3,67 \\ 5,67 \end{pmatrix};\ \delta_{Ay} = \begin{pmatrix} 2,06 \\ 20,17 \\ 2,23 \end{pmatrix};\ \delta_{By} = \begin{pmatrix} 1,84 \\ 49,9 \\ 2,09 \end{pmatrix};$$

$$f_Y = \begin{pmatrix} -0,385 & -0,161 & -0,155 \\ -0,035 & 0,065 & 0,162 \\ -0,121 & 0,251 & -0,118 \end{pmatrix};$$

z axis parameters:
$k_{pz} = 10 \quad k_{dz} = 1$

$$c_{Az} = \begin{pmatrix} -1,02 \\ -0,02 \\ 0,98 \end{pmatrix};\ c_{Bz} = \begin{pmatrix} -3,1 \\ -1,1 \\ 0,9 \end{pmatrix};\ \delta_{Az} = \begin{pmatrix} 2,06 \\ 33,42 \\ 2,14 \end{pmatrix};\ \delta_{Bz} = \begin{pmatrix} 2,01 \\ 5,72 \\ 2,09 \end{pmatrix};$$

$$f_Z = \begin{pmatrix} -0,7 & -0,358 & -0,206 \\ 0,006 & 0,108 & 0,208 \\ -0,073 & 0,027 & 0,127 \end{pmatrix};$$

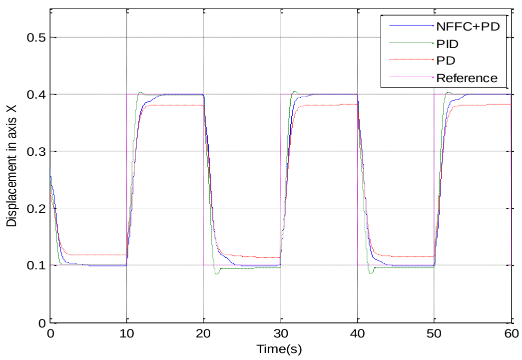

Fig.5. X position

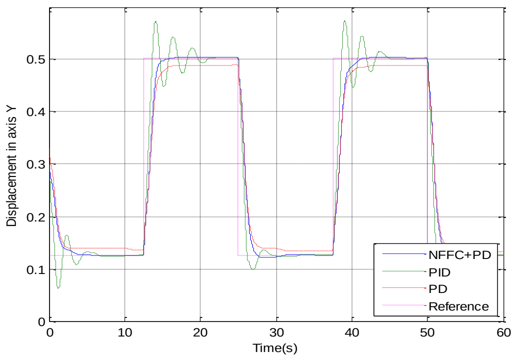

Fig .6. Y position

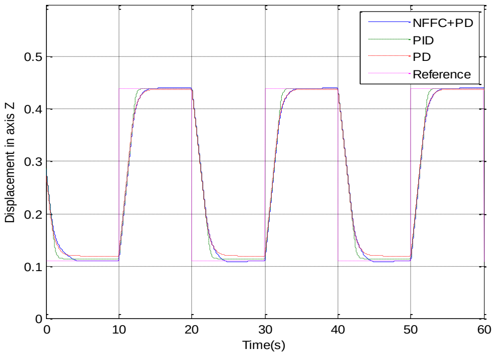

Fig.7. Z position

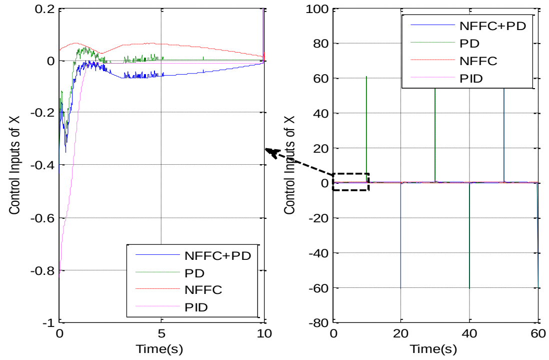

Fig .10. X axis control signal

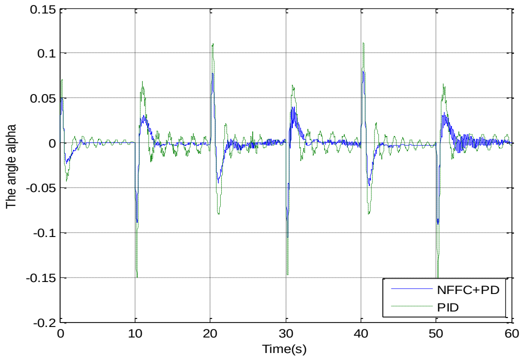

Fig.8. swing angle alpha

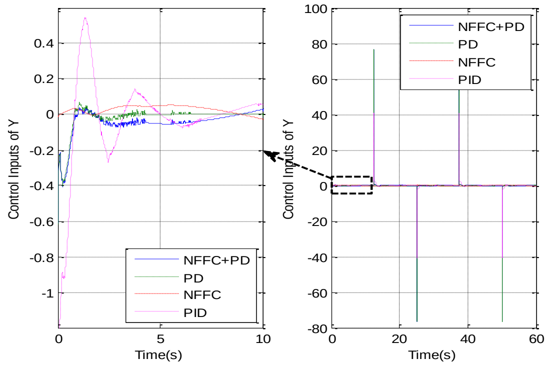

Fig.11. Y axis control signal

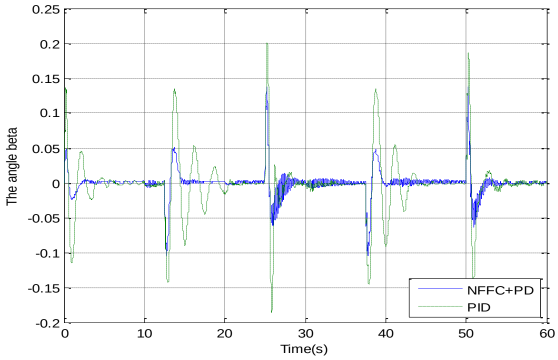

Fig.9. swing angle beta

Experimental results presented in Fig.5, fig.6 and fig.7 shows the difference between the response of the system with the PD controller and the decoupled neuro-fuzzy sliding mode controller proposed in Section 3, and those for the three axes X, Y and Z.

Observed in these results with a Pd controller whose gains Kp and Kd are chosen preciously, the system cannot achieve a desired trajectory. The proposed controller schemes, and with the same values of the gains Kp and Kd forces the system to achieve and pursue the desired trajectory in the three axes controlled with minimum oscillation in the angle alpha and beta system.

It can be clearly seen in Figure 8 and 9 that the swing produced by the proposed control law is smaller than that produced by a PID control, and reached the minimum faster.

In the fig.10 and fig.11, we can see that the signal of the NNFC controller corrects the PD control signals even if these signals are disrupted, for obtain a hybrid signal which gives a good pursuit of desired trajectory and helps to minimize the error until that it tends to zero in permanent regime.

V. Conclusion

This paper deals with the problem of tracking of trajectory and reducing oscillations during the positioning of the payload of 3D crane system. a novel approach for generating and maintaining sliding regime in the behavior of a system with uncertainties in its dynamics is presented. In this control algorithm, a conventional PD controller and an adaptive variable structure neuro-fuzzy controller are used in parallel to system control. The experimental results have demonstrated that the predefined sliding regime could be generated and maintained in case the NNFC parameters are tuned using the proposed approach.

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