A Design of WNN observer based controller Design for static nonlinear systems

Ms Geeta Shakya, Mhd. Ashfaque Khan

Abstract— In this paper design of reduced order observer based controller using WNN for a class of delay nonlinear systems is presented. Actuator saturation is applied on nonlinear part of system. Delay find out by estimator in system and after controlling technique applied on this system. The proposed wavelet adaptive reduced order observer performs the objective of identification of unknown dynamics system with reconstruction of states of the system. Wavelet networks are used in this work as identification tool. This paper attempts to prove analytically the stability of a system by Lyapunov-Krasovski function.

Index Terms— **Actuator Saturation limits, nonlinear system, Wavelet neural networks, Wnn observer based controller.**

I.INTRODUCTION

Control process is most important technique that provides a complete process which makes the systems or plants to behave in a stable process. In which find out the stability and accuracy of system performance also find the error of system, possibility of error in system. However, use of these tools of control science to produce good control system. Some type of major difficulties to be dealt in this work is uncertainties and nonlinearities in system. For the Controlling of system design relies on mathematical of system that characterize which way to real systems evolve in time for given situations (initial conditions) and external expected output. In the point of design of control strategy to attain the desired performance, a required accurate or precise mathematical process point of the physical system or it is non trivial task to obtain such an effective model for all physical systems [1]. There are varying typically be discrepancies between the actual plant and the mathematical modeling process for controller design. These types of inaccuracies can be due to uncertainties regarding system dynamics, finite parameter representation, linearization or model reduction, neglected secondary dynamics, or unforeseen system changes. The Controller designing idea related from the control of systems having uncertain or unmodelled dynamics is treated as a challenging point in the control theory.

Time delay, may occur in input and state of system due to delay affect the performance of system. Time delays are found in dynamic systems e.g. chemical processes, rolling mill, biological systems. Due to time delay creates problems in system are oscillations, degradation and instability in the system [2].

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This paper design wavelet neural network based adaptive observer based controller for nonlinear system in this system present uncertain or time-delayed. In which the wavelet neural network like system identification tool thereby design highly accurate observer . In this paper the aim of observer estimate the performance and state or error of the system in which system may be consider linear or nonlinear system. Observer response depends upon the consider system and applied actuator saturation. Wnn observer controller design in which clear delay and uncertainty or error of system and system come in stable and accurate conditions. To deal with actuator saturation condition applied on design system after this procedure we seen best performance and reshape the system results.

In this work also point out delay independent controller strategy for find the stability of system irrespective to delay value of system. Stability of system proved through Lyapunov Krasovskii functional [3].

The neural network based control technique has been an alternating design method for various control systems to compensate the effect of uncertainty, nonlinearities so that the system stability analysis can be guaranteed. The wavelet neural network was developed by Zhang and Benveniste [4]. Wavelets have been combined with the neural network to create wavelet neural networks. The algorithms for WNN converge using a small number of iterations than the conventional neural networks. These WNN combines the capability of artificial neural network for learning ability and capability of wavelet decomposition for identification ability. It has been analyze that wavelet neural networks are converging optimal approximations for modeling inaccuracies. Wavelet neural networks are optimal in the sense that they require the smallest possible number of bits to store for reconstructing a parameter within a accuracy. Thus WNN based control systems can achieve better control performance than NN based control systems. [5]-[6].

II. SYSTEM MODEL

2.1 Actuator Saturation

Define the actuator saturation parameter in there u(t) shown as output and input write by v(t) and saturation condition on applied system is defined as

$$u = \begin{Bmatrix} u_{\max} \; v \geq u_{\max} \\ v \quad u_{\min} < v < u_{\max} \\ u_{\min} \; v \leq u_{\min} \end{Bmatrix} \tag{1}$$

Where $u_{\max}$ and $u_{\min}$ are maximum saturation or minimum saturation limits as shown in the equation 1.

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Symmetric actuator saturation represented by $u_{\min} = -u_{\max}$. Controlling effort which cannot be implemented under this condition so that defined

$$\Delta u = \begin{cases} u_{\max} - v & v \le u_{\max} \\ 0 & \cdots u_{\min} < v < u_{\max} \\ u_{\min} - v & v \le u_{\min} \end{cases} \quad (2)$$

Where Δu play role effect of actuator saturation and can be effectively approximated by used a self recurrent wavelet neural network.

Saturation function

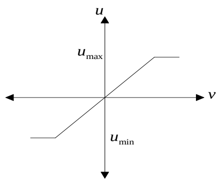

Figure:-1

2.2 NONLINEAR SYSTEM

This research is confined to the class of systems represented by continuous dynamics which can be written as Ordinary Differential Equations (ODEs). The general form of ODE considered is $\dot{x} = f(x,t)$, $x_0 = x(t_0)$ (3)

Where $x \in \Re^n$ indicate state of the system, t is time, t_0 is the initial time, and x_0 is the initial state of the system. For this class of systems, the state derivatives are some nonlinear functions of states, which are represented by $f(x)$. Presence of these nonlinear functions makes the system modeling and analysis complicated up to certain extent. As cited by few researchers, $f(x,t)$ is required to be continuous in time and locally Lipschitz in the state variable for the existence and uniqueness of solutions. However these conditions impose certain constraints over the system nonlinearities, which are not normally satisfied by most of the system dynamics. Also this restriction offers a locally stable and conservative solution for the system under consideration. Select non linear system

$$\begin{aligned} \dot{x}_1 &= x_2 + \phi_1(x(t), x(t-\tau)) \\ \dot{x}_2 &= x_3 + \phi_2(x(t), x(t-\tau)) \\ &\vdots \\ \dot{x}_n &= \phi_n(x(t), x(t-\tau), u) \\ y &= x_1 \end{aligned} \quad (4)$$

Where $x = [x_{1,} x_2 \ldots\ldots x_n]^T, u, y$ are state variable, control input and output respectively, $\phi = [\phi_{1,} \phi_{2,} \ldots\ldots \phi_n]^T : R^{n+1} \to R^n$ Are smooth unknown, nonlinear functions of state variables and input?

Using the actuator saturation defined in system (4) can

$$\dot{x} = Ax + B(\delta(x, \bar{y}_d) + g(v + \Delta u)) + \phi$$

$$y = cx$$

be transformed to where $\delta(x, \bar{y}_d) = f(x) + g\Delta u$

Defining the desired trajectory vector as

$$\bar{y}_d = [y_{d,} \dot{y}_{d,} \ddot{y}_{d,\ldots\ldots} y_d^{n-1}]^T$$

The desired $y_d(t)$ trajectory is assumed to be smooth; in this system y output is measurable.

2.3 Wavelet Neural Network

A wavelet neural network is buildup on place to neural network as a system identification tool. Wavelet neural network integrate the space frequency localization point of wavelet. The idea of combining wavelet theory with neural network built in a new type of neural network name is wavelet neural network. The WNN combination of capability of artificial neural network or wavelet decomposition. In which artificial neural network perform for learning of state or wavelet as identification of system. It is combination the idea of neural network and the merit of the wavelet neural network was developed by Zhang and Benveniste.WNN used as activation function [7]. Wavelet network is a type of building block for function approximation. The building block is obtained by translating and dilating the mother wavelet function. [8]. Output of a biased n dimensional wavelet network with *m* nodes is

$$f = a^T \varphi(x, w, c) + \beta^T \phi(x, w, c) \quad (5)$$

where $x = [x_{1,} x_{2,} \ldots x_n]^T \in R^n$ Represented system input vector, $\phi = [\phi_1, \phi_{2,\ldots} \phi_m] \in R^m$ and $\varphi = [\varphi_1 \varphi_2 \cdots \varphi_m]^T \in R^m$ are wavelet functions and bias functions respectively; $w = [w_{1,} w_{2,\cdots,} w_m] \in R^{mxn}$ and $c = [c_{1,} c_{2,\ldots} c_m]^T \in R^{mxn}$ are dilation parameter or translation parameter;

$a = [a_{1,} a_{2,\ldots} a_m] \in R^m$ and $B = [B_{1,} B_2 \ldots B_m]^T \in R^m$ are wavelet weights function or bias function .

Let f^* be the optimal function nearness used as complete wavelet resemblance then

$$f = f^* + \Delta = a^{*T} \varphi^* + B^{*T} \phi^{*T} + \Delta \quad (6)$$

Where $\varphi^* = \varphi(x, w^*, c^*)$ and $\phi^* = \phi(x, w^*, c^*)$, and a^*, B^*, w^*, c^* are optimal specification vectors of a, B, w, c respectively and Δ express the coincidence error or is made-up to be bounded by $|\Delta| \le \Delta^*$,in which Δ^* is a positive constant. Optimal constant vectors necessary for best similarity of the function are obstacle to dispose so describe an evolution function as

$$\hat{f} = \hat{a}^T \hat{\varphi} + \hat{B}^T \hat{\phi} \quad (7)$$

In here $\hat{\varphi} = \varphi(x, \hat{w}, \hat{c}), \hat{\phi} = \phi(x, \hat{w}, \hat{c})$ or $\hat{\alpha}, \hat{\beta}, \hat{w}, \hat{c}$ are the evolution of $\alpha^*, \beta^*, w^*, c^*$ respectively. Denoted the evolution error as

Where

$$\tilde{\alpha} = \alpha^* - \hat{\alpha}, \tilde{\beta} = \beta^* - \hat{\beta}, \tilde{\varphi} = \varphi^* - \hat{\varphi}, \tilde{\phi} = \phi^* - \phi$$

(8)

After selecting the number of nodes, the evaluated error $\tilde{f}$ can be made expeditiously small on the compact set so that the bound $\|\tilde{f}\| \le \tilde{f}_m$ holds for all $x \in \Re$. Using Taylor expansion linearization technique to transform the nonlinear function into a partially linear form as a step towards the

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derivation of online tuning laws for the wavelet parameters to achieve the favorable estimation of system dynamics [9]

$$\tilde{\varphi} = A_1^T \tilde{w} + B_1^T \tilde{c} + h_1$$

$$\tilde{\phi} = A_2^T \tilde{w} + B_2^T \tilde{c} + h_2 \qquad (9)$$

Where $\tilde{w} = w^* - \hat{w}, \tilde{c} = c^* - \hat{c}$ and h_1, h_2 are the vectors of higher order terms and

$$A_1 = [\frac{d\varphi_1}{dw}, \frac{d\varphi_2}{dw}, ... \frac{d\varphi_m}{dw}]_{w=\hat{w}}$$

$$A_2 = \left[\frac{d\phi_1}{dw}, \frac{d\phi_2}{dw}, ..., \frac{d\phi_m}{dw}\right]_{w=\hat{w}}$$

$$B_1 = \left[\frac{d\varphi_1}{dc}, \frac{d\varphi_2}{dc}, ..., \frac{d\varphi_m}{dc}\right]_{c=\hat{c}}$$

$$B_2 = \left[\frac{d\phi_1}{dc}, \frac{d\phi_2}{dc}, ..., \frac{d\phi_m}{dc}\right]_{c=\hat{c}}$$

with $\frac{d\hat{\varphi}_i}{dw} = [0..0 \frac{d\hat{\varphi}_i}{dw_{1i}}, \frac{d\hat{\varphi}_i}{dw_{2i}}, ... \frac{d\hat{\varphi}_i}{dw_{ni}}, 0...0]^T$

$$\frac{d\hat{\varphi}_i}{dc} = [0..0 \frac{d\hat{\varphi}_i}{dc_{1i}}, \frac{d\hat{\varphi}_i}{dc_{2i}}, ... \frac{d\hat{\varphi}_i}{dc_{ni}}.0...0]^T$$

$$\frac{d\hat{\phi}_i}{dw} = [0..0 \frac{d\hat{\phi}_i}{dw_{1i}}, \frac{d\hat{\phi}_i}{dw_{2i}}, ... \frac{d\hat{\phi}_i}{dw_{ni}}, 0..0]^T$$

$$\frac{d\hat{\phi}_i}{dc} = [0..0 \frac{d\hat{\phi}_i}{dc_{1i}}. \frac{d\hat{\phi}_i}{dc_{2i}}, ... \frac{d\hat{\phi}_i}{dc_{ni}}, 0..0]^T$$

After solving equation (8) into equation (9)

$$\tilde{f} = \begin{pmatrix} \tilde{\alpha}^T (\hat{\varphi} - A_1^T \hat{w} - B_1^T \hat{c}) + \hat{w}^T (A_1 \hat{\alpha} + A_2 \hat{B}) + \tau^t (B_1 \hat{\alpha} + B_2 \hat{B}) \\ + \tilde{\beta}^T (\hat{\phi} - A_2^T \hat{w} - B_2^T \hat{c}) + \varepsilon \end{pmatrix}$$

(10)

in above equation uncertain term is represented by this form $\varepsilon = \begin{pmatrix} \alpha^{*T} h_1 + \tilde{\alpha}^T A_1^T w^* + \tilde{\alpha}^T B_1^T c^* + \beta^{*T} h_2 + \\ \tilde{\beta}^T A_2^T w^* + \tilde{\beta}^T B_2^T c^* \end{pmatrix}$

Wavelet Network Representation

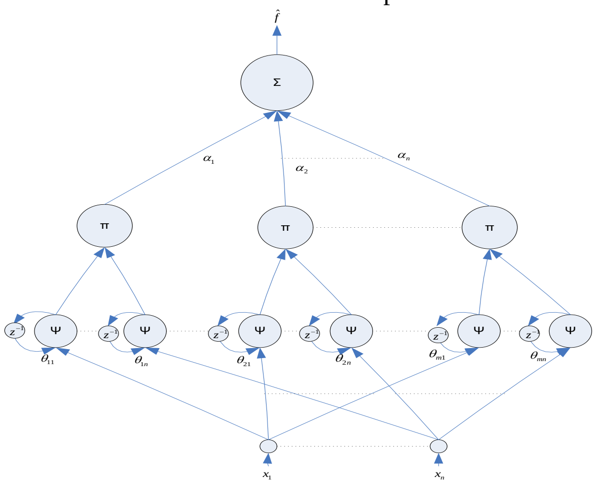

Figure : 2

III . PROPOSED METHODOLOGY

Block Diagram of Wnn based adaptive observer controller

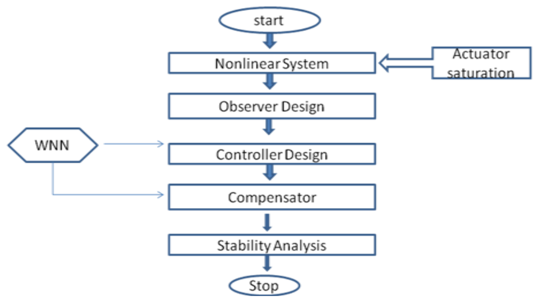

Figure.3

WNN ADAPTIVE OBSERVER BASED CONTROLLER DESIGN

WNN NEURAL network based controller design are based on adaptive observer and in which stability analysis find Out by lyapunov- krasovskii functional. In this proposed methodology firstly consider nonlinear system with actuator saturation. In this system actuator saturation provide the limit of system and observer observe the state and performance of system. Due to their uncertainty and create external disturbance show delay in system and due to their delay effect the performance of system and in this research paper design wnn adaptive based controller design. The result of controller gives the proper output of nonlinear system and eliminated the uncertainty of system. Stability analysis proved through lyapunov-krosovskii functional [12].

In Wavelet based observer is observe and estimates the states of the system (10) is given by

$$\dot{\hat{x}} = A\hat{x} + B(\hat{\delta}(\hat{x}, \bar{y}_d) + gv + v_r) + \phi(\hat{x}(t), x(t-\tau)) + m(y - cx)$$

$$\hat{y} = c\hat{x}$$

(11)

Where $\hat{x}$ = Estimation state vector x,

$\hat{\delta}(\hat{x}, \bar{y}_d)$ =Wavelet estimate of $\delta(\hat{x}, \bar{y}_d)$,

$m = [m_1, m_2, ... m_n]^T$ = observer gain matrix, selected such that the matrix $A - mC$ is stable and v_r is the robust control term. In this work a single wavelet network is used for system identification as well as for saturation compensation.

Write the error of state

$$\dot{\tilde{x}} = (A - mc)\tilde{x} + B(\delta(x, \bar{y}_d) - \delta(\hat{x}, \bar{y}_d) +$$
$$\bar{\delta}(\hat{x}, \bar{y}_d) - v_r) + \phi(x(t), x(t-\tau)) - \phi(\hat{x}(t), \hat{x}(t-\tau))$$

(12)

With the help of the proposed tuning laws presented in the next part of this subsection, the error term $\tilde{\delta}(\hat{x}, \bar{y}_d)$ is reduced to a small arbitrary value which is further

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attenuated by robust control term v_r [13,14].Tuning laws are given as:

Adaptation laws for the wavelet network used to approximate $\delta(\hat{x}.\bar{y}_d)$ will be:

$$\dot{\hat{\alpha}}_\delta = -\dot{\tilde{\alpha}}_\delta = \beta_1 \tilde{y}(\hat{\varphi}_\delta - A_1^T \hat{w}_\delta - B_1^T \hat{c}_\delta)$$
$$\dot{\hat{w}}_\delta = -\dot{\tilde{w}}_\delta = B_2 \tilde{y}(A_1 \hat{\alpha}_\delta)$$
$$\dot{\hat{C}}_\delta = -\dot{\tilde{C}}_\delta = B_3 \tilde{y} B_1 \hat{\alpha}_\delta$$

(13)

Where $B_1, B_{2.} B_3$ are the learning rates with positive constants?

The robust control term is defined as

$$v_r = \frac{\tilde{y}(\rho^2+1)}{2\rho^2} \tag{14}$$

Where ρ is the prescribed attenuation?

IV. Wnn Based Controller Design

Defining the state tracking error vector $\hat{e}(t)$ as

$$\hat{e}(t) = \hat{x}(t) - \bar{y}_d(t)$$

The filter tracking error is defined as $\hat{r} = k\hat{e}$ where $k = [k_1.k_{2,}.....k_{n-1},1]$ is an appropriately chosen coefficient vector such that $\hat{e} \to 0$ exponentially as $R \to 0$

Applying the feedback linearization method the control law is defined as

$$v = \frac{1}{g}(y^n{}_d - \hat{\delta}(\hat{x},\bar{y}_d) - k(\phi(\hat{x}(t),\hat{x}(t-\tau) + mc\hat{x} - k_e\hat{e} - k_r r) \tag{15}$$

where K $K_e = [0, k_1, k_{2..........}k_{n-1}]$

Stability of the system (10) with the proposed observer and controller strategy will be analyzed in the below section [15]. For the Stability Analysis Consider a Lyapunov-Krasovskii functional of the form

$$v = \frac{1}{2}\tilde{x}^T p\tilde{x} + \frac{1}{2}\hat{r}^2 + \frac{1}{2}\eta_1\tilde{\alpha}_\delta{}^T\tilde{\alpha}_\delta + \frac{1}{2}\eta_2\tilde{c}_\delta{}^T\tilde{c}_\delta + \int_{t-\tau}^{t} u$$

(16) After solving all equation of system got stable form.

$$k_r\hat{r}^2 + \frac{\tilde{y}^2}{2} + \frac{1}{2}Q_{\min}\|\tilde{x}^2\| \ge (M_1 + M_2 + \frac{M_3 u^2}{2} + \frac{M_3}{2u^2}\|\tilde{x}\|^2 + \frac{\rho^2}{2})\varepsilon^2{}_\delta + M_4$$

V.SIMULATION RESULTS

System output, observer output, and desired trajectory

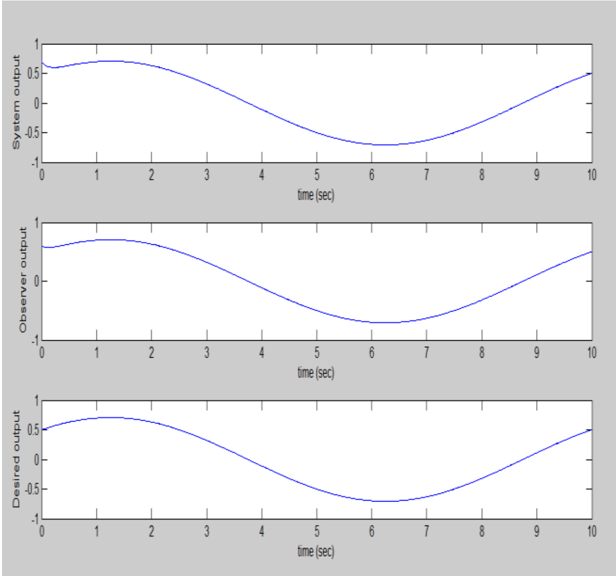

Figure.4.

Estimation error, Control error and control Effort.

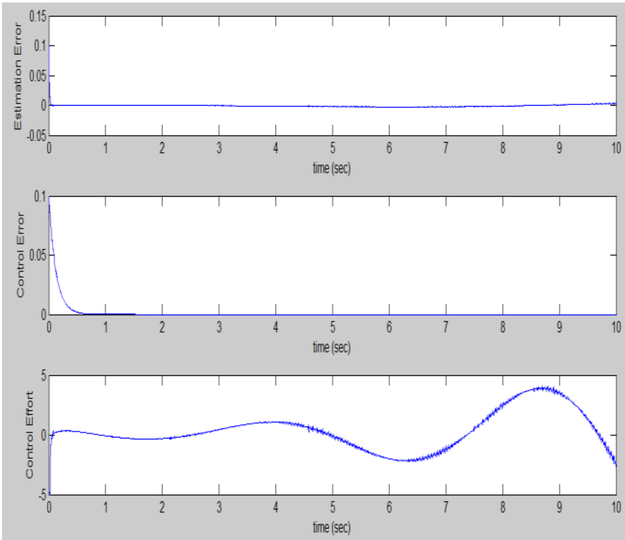

Figure. 5

VI . CONCLUSION

The research aims to provide a wavelet observer based controller scheme for a class of delayed nonlinear systems this observer-controller strategy would have to overcome the effects of actuator saturation. This work presents the development and design of a WNN based nonlinear observer-controller strategy for a class of uncertain nonlinear time delayed systems subjected to actuator saturation by this controller control the delay and uncertainty of system and after stability analysis get stable and accuracy of system performance.

VII. FUTURE SCOPES

Real time implementation of the proposed observer based control strategy can be possible future extension of this work.

Available algorithms for online adjustment of the nodes of the WNN lead to the problem known as

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'Curse of Dimensionality'. To offer an optimal solution for dynamically structured WNN thereby avoiding the curse of dimensionality may be the future extension of the proposed work.

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