Journal of Engg. Research Vol. 9 No. (3A) September 2021 pp. 197-208 DOI : 10.36909/jer.v9i3A.9159

Nonlinear state feedback controller combined with RBF for nonlinear underactuated overhead crane system

Ali Hussien Mary*, Abbas H. Miry**, T. Kara*** and Mohammed H. Miry****

*University of Baghdad, Al-Khwarizmi College of Engineering, Mechatronics Engineering Department, Baghdad
**Mustansiriyah University, Department of Electrical Engineering
***University of Gaziantep, Department of Electrical and Electronics Engineering
****University of Technology- communication engineering Dept.
*Corresponding Author: alimary76@kecbu.uobaghdad.edu.iq.

Submitted: 01/12/2019
Revised: 01/10/2020
Accepted: 12/10/2020

ABSTRACT

This paper proposes a robust control scheme for an underactuated crane system. The presented scheme contains two control strategies, feedback control term and corrective control term, based on Radial Basis Function (RBF) neural networks. A feedback control term is deigned based on the nominal dynamic model of the controlled system. RBF neural networks have been used as adaptive control term to compensate for the system uncertainties and external disturbance. Lyapunov stability theorem has been used to derive updating laws for the weights of the RBF neural networks. To illustrate the robustness and effectiveness of the proposed controller, Matlab program is used to simulate the model of the nonlinear overhead crane system with the proposed control method, taking into account system uncertainties and external disturbance. Simulation results indicated superior control performance of the proposed control method compared to the other control methods used in the test.

Keywords: Overhead crane system; Nonlinear control; Adaptive control; and Neural networks.

INTRODUCTION

In recent years, overhead crane has been used widely in constructions site, factories, and workshops for lifting and transporting cargoes from one location to another. A nonlinear overhead crane system is considered as an underactuated mechanical system because its control inputs are less that its output variables. Complexity and high nonlinearity of the carne system make problem of design a good controller a big challenge (Le *et al*., 2019). Then, the important goal in designing a good controller for underactuated carne system is eliminating payload swing with moving a trolley to desired position with minimum time. Different control methods had been suggested to achieve this goal, but most of them consider the payload oscillation as single pendulum without taking into account the mass of the hook and the additional cable (Zhang *et al.,* 2019). In practice, most industrial applications use double pendulum crane system. Therefore, design robust controller for double pendulum crane system will be significant. In general, two control strategies had been applied successfully for control the double pendulum crane system; open loop control and closed loop (Zhang *et al.,* 2019). Input shaping control strategy is an efficient open loop control method that applied successfully in control of crane system by generating sequences of impulses. However, this method is model based which means it's not robust and sensitive to the parameter variations and external disturbance. This drawback solved by combing the original input shaping method with other control schemes (Abdullahi *et al.,* 2018, Fujioka & Singhose

2015, Huang *et al.,* 2013, Veciana *et al.,*2015). On other hand, many feedback control methods used for control crane system by adjust actuator to reach the desired output by measuring the system states. Simplicity of PID controller motived many researchers to use it to move trolley with small oscillation (Maghsoudi *et al.,* 2016). Several researchers combined PID controller with other control schemes to reduce the payload oscillation (Solihin *et al.,* 2010, Jaafar *et al.,* 2015). Optimal performance of PID controller can be obtained by using optimization algorithm to tune PID gains, and particle swarm optimization (PSO) is one of the most important algorithms applied successfully in crane system control, and the selection of fitness function represents the key to design optimum controller and getting good performance. Fang et al. presented 2 degree of freedom of proportional derivative controller (Fang *et al.,* 2003). In (Yu *et al.,* 2014) a composite nonlinear feedback controller designed to eliminate payload oscillations and improve transient specifications. Partial feedback linearization presented by to Park et al to control the position of trolley with minimum payload swing angle (Park *et al.,* 2007). In term of robustness, sliding mode control (SMC) represents a best method in control-complicated systems. Most of robust control methods that designed based SMC designed sliding surface by combining actuated state with errors of unactuated states (Ngo & Hong 2010, Pan *et al.,* 2017). SMC is combined with Luenberger observer is proposed by (Almutairi and Zribi 2016) to control an overhead crane system. However, chattering is the big drawback in SMC and also the need for the knowledge of upper bound of uncertainty is another weak point in SMC (Mary & Kara 2016, Hamoudi 2017**)**. An intelligent controller is proposed in (Almutairi and Zribi 2016) based fuzzy logic control schemes with experimental verifications. Hence, this work aims to design a robust and adaptive control for double pendulum crane system with minimum payload swing angle. Capability of Artificial Neural Networks (ANN) to identify complicated system motivated us to estimate uncertainties of the crane system and external disturbance. Firstly, feedback control law designed based only on the nominal model of crane system. Then updating laws for the neural network weights have been derived by using the Lyapunov theorem to estimate variations of the parameter and disturbances.

SYSTEM MODELLING

Fig. 1. Shows the block diagram of the double pendulum crane system with the following dynamic model expression:

$$\begin{cases}\dot{x}_1 = x_2 \\ \dot{x}_2 = f_2(x) + \Delta f_2(x) + (g_2(x) + \Delta g_2(x))u \\ \dot{x}_3 = x_4 \\ \dot{x}_4 = f_4(x) + \Delta f_4(x) + (g_4(x) + \Delta g_4(x))u \\ \dot{x}_5 = x_6 \\ \dot{x}_6 = f_6(x) + \Delta f_6(x) + (g_6(x) + \Delta g_6(x))u\end{cases} \tag{1}$$

where $f_i(\mathrm{x})$ and $g_i(\mathrm{x})$ are known nominal functions. The $\Delta f_i(\mathrm{x})$ and $\Delta g_i(\mathrm{x})$ denotes the system uncertainties for $i = 2,4,6$. System states can be defined as follows: $x_1 = x$, $x_3 = \theta_1$, $x_5 = \theta_2$, and $x_2,\ x_4,\ x_6$ are their respective derivatives. The nonlinear functions of the state vector $\mathrm{x} = [x_1,\ x_2,\ x_3,\ x_4,\ x_5,\ x_6\,]^T$ in (1) are given by:

$$\dot{\mathrm{x}} = f(x) + g(x)u + \Delta f(x) + \Delta g(x)u + d \tag{2}$$

where

$$x = \begin{bmatrix} x \\ \dot{x} \\ \theta \\ \dot{\theta} \\ \varphi \\ \dot{\varphi} \end{bmatrix}, f(x) = \begin{bmatrix} 0 \\ f_2 \\ 0 \\ f_4 \\ 0 \\ f_6 \end{bmatrix}, g(x) = \begin{bmatrix} 0 \\ g_2 \\ 0 \\ g_4 \\ 0 \\ g_6 \end{bmatrix}, \Delta f(x) = \begin{bmatrix} 0 \\ \Delta f_2 \\ 0 \\ \Delta f_4 \\ 0 \\ \Delta f_6 \end{bmatrix}, \Delta g(x) = \begin{bmatrix} 0 \\ \Delta g_2 \\ 0 \\ \Delta g_4 \\ 0 \\ \Delta g_6 \end{bmatrix}, d = \begin{bmatrix} 0 \\ d_2 \\ 0 \\ d_4 \\ 0 \\ d_6 \end{bmatrix}$$

Assumption 1: the model uncertainties and external disturbance in (2) satisfy the matching condition and this means:

$$\Delta f_i(x) \text{ and } d_i \in span\{b_i(x)\} \tag{3}$$

Then, the system uncertainties and external disturbance can be expressed as follows

$$\Delta f_i(x) = b_i(x)\Delta\hat{f}_i(x) \tag{4}$$

$$d_i(x) = b_i(x)\hat{d}_i(x) \tag{5}$$

3. Controller Design

An adaptive robust controller is suggested to move the trolley to the desired position as soon as possible with a minimum payload swing angle. The proposed control law combined feedback control term designed based nominal model and an adaptive control term to estimate the parameters variations and external disturbance. The proposed control law is:

$$u = u^{FB} + u^{NN} \tag{6}$$

where u^{FB} is a feedback control signal that controls the behavior of the crane system and u^{NN} is a control signal that rejects external disturbance and compensate the system uncertainties. The block diagram of the proposed control scheme is shown in Fig. 2.

3.1 Nominal Controller Design

This subsection discuss design the feedback control term (u^{FB}) by using only the nominal mode of crane system and assume there is no system uncertainty neither external disturbance, i.e. $\Delta f_i(\mathrm{x}) = 0, \Delta g_i(\mathrm{x}) = 0$ and $d_i = 0;\ i = 2,4,6$. Moreover, the stability of the closed loop system is approved based on Lyapunov theorem. The function V that defined below is selected as a candidate Lyapunov function:

$$V = \frac{1}{2}\gamma^2 \tag{7}$$

where

$$\gamma = e_1 + x_2 + x_3 + x_4 + x_5 + x_6 \tag{8}$$

$$e_1 = x_1 - x_d \tag{9}$$

$$\dot{V} = \gamma\dot{\gamma} = \gamma[\dot{e}_1 + \dot{x}_2 + \dot{x}_3 + \dot{x}_4 + \dot{x}_5 + \dot{x}_6] \tag{10}$$

$$= \gamma[x_2 - \dot{x}_d + f_1(x) + g_1(x)u + x_4 + f_2(x) + g_2(x)u + x_6 + f_3(x) + g_3(x)u^{FB}] \tag{11}$$

Let

$$F(x) = f_1(x) + f_2(x) + f_3(x) \tag{12}$$

$$G(x) = g_1(x) + g_2(x) + g_3(x) \tag{13}$$

Then (10) becomes

$$\dot{V} = \gamma[-\dot{x}_d + x_2 + x_4 + x_6 + F(x) + G(x)u^{FB}] \tag{14}$$

The control signal u will be selected in such way that ensures the term $x_2 + x_4 + x_6 + F(x) + G(x)u^{FB}$ equal to $-k\gamma$, i.e;

$$x_2 + x_4 + x_6 + F(x) + G(x)u^{FB} = -k\gamma \quad (15)$$

Then;

$$u^{FB} = \frac{-1}{G(x)}[k\gamma + x_2 + x_4 + x_6 + F(x)] \quad (16)$$

Sub in (14); yields

$$\dot{V} = -k\gamma^2 \quad (17)$$

Remark 1: the control gins which expressed in (12), (13) and (16) indicate that the gains can be determined by using only the nominal model of the crane system.

Remark 2: in real application, the system uncertainties and external disturbance cannot be ignored; therefore, a robust term will be added to the proposed control law to suppress the effects of the parameter variations, modeling error and reject the external disturbance.

3.2 RBF Corrective Controller

In particular, there is no expression that can express the system uncertainties; therefore RBFNN utilized to estimate the system uncertainties f_i(x) and g_i(x). Based on assumption 1, and the matching property that expressed in (4) and (5), the lumped uncertainty $\delta(x,t)$ can be expressed as

$$\mathcal{S}(\mathrm{x},t) = u\left[\Delta g_2(x) + \Delta g_4(x) + \Delta g_6(x) + \Delta\hat{f}_2(x) + \Delta\hat{f}_4(x) + \Delta\hat{f}_6(x) + \textstyle\sum_{i=1}^{6}\hat{d}_i\right] \quad (18)$$

RBFNN will estimate lumped uncertainty $\delta(x,t)$ as $\hat{\delta}(x,t)$ and use it in the proposed control law to compensate the effect of lumped uncertainty. $\delta(x,t)$ can be estimated as

$$\hat{\mathcal{S}}(\mathrm{x},t) = \widehat{w}h = \mathcal{S}(\mathrm{x},t) + \varepsilon_0 \quad (19)$$

where $\widehat{w}$ denotes the neural network weights, h is the Gaussian function, and ε_0 represents the difference between actual and estimated lumped uncertainty.

The proposed adaptive control term is:

$$u^{NN} = \frac{-1}{G(x)}\widehat{w}h \quad (20)$$

RBF is a simple neural network that contains one hidden layer. The proposed RBF NN is shown in Fig. 3. The inputs of the RBF NN are states of the crane system $x = [x_1 x_2 x_3 x_4 x_5 x_6]$ and the hidden layer has 10 neurons. The output of the neural network is :

$$y = \textstyle\sum_{i=1}^{10}\widehat{w}_i h_i(\mathrm{x}) = \widehat{\mathrm{w}}^T h \quad (21)$$

$$\dot{\widehat{\mathrm{w}}} = L^{-1}|\gamma|h(\mathrm{x}) \quad (22)$$

$$h_i(\mathrm{x}) = e^{\frac{\|x-c_i\|}{2b_i^2}} \quad i = 1,2,\cdots,6. \quad (23)$$

$$\widehat{\mathrm{w}} = [\widehat{w}_1 \;\; \widehat{w}_2 \;\; \cdots \;\; \widehat{w}_{10}] \quad (24)$$

$$h = [h_1(\mathrm{x}) \;\; h_2(\mathrm{x}) \;\; \cdots h_{10}(\mathrm{x})]^T \quad (25)$$

where c_i represents the center of the i^{th} Gaussian function and b_i represents the width of the i^{th} Gaussian function. Designed control law assumes the followings:

Assumption 2. The model uncertainties $\Delta f_i(\mathrm{x})$ and $\Delta g_i(\mathrm{x})$ can be estimated by RBF NN with the following optimal weight expression:

$$\left| \mathrm{w}^{*T} h - sup|\mathcal{S}(\mathrm{x}, t)| \right| = \varepsilon(x) < \varepsilon_0 \tag{26}$$

where w^* denotes the optimal weights that can give minimum difference between actual and estimated uncertainties.

Assumption 3. The difference between the supermom value of system uncertainty and the norm of system uncertainty is greater than ε_0 and satisfies the following inequality:

$$sup|\mathcal{S}(\mathrm{x}, t)| - |\mathcal{S}(\mathrm{x}, t)| > \varepsilon_1 > \varepsilon_0 \tag{27}$$

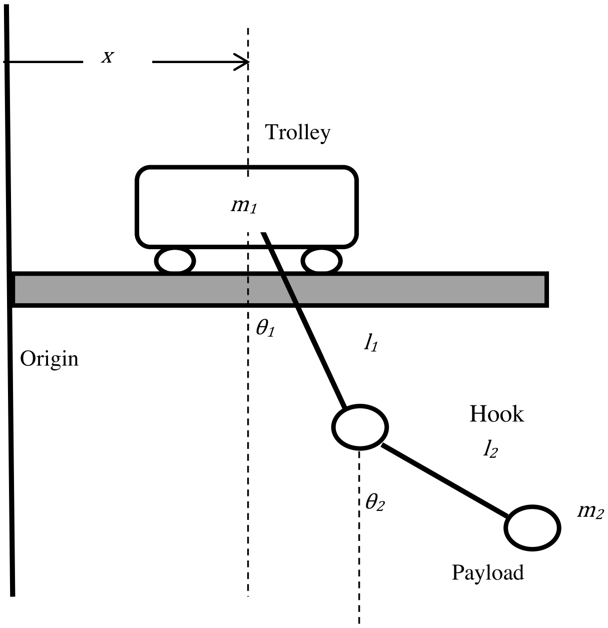

Figure 1. Schematic of the double-pendulum overhead crane system.

Theorem: The proposed control law expressed in (6, 16, 20) with assumptions 1 and 2 addressed in (4,5,26,27) makes the closed loop controlled system asymptotically stable to their desired values in presence of system uncertainty and external disturbance.

Proof: stability of the proposed controller is approved based Lyapunov theorem. Then define V as candidate Lyapunov function.

$$\mathrm{V} = \frac{1}{2}\gamma^2 + \frac{1}{2}\widetilde{\mathrm{w}}^T L\, \widetilde{\mathrm{w}} \tag{28}$$

where

$$\widetilde{\mathrm{w}} = \mathrm{w}^* - \widehat{\mathrm{w}} \tag{29}$$

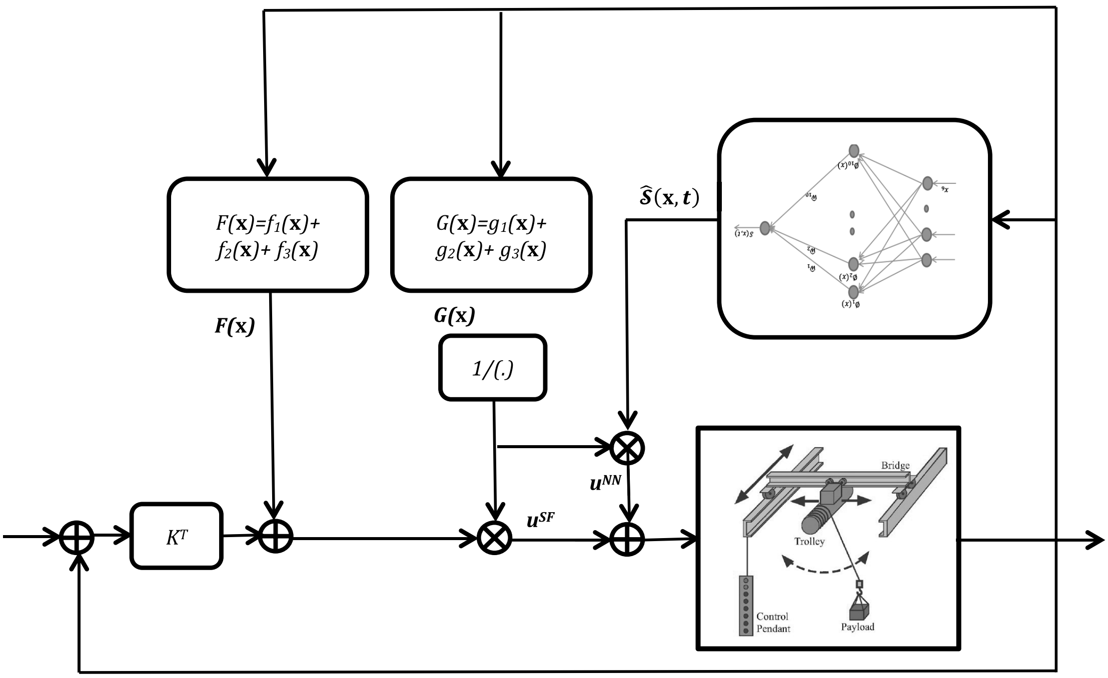

Figure 2. Proposed Control System.

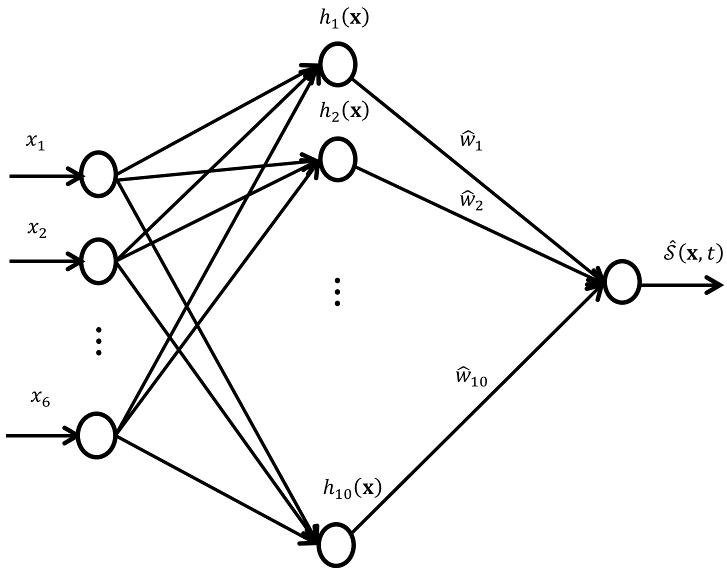

Figure 3. Neural Networks Structure.

$$\dot{V} = \gamma.\dot{\gamma} - \widetilde{\mathrm{w}}^T L \dot{\widehat{\mathrm{w}}} \tag{30}$$

$$\dot{V} = \gamma[x_2 - \dot{x}_d + f_1(\mathrm{x}) + g_1(\mathrm{x})u + x_4 + f_2(\mathrm{x}) + g_2(\mathrm{x})u + x_6 + f_3(\mathrm{x}) + g_3(\mathrm{x})u + \mathcal{S}(\mathrm{x},\mathrm{t})] - \widetilde{\mathrm{w}}^T L \dot{\widehat{\mathrm{w}}} \tag{31}$$

$$\dot{V} = \gamma[x_2 - \dot{x}_d + x_4 + x_6 + F(\mathrm{x}) + G(\mathrm{x})(u^{FB} + u^{NN}) + \mathcal{S}(\mathrm{x},t)] - \widetilde{\mathrm{w}}^T L \dot{\widehat{\mathrm{w}}} \tag{32}$$

Sub (16) and (20) in (32) and after simple rearrangement

$$\dot{V} = \gamma\left[-k\gamma + G(\mathrm{x})\left[\frac{-1}{G(\mathrm{x})}\left[\hat{\mathcal{S}}(\mathrm{x},t)\right]\right] + \mathcal{S}(\mathrm{x},t)\right] - \widetilde{\mathrm{w}}^T L\dot{\hat{\mathrm{w}}} \tag{33}$$

$$= \gamma\left[-k\gamma + \mathcal{S}(x,t) - \hat{\mathcal{S}}(\mathrm{x},t)\right] - \widetilde{w}^T L\dot{\hat{w}} \tag{34}$$

$$= \gamma\left[-k\gamma - (\hat{\mathcal{S}}(\mathrm{x},t) - \mathcal{S}(x,t))\right] - (\mathrm{w}^* - \widehat{\mathrm{w}})^T|\gamma|h(\mathrm{x}) \tag{35}$$

$$\leq -k\gamma^2 - |\gamma|(\varepsilon_0 - \varepsilon_1) \tag{36}$$

According to Assumption 2

$$\dot{V} \leq -k\gamma^2 \tag{37}$$

$$\dot{V} \leq 0 \tag{38}$$

Therefore, the double pendulum crane system with the suggested control method is asymptotically stable.

Simulation results

The robustness of the proposed controller is compared with the Incremental Hierarchical Sliding Mode Controller (IHSMC) (Yunyun *et al.,* 2008) and improved PSO-tuned PID controller (PSO-PID) (Jaafar *et al.,* 2019). To check the transient performance and robustness of the proposed controller against system uncertainties and disturbances, four simulation scenarios are considered. In first scenario: Robustness to the system uncertainties is verified while in the second scenario, the robustness to the external disturbance is examined. The performances of the proposed controller and aforementioned two controllers have been checked for different initial payload swing angles in the third scenario. Last scenario discusses control performance of the proposed controller and other methods with respect to different travelling distance. The same values of the proposed controller's gains used for all scenarios, The nominal values of the crane system are as follows: $m_o = 6.5\,\mathrm{kg}, m_1 = 2\,\mathrm{kg}, m_2 = 6.5\,\mathrm{kg}, l_1 = 6.5\,\mathrm{kg}, l_2 = 6.5\,\mathrm{kg}$. The control gains of the proposed control algorithm are selected as follows: $k = 70, L = 10^{75}$. The control laws of IHSMC and PSO-PID can be expressed as follows:

1- IHSMC

$$u = u_{eq} + u_s \tag{39}$$

where

$$u_{eq} = \frac{\alpha_1\dot{x}+\alpha_2F_1+\alpha_3\dot{\theta}_1+\alpha_4F_2+\alpha_5\dot{\theta}_2+\alpha_6F_3}{\alpha_2\beta_1+\alpha_4\beta_2+\alpha_6\beta_3}, u_s = -\frac{\gamma s_5+ksgn(s_5)}{\alpha_2\beta_1+\alpha_4\beta_2+\alpha_6\beta_3}$$

$$s_5 = \alpha_6\dot{\theta}_2 + s_4\,, s_4 = \alpha_5\theta_2 + s_3\,, s_3 = \alpha_4\dot{\theta}_1 + s_2\,,\ s_2 = \alpha_3\theta_1 + s_1, s_1 = \alpha_1(x - x_d)$$

F_i and β_i are defined in detail in [16]. Control gains of this controller are chosen as follows: $\gamma = 1$, $k = 0.1$, $\alpha_1 = 137, \alpha_2 = 144.9, \alpha_3 = -240, \alpha_4 = 52, \alpha_5 = -150, \alpha_6 = -10.4$

2-PSO-PID

$$u = k_{p1}(x - x_d) + k_{i1}\int_0^t (x - x_d)\, dt + k_{d1}\frac{d(x-x_d)}{dt} + k_{p2}\theta_1 + k_{i2}\int_0^t \theta_1\, dt + k_{d2}\frac{d\theta_1}{dt} + k_{p3}\theta_2 + k_{i3}\int_0^t \theta_2\, dt + k_{d3}\frac{d(\theta_2)}{dt} \quad (40)$$

where k_{pi}, k_{ii} and $k_{di} \in R^+$ are proportional, integral, and derivative gains, respectively. The values of these gains are $k_{p1} = 19.7$, $k_{i1} = 0.007$, $k_{d1} = 19.8$, $k_{p2} = 8.09$, $k_{i2} = 0.27$, $k_{d2} = 21.9$, $k_{p3} = 10.198$, $k_{i3} = 28.35$, $k_{d3} = 1.157$.

1st scenario: Robustness to system uncertainties

In this scenario, the performance of the proposed controller is illustrated under parameter variations of the crane system by changing the Payload mass m_2 and the length of the cable between trolley and hook l_1 from their nominal values to 13.5 kg and 3.25 m, respectively, at t=12 sec. Position, Hook Swing angle, and Payload angle are shown in Figure 4.

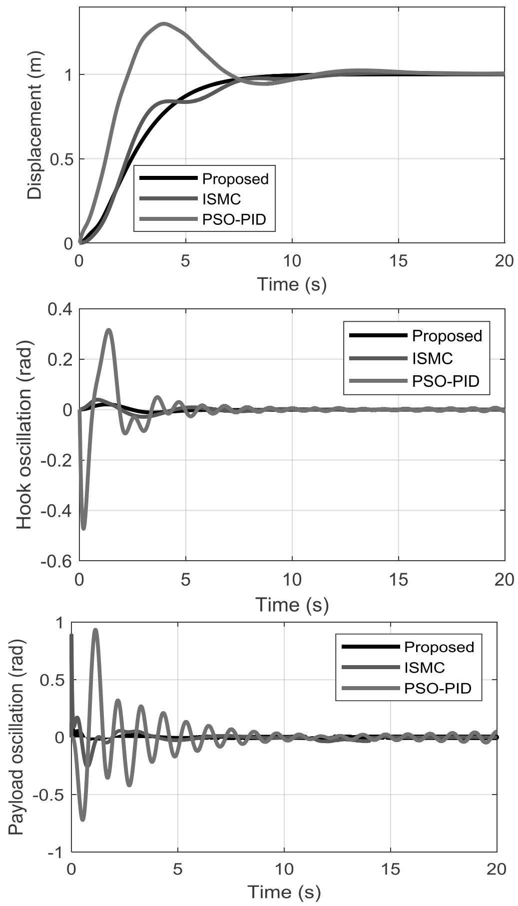

Figure 4. Robustness test against system uncertainties.

It can be seen from this figure, that the transient specifications of the proposed controller are better than others controllers. The swing of the payload and hook have been eliminated very quickly by the proposed controller. Moreover, it can be notice that the payload and hook are swinging within a smaller range when compared with the ISMC and PID controllers. Fig. 4 shows that the response of PSO-PID reaches the desired position faster than other methods but with very big overshoots and with an oscillation around the desired position. However, this test indicates clearly ability of the proposed method to reduce the oscillation of hook and payload very quickly with respect to the other methods. This scenario indicates clearly robustness of the proposed controller against system uncertainties.

2nd scenario: External Disturbance Rejection

In this case, an external disturbance rejection of the proposed controller is discussed by applying two kinds of disturbances impulsive and sinusoidal disturbance are added as follows:

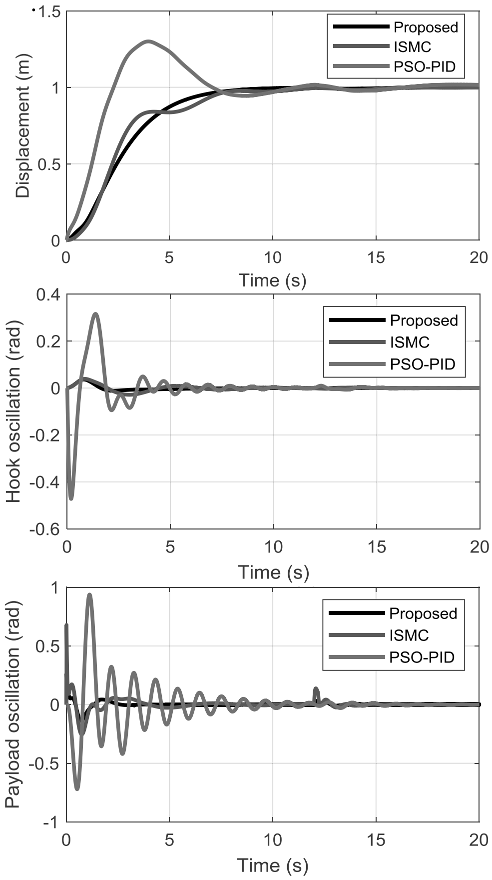

Figure 5. Simulation results for the impulse disturbance.

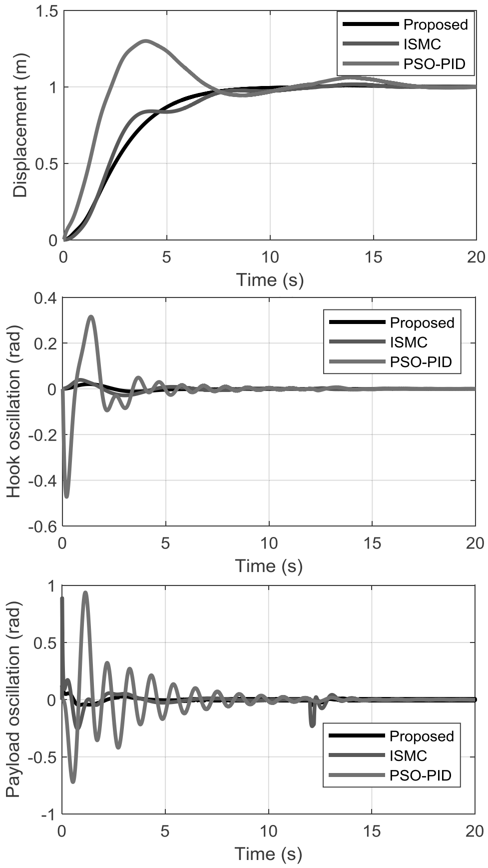

Figure 6. Simulation results for the sinusoidal disturbance.

Case 1: impulse disturbance is added at 10 sec.

Case 2: sinusoidal disturbance is applied at t =12 sec. The amplitude of all applied disturbances are 1.5.

Figs. 5-6 show the behavior of the proposed controller and other control methods to these disturbances. These figures indicate that proposed controller has faster and robust response with good accuracy. Fig. 5 and 6 indicate that the position of the proposed controller does not affect with disturbance. Also, Figures 5 and 6 illustrated that the hook swing angle and payload swing angle provided by the proposed controller are slightly affected by the disturbance with respect to the other two methods. The results of simulation test indicated clearly ability of the proposed control scheme in disturbance rejection.

3rd scenario: Non-zero initial swing angles

The robustness of the proposed controller is illustrated by disturb the careen system with the nonzero initial payload and hook swing angles. Two cases have been considered in this scenario:

Case 1: $\theta_1(0) = 0.1\ rad$

Case 2: $\theta_2(0) = 0.2\ rad$

Figs. 7-8 show the response of the proposed controller and other controllers to the non-zero initial swing angles.

This figure indicates that the proposed control method is slightly affected with this disturbance, while PID controller is highly effected. The proposed control method suppresses the swing of payload and hook in very short time with respect to the other control methods.

4th scenario Different desired displacement

In this test, the efficiency and robustness of the proposed control method to the different desired displacement are examined. Then, the following cases are considered:

Case 1: $x_d = 8\ m$

Case 2: $x_d = 4\ m$

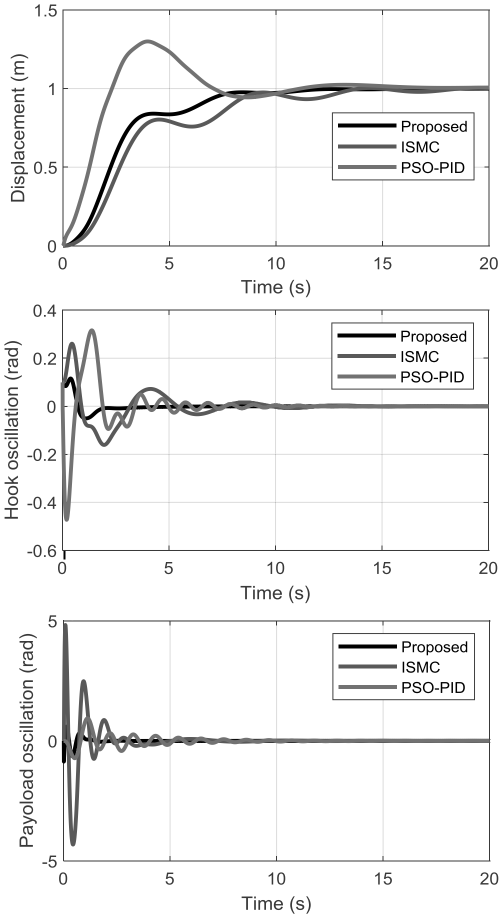

Figure 7. Simulation results for non- zero initial Hook angle.

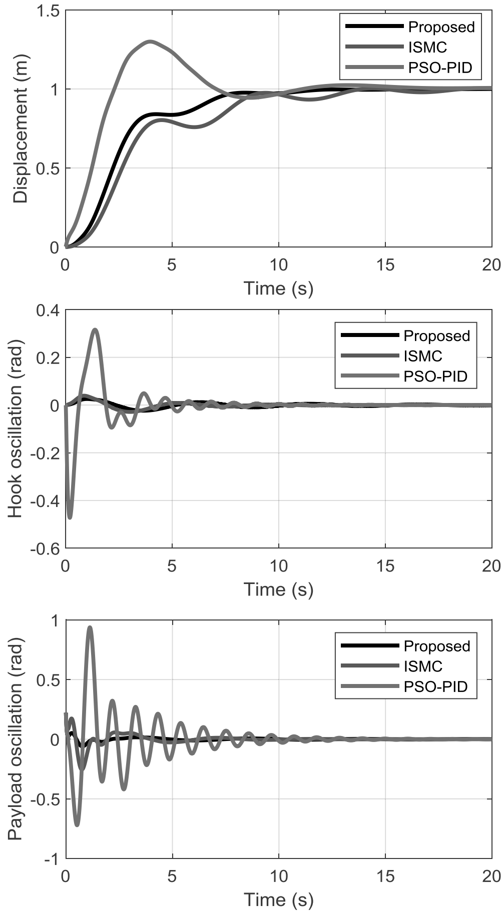

Figure 8. Simulation results for non- zero initial Payload angle.

Figures 9 and 10 show results of this test. These figures indicate that the proposed control method eliminate the swing of Hook and Payload angles very quickly and push the trolley to the desired displacement in very smooth movement without overshoot.

CONCLUSIONS

This adaptive robust control for crane system considered in this paper takes into account system uncertainty and external disturbance. At first, the system uncertainty and external disturbance have been ignored, and feedback control term is derived only based on the available information about the dynamic of controlled system.

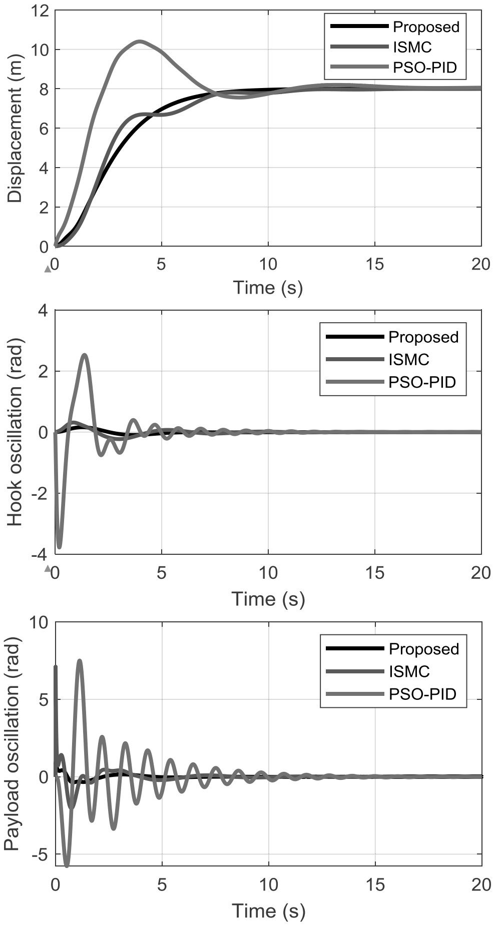

Figure 9. Control performance for $x_d = 8\,m$.

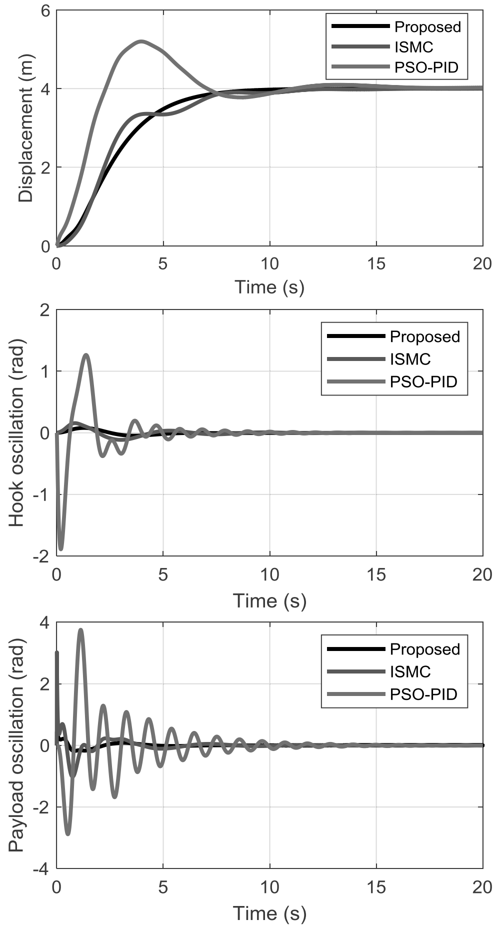

Figure 10. Control performance for $x_d = 4\,m$.

Robust control term is designed based on Lyapunov theorem to derive updating laws for the RBF weights to compensate the system uncertainties and external disturbances. The performance and robustness of the proposed controller were also examined with four different cases as discussed above. The simulation results illustrated that the proposed controller is more robust than ISMC and PID controllers. In addition, the transient performance of the proposed control method is better than ISMC and PID controllers used in the comparison.

REFERENCES

Almutairi, N.B. and Zribi, M., 2016. Fuzzy controllers for a gantry crane system with experimental verifications. Mathematical Problems in Engineering, 2016.

Almutairi, N.B. and Zribi, M., 2009. Sliding mode control of a three-dimensional overhead crane. Journal of vibration and control, **15**(11): pp.1679-1730.

Abdullahi, A.M., Mohamed, Z., Selamat, H., Pota, H.R., Abidin, M.Z., Ismail, F.S. and Haruna, A. 2018. Adaptive output-based command shaping for sway control of a 3D overhead crane with payload hoisting and wind disturbance. Mechanical Systems and Signal Processing, **98**: pp.157-172.

Fang, Y., Dixon, W.E., Dawson, D.M. and Zergeroglu, E. 2003. Nonlinear coupling control laws for an underactuated overhead crane system. IEEE/ASME transactions on mechatronics, **8**(3): pp.418-423.

Fujioka, D. and Singhose, W. 2015. Performance comparison of input-shaped model reference control on an uncertain flexible system. IFAC-PapersOnLine, **48**(12): pp.129-134.

Hamoudi, A.K. 2017. Design an Integral Sliding Mode Controller for a Nonlinear System. Al-Khwarizmi Engineering Journal, **13**(1): pp.138-147.

Huang, J., Maleki, E. and Singhose, W. 2013. Dynamics and swing control of mobile boom cranes subject to wind disturbances. IET Control Theory & Applications, **7**(9): pp.1187-1195.

Jaafar, H.I., Mohamed, Z., Mohd Subha, N.A., Husain, A.R., Ismail, F.S., Ramli, L., Tokhi, M.O. and Shamsudin, M.A., 2019. Efficient control of a nonlinear double-pendulum overhead crane with sensorless payload motion using an improved PSO-tuned PID controller. Journal of Vibration and Control, **25**(4): pp.907-921.

Jaafar, H.I., Hussien, S.Y.S., Ghazali, R. and Mohamed, Z., 2015. Optimal tuning of PID+ PD controller by PFS for gantry crane system. In 2015 10th Asian Control Conference (ASCC) (pp. 1-6). IEEE.

Le, V.A., Le, H.X., Nguyen, L. and Phan, M.X., 2019. An efficient adaptive hierarchical sliding mode control strategy using neural networks for 3D overhead cranes. International Journal of Automation and Computing, **16**(5): pp.614-627.

Maghsoudi, M.J., Mohamed, Z., Husain, A.R. and Tokhi, M.O. 2016. An optimal performance control scheme for a 3D crane. Mechanical Systems and Signal Processing, **66**: pp.756-768.

Mary, A.H. and Kara, T. 2016. Robust proportional control for trajectory tracking of a nonlinear robotic manipulator: LMI optimization approach. Arabian Journal for Science and Engineering, **41**(12): pp.5027-5036.

Ngo, Q.H. and Hong, K.S. 2010. Sliding-mode antisway control of an offshore container crane. IEEE/ASME transactions on mechatronics, **17**(2): pp.201-209.

Pan, H., Jing, X. and Sun, W. 2017. Robust finite-time tracking control for nonlinear suspension systems via disturbance compensation. Mechanical Systems and Signal Processing, **88**: pp.49-61.

Park, H., Chwa, D. and Hong, K.S. 2007. A feedback linearization control of container cranes: Varying rope length. International Journal of Control, Automation, and Systems, **5**(4): pp.379-387.

Solihin, M.I., Wahyudi and Legowo, A. 2010. Fuzzy-tuned PID anti-swing control of automatic gantry crane. Journal of Vibration and Control, **16**(1): pp.127-145.

Veciana, J.M., Cardona, S. and Català, P. 2015. Modified adaptive input shaping for maneuvering cranes using a feedback MEM gyroscope with null drift. International journal of precision engineering and manufacturing, **16**(9): pp.1911-1917.

Yu, X., Lin, X. and Lan, W. 2014. Composite nonlinear feedback controller design for an overhead crane servo system. Transactions of the Institute of Measurement and Control, **36**(5): pp.662-672.

Yunyun, D., Zhonghua, W., Zhiquan, F. and Jin, C. 2008. Incremental sliding mode control for double-pendulum-type overhead crane system. In 2008 27th Chinese Control Conference (pp. 368-371). IEEE.

Zhang, M., Zhang, Y. and Cheng, X., 2019. An enhanced coupling PD with sliding mode control method for underactuated double-pendulum overhead crane systems. International Journal of Control, Automation and Systems, **17**(6): pp.1579-1588.