

Takagi-Sugeno Observer for Tower Crane System

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Abstract

In this paper, a new representation of the nonlinear dynamics of the tower crane system in Takagi-Sugeno (TS) fuzzy form is proposed and used for observer design. The TS fuzzy nonlinear observer is utilized to estimate unmeasurable states with guaranteed global asymptotic stability. The stability analysis is formulated as linear matrix inequalities (LMIs). The TS fuzzy model is equivalent to a reduced-order nonlinear model of the tower crane system with a varying cable length. For verification, simulation results of the reduced-order model, TS nonlinear fuzzy model and the estimated observer states are compared to the results of a tower crane on a laboratory scale.

1 Introduction

Cranes are widely used for heavy load transportation and are typically classified into (1) tower cranes, (2) rotary cranes and (3) overhead cranes. Due to their wide range of applications on the construction site, tower cranes are the subject of investigations in automation and control engineering. It must

be taken into account that this type of crane system has a non-linear under-actuated complicated dynamics. Therefore, controlling of tower crane systems is a challenge.

Various crane control techniques have been proposed to achieve precise positioning and oscillation suppression of the payloads. Model-based fuzzy control has been recognized as an alternative approach to conventional techniques for overhead cranes. Adaptive fuzzy sliding-mode control is designed to guarantee asymptotic stability for payload oscillations [1]. A discrete-time TS fuzzy observer and controller is designed by [3]. In addition, the Mamdani-type fuzzy approach was used in [2] to design an active anti-swing controller.

Few of these techniques have been extended to the application of tower cranes [4]. Mainly conventional methods were used such as command shaping for oscillation reduction [5] and an optimal iterative method is presented in [6]. Just a fuzzy anti-swing controller for tower cranes based on the Mamdani type with consideration of friction and time delay was proposed in [7].

Regarding robust controllers, sliding mode control based on the nonlinear model is proposed in [8] and extended to an adaptive scheme [9]. Optimal control has been proposed with the path-following method [10]. The parametric uncertainties are handled using adaptive control in [11], adaptive backstepping for 2D system is proposed in [12] and adaptive nonlinear integral sliding mode was investigated in the work [13].

The existing methods are developed based on simplified control-oriented models using approximations and assumptions of the original tower crane dynamics. The difference between the original dynamics and the simplified model affects the controllers' performance and might lead to instability [11]. On the other hand, the consideration of the full nonlinear model increases the complexity of the control design and the closed-loop stability assessment. This complexity can be eliminated by reaching a proper reduced-order system. The main aim of this paper is to derive a suitable Takagi-Sugeno (TS) fuzzy model equivalent to a reduced-order nonlinear model for actual reflection of the system's dynamics. The Takagi-Sugeno framework is chosen for the advantage of an exact representation of the original nonlinear model and facilitation of the stability analysis and observer design of nonlinear systems. [14].

Moreover, the estimation convergence of state observer depends on the mathematical model [3]. Therefore, TS fuzzy observer is designed based on the aforementioned model. The observer is used to estimate the unmeasurable system states found in practical applications, such as the velocities that are required to be known for the controller. The previous closed-loop controllers' feedback depended on differentiating the measured positions [10] and filtering the results [11], which cause a time delay and reduction in the accuracy of the feedback.

This paper is organized as follows: Section II presents the nonlinear reduced order model of the tower crane and the state space representation. The equivalent TS fuzzy model is presented in Section III. In Section IV, the TS fuzzy observer is designed and its stability is analyzed. Section V presents a comparison study of the models, estimated observer states with the experimental results. Section VI presents the conclusion.

2 Continuous-time Nonlinear Dynamical Model

The model is derived based on the Euler Lagrange method [15] resulting in highly nonlinear under-actuated MIMO equations:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}_i}\right) - \frac{\partial L}{\partial q_i} = F_{q_i}, \quad i = 1, \dots, 5, \quad (1)$$

where q_i is a vector of the tower crane's five degrees of freedom shown in Figure 1. The vector $q_i = [x_t, \theta, \alpha, \beta, l]^T$ contains the trolley position, jib rotation, alpha, beta oscillation and the cable length respectively. The joint torque vector is given by $F_{q_i} = [F_x, F_\theta, F_l, 0, 0]^T$, where F_x denotes the trolley driving force, F_θ denotes the tower rotating torque and F_l denotes the cable driving force.

2.1 Continuous-time Nonlinear Model

The equations can be reformulated by dividing the tower crane's DOF into (1) actuated states q_1 and (2) un-actuated states q_2 . The actuated states are the trol-

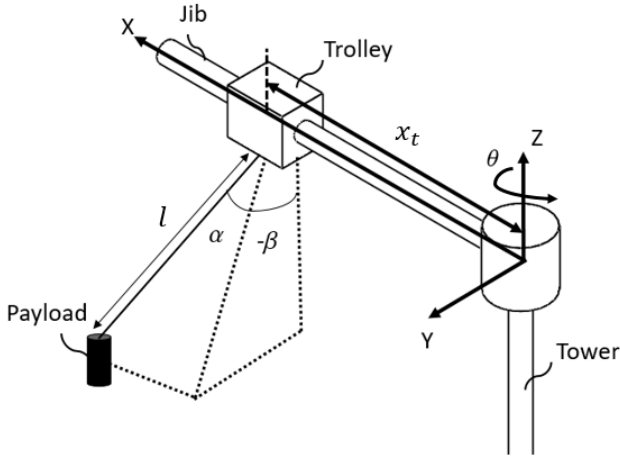


Figure 1: Schematic Representation of Tower Crane

ley position, the tower rotation and cable length denoted by $q_1 = [x_t \ \theta \ l]^T$. The un-actuated states are the swing angles of the payload where $q_2 = [\alpha \ \beta]^T$. Using the method of order analysis [1], the complete nonlinear model is reduced for each term [16]. Small swing angles are assumed [17], the un-actuated states' equations are substituted into the actuated states' equations, and the actuated states' equations are substituted into the un-actuated states' equations, resulting in the following equations:

$$\ddot{x}_t + \left(\frac{B_x}{m_t} + K_2 \frac{1}{r_x^2 m_t} \right) \dot{x}_t - g \frac{m_p}{m_t} \alpha = \frac{1}{m_t} K_1 u_x, \quad (2)$$

$$\left(1 + \frac{m_t}{J_\theta} x_t^2 \right) \ddot{\theta} + (B_\theta + K_2) \frac{\dot{\theta}}{J_\theta} - g \frac{m_p}{J_\theta} x_t \beta = \frac{1}{J_\theta} K_1 u_\theta, \quad (3)$$

$$\ddot{l} + \left(\frac{B_l}{m_p} + K_2 \frac{1}{r_x^2 m_p} \right) \dot{l} = \frac{1}{r_x m_p} K_1 u_l, \quad (4)$$

$$(J_p + m_p l^2) \ddot{\alpha} + B_\alpha \dot{\alpha} + g m_p l \alpha + m_p l \ddot{x}_t - m_p x_t l \dot{\theta}^2 - 2 m_p l^2 \dot{\theta} \dot{\theta} = 0 ,$$

$$m_p x_t l \ddot{\theta} + (J_p + m_p l^2) \ddot{\beta} + B_\beta \dot{\beta} + g m_p l \beta = 0 , \quad (5)$$

where

$$F_{q_i} = K_1 u_{(q_i)} - K_2 \dot{q}_i , \quad (6)$$

$$K_1 = \frac{\eta_{(q_i)} K_{g(q_i)} K_{m(q_i)}}{R_{a(q_i)}} G_{a(q_i)} , \quad K_2 = \frac{\eta_{(q_i)} k_{g(q_i)}^2 k_{m(q_i)}^2}{R_{a(q_i)}} .$$

m_t is the mass of the trolley, m_p is the mass of the payload, $B_{(q_i)}$ is the viscous friction coefficient, g is the gravitational constant, J_θ and J_p are the moment of inertia for the jib and load respectively. The motor parameters are: $K_{g(q_i)}$ is the gear ratio, $\eta_{(q_i)}$ is the motor gearbox and motor efficiency, $k_{m(q_i)}$ is the torque constant, r_x is the radius of pulley, $R_{a(q_i)}$ is the armature resistance and $G_{a(q_i)}$ is the amplifier gain. The equations of motion of the tower crane is in the form of:

$$M(q)\ddot{q} + B(q, \dot{q}) + G(q) = F , \quad (7)$$

where $M(q) \in R^{n \times n}$ is the inertia matrix which is a positive definite matrix for $l > 0$ and its inverse exists, $B(q, \dot{q}) \in R^{n \times 1}$ is the Coriolis, centripetal and friction matrix and $G(q) \in R^{n \times 1}$ denotes the gravitational force vector.

2.2 Continuous-time Nonlinear State Space Representation

A representation of a given nonlinear system in Takagi-Sugeno form is obtained in a compact set if the state space of a nonlinear system can be expressed as follows:

$$\begin{aligned} \dot{x} &= f(x, u)x + g(x, u)u, \\ y &= h(x, u)x. \end{aligned} \quad (8)$$

f , g and h are smooth nonlinear matrix functions and assumed to be bounded. $x = [x_t, \dot{x}_t, \theta, \dot{\theta}, l, \dot{l}, \alpha, \dot{\alpha}, \beta, \dot{\beta}]^T$ is the state vector of (8) and $u = [u_x, u_\theta, u_l]^T$ is the input vector. In detail with (2) - (5) this results in

$$\begin{aligned}
 \dot{x}_1 &= x_2 \\
 \dot{x}_2 &= A_1 \\
 \dot{x}_3 &= x_4 \\
 \dot{x}_4 &= A_2 \\
 \dot{x}_5 &= x_6 \\
 \dot{x}_6 &= \frac{1}{m_p} [K_1 u_l - (B_l + K_2) x_6] \\
 \dot{x}_7 &= x_8 \\
 \dot{x}_8 &= \frac{m_t x_5 (-A_1 + x_1 x_4^2 + 2 x_{10} x_4 x_5 - x_7 g) - B_\alpha x_8}{m_p x_5^2 + J_p} \\
 \dot{x}_9 &= x_{10} \\
 \dot{x}_{10} &= \frac{-B_\beta x_{10} - g m_p x_5 x_9 - m_p A_2 x_1 x_5}{(m_p x_5^2 + J_p)}
 \end{aligned} \tag{9}$$

where

$$\begin{aligned}
 A_1 &= \frac{1}{m_t} [K_1 u_x - x_2 (B_x + K_2) + x_7 g m_p], \\
 A_2 &= \frac{K_1 u_l - x_4 (B_\theta + K_2) + g m_p x_1 x_9}{m_t x_1^2 + J_p}
 \end{aligned} \tag{10}$$

3 Nonlinear Dynamic TS Fuzzy Model

In this paper the TS model of the tower crane is constructed analytically based on the previously presented state space model (9).

3.1 Sector Nonlinearity Approach

Takagi-Sugeno fuzzy representation of the crane model is derived using sector non-linearity approach [18] to be used in the design process of the continuous-time observer. The scheduling variables are chosen as $z_j \in [\underline{z}_j, \bar{z}_j]$, $j = 1, 2, \dots, p$ where \underline{z}_j and \bar{z}_j are the minimum and maximum values in the considered operating range respectively. The six premise variables are chosen as:

$$z = [x_t, \frac{1}{m_t x_t^2 + J_\theta}, l, \dot{\theta} l, \beta, \frac{1}{m_p l^2 + J_p}]^T \quad (11)$$

The system's states are bounded and the bounds are based on the physical constraints of the real system to be investigated [21]: $z_1 \in [0.22, 0.52]$, $z_2 \in [0.386, 0.41]$, $z_3 \in [0.15, 1.2]$, $z_4 \in [-0.15, 1.2]$, $z_5 \in [-\pi/2, \pi/2]$ and $z_6 \in [2.1, 45]$. The rules of the TS system are constructed:

$$\begin{aligned} &\text{if } z_1 \text{ is } Z_1^i \text{ and } \dots \text{ and } z_p \text{ is } Z_p^i \text{ then} \\ &\dot{x} = A_i x + B_i u, y = C_i x, \end{aligned} \quad (12)$$

where Z_1^i, \dots, Z_p^i are the corresponding sets of the premise variables with the number of rules $i = 1, 2, \dots, m$ equal to $m = 2^p = 64$, where $p = 6$ is the number of premise variables and 2 is the number of weighting functions per premise variable. The nonlinear system is represented as TS fuzzy model in the form of

$$\begin{aligned} \dot{x} &= \sum_{i=1}^m h_i(z) (A_i x + B_i u), \\ y &= \sum_{i=1}^m h_i(z) C_i x \end{aligned} \quad (13)$$

$h_i(z(t)) \geq 0$ are the normalized membership function with convex sum property $\sum_{i=1}^m h_i(z(t)) = 1$ [14] and is calculated as the product of the weighting functions:

$$h_i(z) = \prod_{j=1}^p w_{i_j}^j(z_j) \quad (14)$$

where $i_j \in \{0, 1\}$. For each z_j , two weighting functions are constructed:

$$w_0^j = \frac{\bar{z}_j - z_j}{\bar{z}_j - \underline{z}_j}, \quad w_1^j = 1 - w_0^j, \quad j = 1, 2, \dots, p. \quad (15)$$

4 TS Fuzzy Observer

In this section, the nonlinear observer is designed to estimate the unmeasured states relying on the system model (13):

$$\begin{aligned} \dot{\hat{x}} &= \sum_{i=1}^m h_i(z) [A_i \hat{x} + B_i u + L_i(y - \hat{y})], \\ \hat{y} &= C \hat{x}, \end{aligned} \quad (16)$$

where

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (17)$$

that refers to the five measured states, and \hat{x} is the estimated state vector, \hat{y} is the estimated measurement and L_i are the observer gains.

4.1 Stability analysis via Lyapunov Approach

The stability analysis is reduced to linear matrix inequality (LMI) problem, which is equivalent to finding solutions to original problems. The estimation error is defined as $e = x - \hat{x}$, while the error dynamics are [19]:

$$\begin{aligned} \dot{e} &= \dot{x} - \dot{\hat{x}} = \sum_{i=1}^m h_i(z) [A_i (x - \hat{x}) - L_i(y - \hat{y})] \\ &= \sum_{i=1}^m h_i(z) (A_i - L_i C) e \end{aligned} \quad (18)$$

Theorem 4.1 [14](page 64): The estimation error dynamics with common measurement matrix C in (18) is asymptotically stable, if there exist $P = P^T$ and L_i , so that

$$\mathcal{H}(P(A_i - L_i C)) < 0 \quad (19)$$

for all $i = 1, 2, \dots, m$, where $\mathcal{H}(X) = X^T + X$. The following LMI problem is feasible using the variable $M_i = P L_i$. The performance measure is satisfied by adding a convergence rate of the observer, such that:

$$\mathcal{H}(P A_i - M_i C_i) + 2\alpha P < 0, \quad (20)$$

where α is the decay rate of the estimation error e .

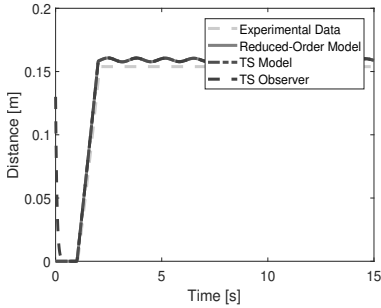
The stability condition of Theorem 4.1 is derived using the quadratic function $V(e) = e^T P e$. The derivative of the Lyapunov function is:

$$\begin{aligned} \dot{V}(e) &= \dot{e}^T P e + e P \dot{e} \\ &= \sum_{i=1}^m h_i(z) ((A_i - L_i C)e)^T P e + e^T P (A_i - L_i C) e \\ &= \sum_{i=1}^m h_i(z) e^T ((A_i - L_i C)^T P + P(A_i - L_i C)) e < 0 \end{aligned} \quad (21)$$

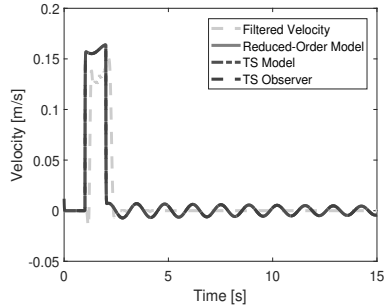
If a common positive definite matrix $P = P^T > 0$ exists for all $m = 64$ fuzzy models and the Lyapunov function is decreasing, therefore the system is globally asymptotically stable. The observer by design guarantees, that the estimation error converges asymptotically to zero. The system equation are used to obtain M_i for observer gains L_i with $L_i = P^{-1} M_i$. The solution of the observer is computed using YALMIP toolbox [20] and SEDUMI solver in MATLAB

Table 1: The values of the estimated parameters

Crane parameter mechanics	Crane parameter drives
$m_t = 0.7 \text{ Kg}$	$K_{g(x_t)} = K_{g(l)} = 76.84$
$m_p = 0.32 \text{ Kg}$	$K_{g(\theta)} = 275$
$B_x = 28 \text{ Nm/s}$	$\eta_{(x_t)} = \eta_{(l)} = 0.36$
$B_\theta = 14 \text{ Nm/s}$	$\eta_{(\theta)} = 0.24$
$B_l = 19.5 \text{ Nm/s}$	$k_{m(x_t)} = k_{m(l)} = 0.032 \text{ Nm/A}$
$B_\alpha = 0.001 \text{ Nm/s}$	$k_{m(\theta)} = 0.0195 \text{ Nm/A}$
$B_\beta = 0.001 \text{ Nm/s}$	$r_x = 0.0375 \text{ m}$
$J_\theta = 1.7 \text{ Kgm}^2$	$R_{a(x_t)} = R_{a(l)} = 25 \text{ V/A}$
$J_p = 0.023 \text{ Kgm}^2$	$R_{a(\theta)} = 0.5 \text{ V/A}$
$g = 9.81 \text{ m/s}^2$	$G_{ax} = 15$
	$G_{a(\theta)} = G_{a(l)} = 12$

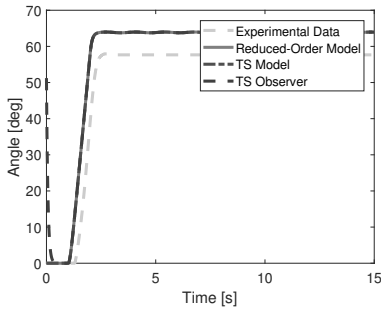


(a) Trolley position x_t

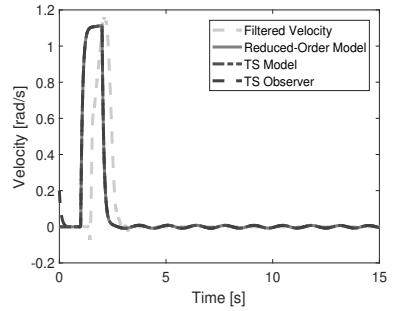


(b) Trolley velocity \dot{x}_t

Figure 2: Trolley motion

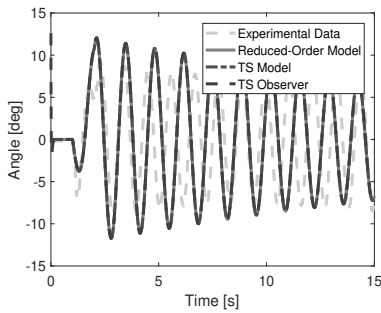


(a) Jib angle θ

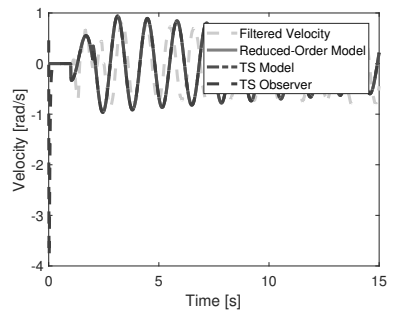


(b) Jib angular velocity $\dot{\theta}$

Figure 3: Jib motion

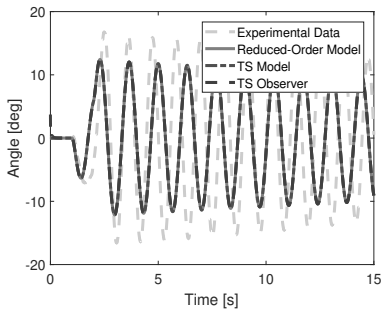


(a) Payload angle α

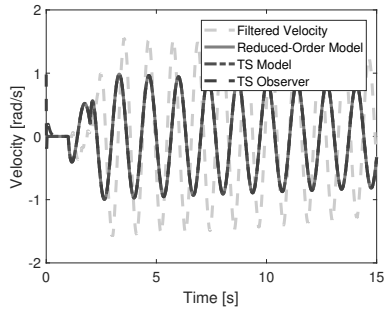


(b) Payload angular velocity $\dot{\alpha}$

Figure 4: Payload motion: α coordinate

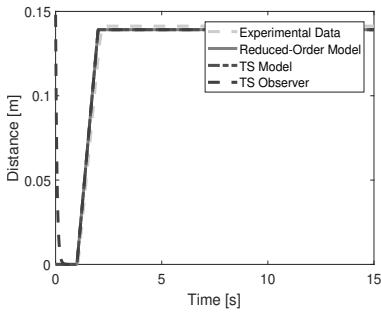


(a) Payload angle β

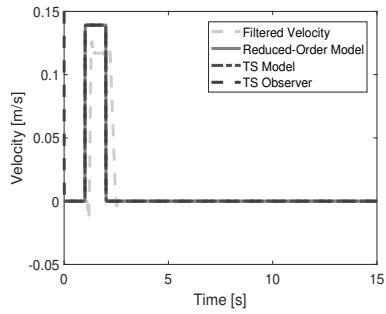


(b) Payload angular velocity $\dot{\beta}$

Figure 5: Payload motion: β coordinate



(a) Cable length l



(b) Payload velocity: l -coordinate

Figure 6: Payload motion: cable coordinate l

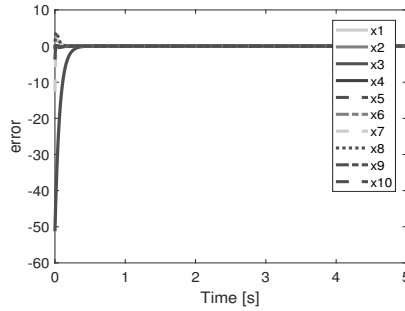


Figure 7: Estimation error $e = x - \hat{x}$

5 Experiments

For the experimental investigations, a real-time data acquisition (RT-DAC /USB2 board) is used as an interface between the personal computer and the tower crane in laboratory scale [21]. The crane's parameters used in the model equations were estimated by [22] using the prediction error method. Other parameters such as friction coefficients and the inertia are estimated using an off-line identification parameter estimation tool in MATLAB via sum square method based on the structure of the model. The motor parameters are presented by [17] and the parameter values are given in Table 1. The decay rate used is $\alpha = 10$, hence the observer dynamics is faster than the dynamics of the closed loop system. The controller needs a fast reconstructed signal, giving an advantage over existing methods. The initial conditions used for the experimental setup and the model are equal to the home position. The home point of the mechanical system is equal to 0.22 m for the trolley position and zero for the rest of the states. The initial conditions for the estimated states are $\hat{x}_0 = [0.35, 0.0118, 0.894, 0.1991, 0.298, 0.15, 0.22, 0.46, 0.065, 0.98]^T$. The input used for moving the system is a pulse signal for 1 second and the corresponding experimental data is measured. This data is plotted against the results of the TS model and TS observer using the same input. The comparison between the three results is carried out for a typical crane maneuver which is a superposition of three motions: the trolley translation, jib rotation and cable motion.

From Figure 2 to 6 it can be seen that the error between the experimental data and the reduced-order model is equal to 0.62 cm in the trolley position x_t , 6 degrees in the jib position θ , 3 degrees in the α oscillation and 4 degrees for the β oscillation. The velocities are calculated using the conventional method of differentiating the position and filtering the results. However, the controller will be based on the observer's result to avoid using inaccurate feedback. The estimated velocities have the same profile as the filtered velocities while the differences are due to the differentiation error and the time delay found in the filtered data. Therefore, the results show that the reduced-order model captures the actual dynamics accurately with small magnitude of error.

Moreover, in Figure 2 to Figure 6, the overlapping of the data shows that the obtained TS model is same as the original in the considered limits. The estimation error converges to zero in less than 1 second for all states as shown in Figure 7.

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