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Comparison of Kalman Observer and H Infinity Observer Designed for TRMS

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Abstract

In this paper the identified stochastic model for Twin Rotor MIMO system (TRMS) is used for designing Kalman observer and H infinity observer. The performance of Kalman observer and H infinity observer designed for Twin Rotor MIMO System are compared. In this case the process noise and measurement noise getting impact on the system is assumed to be worst case noise with unknown statistics. The H infinity observer results in better performance than the Kalman observer for TRMS under worst case noise impact on the uncertain system.

Keywords*: Black box system identification; Kalman observer; H infinity observer; Estimation; TRMS*

1. Introduction

The Twin Rotor MIMO System (TRMS) is a laboratory setup that is designed for flight control experiments. In certain aspects its behaviour resembles that of a helicopter system. Like in a real helicopter, in TRMS there is a significant cross coupling between two rotors. If the vertical position of rotor is activated the beam of TRMS will also turn in the horizontal plane. With two inputs (the voltages supplied to the motors which drive main rotor and tail rotor) and two outputs (Pitch and Yaw angles) the TRMS is an excellent MIMO plant[1].

As obtaining exact model of TRMS is difficult due to non linearities and cross coupling, system identification method is used to get a stochastic approximate model of the system on performing experimentation on TRMS. The model which has been used in [13] is of the order 28 which seems to be very high compared to the order obtained in this work which is 10^{th} order which gives satisfactory results. The TRMS model is identified using system identification method as given in [2][7].

The identified model for TRMS is approximate model. Therefore it is considered as a system with uncertainties. In this paper this identified model is used to design Kalman observer and H_∞ observer using the design technique as given in [6][7][9][10]. The performance of Kalman observer and H_∞ observer designed for TRMS is compared and presented. In section 2 the identification method of TRMS model is briefly explained. The details of system identification for TRMS are given in the author's previous work mentioned in [7]. In section 2.1 and 2.2 the design equations for Kalman observer and H_∞ observer are given. In this work the TRMS system matrix is having the dimension of 10X10. Section 3 shows the results obtained for TRMS with Kalman observer and H_∞ observer. Section 4 is the conclusion.

2. Experimental Setup

TRMS setup is shown in Figure 1. System identification with black box modeling uses statistical methods to build mathematical models of dynamical systems from measured data [3][4]. System identification toolbox constructs mathematical models

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of dynamic systems from measured input-output data. Black Box identification doesn't assume anything about the system and thus gives a good estimate of the system's characteristics.

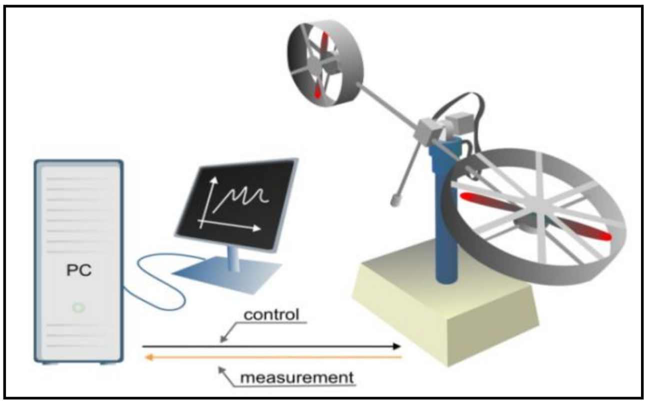

Figure 1. The Twin Rotor MIMO System

Logical flow of system identification is, Collect data →choose a model set →pick the best model in this set→model validation. The models used in the present work are Auto Regressive Moving Average Exogenous (ARMAX) models. Other models like Box Jenkins, output error, Autoregressive exogenous (ARX) were also used for experimentation. Among all ARMAX model was found to be the best for the given TRMS setup giving almost 75% fit. Hence that is finally chosen as the model for TRMS. In ARMAX model, the current output is a function of previous outputs (auto regressive part), past inputs (exogenous part) and current and previous noise terms (moving average part) shown in (1) and (2).[5].

$$A(z)y(n) = B(z)u(n) + C(z)\xi(n) \tag{1}$$

The output is shown in (2)

$$y(n) = \frac{B(z)}{A(z)}u(n) + \frac{C(z)}{A(z)}\xi(n) \tag{2}$$

Where $G(z) = \frac{B(z)}{A(z)}$ is system transfer function and $H(z) = \frac{C(z)}{A(z)}$ is noise transfer function, ξ is the actual noise getting impact on the system. Using ARMAX we can arrive at a linear model by guessing $C(z)$. A good initial guess is $C(z) = 1$. That is start with an ARX model. Then proper value for $C(z)$ is obtained by iterative process which is achieved using MATLAB System Identification Toolbox. The mixed frequency input ranging from (0-1) hertz is given to TRMS and response is observed. The time domain data is collected and saved in the MATLAB workspace. Then the data is imported into the system identification toolbox and means of the input-output pair data is removed. The data is split into two parts. One part is used to estimate the model and the other part is used to validate the estimated model. First the correct order of the transfer function is determined by using ARX models, with orders from 1 to 10 and the best fit is found. Then, once the order is fixed the type of model is changed to ARMAX. Many trial and error experimentation is required to get a good model. This process is repeated for four times to record all the dynamics of the system. That is Main pitch, Main Yaw, Cross Pitch and Cross Yaw dynamics. After obtaining the best fit models, the order is reduced to get a good low order approximation without compromising too much on the quality of the model to fit the validation data. Figure 2 shows the transfer function block diagram of TRMS. The identified models used in [7][12] were not sufficient to capture all the dynamics of the system. So same procedure is followed again and new model is obtained which is shown in (3) and (4).

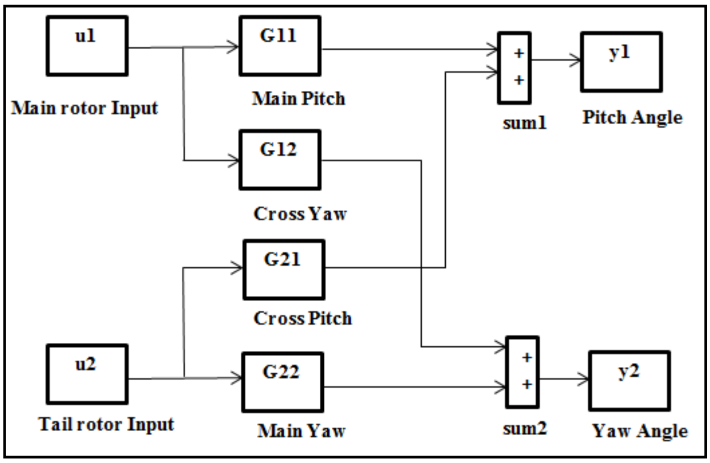

Figure 2. TRMS Block Diagram

After many trials, the following models got are the best fit models for TRMS,
Main yaw – amx 101055
Main pitch – amx 10123
Cross yaw – amx 101023
Cross pitch – amx 10333
The Transfer functions of TRMS in continuous domain obtained is as shown in (3).

1) Main pitch : $\frac{0.01657s^2+0.4194s+2.454}{s^3+1.482s^2+4.403s+5.449}$

2) Main yaw : $\frac{0.0009881s^2-0.03361s+0.4065}{s^3+1.345s^2+0.4568s+0.3826}$

3) Cross pitch : $\frac{0.02248s+0.4527}{s^2+0.4099s+0.2181}$ (3)

4) Cross yaw : $\frac{0.04986s+0.0962}{s^2+0.2377s+4.902}$

The state space model of the TRMS obtained through System Identification process is given in (4). The state space model of TRMS has 2 inputs, 2 outputs and 10 states.

$$A = \begin{bmatrix} -1.1930 & -2.1415 & -1.7570 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.9204 & -1.5760 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1.6760 & -1.1610 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1.2510 & -0.7983 & -0.8150 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0.25 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \qquad D = \begin{bmatrix} 0 & -0.0103 \\ 0 & 0.0016 \end{bmatrix} \qquad (4)$$

$$C = \begin{bmatrix} 0.0002 & 0.0075 & 0.637 & 0 & 0 & 0.0099 & 0.6174 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.1943 & 0.0410 & 0 & 0 & -0.0189 & 0.1286 & 0.7607 \end{bmatrix}$$

A comparison of the step response of the identified model and real time TRMS done and it is observed that they are fitting close to each other[9]. In this paper that is not presented.

3. Comparison between Kalman Observer and H_∞ Observer Designed for TRMS

3.1. Kalman Observer Design for TRMS

The identified model of order 10 is used for designing Kalman observer for TRMS. The Kalman observer is an efficient recursive filter which estimates the state of a dynamic system from a series of incomplete and noisy measurements. This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state [6][8][9][10].

Assumptions made while designing Kalman observer are as follows.

a. The process noise and measurement noise both have to be white noise.
b. The covariances of the process and measurement noises need to be known.
c. It minimises the variance of estimation error and hence it is called the minimum variance filter.
d. The exact knowledge of system matrix A and output matrix C is needed. That is uncertainties should not be there.

If the above assumptions are violated then the Kalman observer fails in giving required performance. The Kalman observer estimates the state of the dynamic system which is disturbed by some noise, assumed as white noise. The Kalman filter has two distinct phases. Predict and Update. The predict phase uses the estimate from the previous time step to produce an estimate of the current state. In the update phase, measurement information from the current time step is used to refine this prediction to arrive at a new, more accurate estimate. In this work purposely the worst case noise of unknown statistics is considered to be impact on TRMS. Then the Kalman observer equations are used to see its performance with worst case noise.

Assuming TRMS to be a continuous time linear system as in (5) which is subjected to the noise with unknown statistics.

$$
\begin{aligned}
\dot{x} &= Ax + Bu + w_1 \\
y &= Cx + Du + v_1
\end{aligned} \tag{5}
$$

where the covariance of process noise, q is decided by process noise w_1, which is worst case noise with unknown statistics. Covariance of measurement noise, r is decided by the measurement noise v_1, which is also a worst case noise. x is the state and y is the output of the system. From (2) Values for A, B, C and D are taken. The Kalman observer equations are given in (6). Initial values of x *is* assumed to be zero. In Kalman observer the covariances q and r need to be defined given in (6). The initial estimated state and the initial value of solution for Ricatti equation has to be in a specific format as shown in (6)[8].

$$
\begin{aligned}
q &= E[w_1] \\
r &= E[v_1] \\
\hat{x}(0) &= E[x(0)] \\
P_0 &= E[\big(x(0) - \hat{x}(0)\big)\big(x(0) - \hat{x}(0)\big)^T] \\
P &= P_0 \\
K_k &= PC^T(CPC^T + r)^{-1} \\
\dot{\hat{x}} &= A\hat{x} + Bu + K_k(y - C\hat{x}) \\
\dot{P} &= PC^T r^{-1} CP + AP + PA^T + q
\end{aligned} \tag{6}
$$

Where $\hat{x}$ is the estimated state and K_k is the Kalman gain. P is a symmetric positive definite matrix, which is a solution for differential Riccati equation given in (6).

3.2. H_∞ Observer Design for TRMS

The 10th order approximated model of TRMS shown in (3) and (4) are used to realize a full order H_∞ observer, so that the predicted output $\hat{y}$ is close to actual output y in spite of measurement noise v_1 and process noise w_1, that corrupt the final output measurement. While designing the H_∞ observer, $x(0)$ and $\hat{x}(0)$ are assumed to be zero and $P(0)$ and S as identity matrices. Q and R are co-variances of process noise (w_1) and measurement noise (v_1) respectively. Where w_1 and v_1 have unknown statistics with non zero mean. Any process and measurement noise can impact on the system. Covariances of process and measurement noises need not be known. Only restriction on Q and R is that they have to be positive definite matrices. Moreover accurate knowledge of system matrix A and output matrix C is not needed. That means H_∞ observer works well in presence of uncertainties [6][11][12][14]. In this case, model obtained for TRMS using system identification is an approximate stochastic model. This is one of the uncertainties of the system. Since TRMS has two inputs and two outputs the other uncertainty may be cross coupling.

The game theory approach is used to design H_∞ observer [6][7][12]. The goal of designing an H_∞ observer is to find the correct observer gain K_h which minimizes the difference between the predicted output and the true output even in presence of uncertainties like sensor failure. Here, by varying the observer gain the H_∞ observer decides which output to place more emphasis on. Its task is to place less emphasis on noisy measurements and more emphasis on actual measurements. In this paper a dynamic real time estimation is done in which the gain of the observer changes as the noise changes.

The design of H_∞ observer for TRMS is shown below.

Let us consider a continuous time linear system as in (7)

$$\begin{aligned} \dot{x} &= Ax + Bu + w_1 \\ y &= Cx + Du + v_1 \\ z &= Lx \end{aligned} \tag{7}$$

Where L is the user-defined matrix and z is the vector to be estimated. The estimate of z is denoted by $\hat{z}$ and the estimate of state at time 0 is $\hat{x}(0)$. The vectors w_1 and v_1 are worst case noises with unknown statistics, they may not even be zero mean. y is the system output and x is the state matrix. A, B, C and $D$are the system matrices of TRMS. The cost function used is given in (8).

$$J = \frac{avg\|(z-\hat{z})\|_S}{avg\|(x(0)-\hat{x}(0))\|_{P_0^{-1}} + avg\,\|w_1\|_{Q^{-1}} + avg\|v_1\|_{R^{-1}}} \tag{8}$$

Where J is the measure of the performance of the state estimator. The nature's goal is to impose worst case disturbances and noises (w_1 & v_1) on the system and maximise J. But the observer's aim is to derive a gain which makes J very small in spite of worst w_1 & v_1.

Where P_0, Q, R, S are positive definite matrices chosen by the designer based on a specific problem. The goal is to find an estimator such that

$$J < \frac{1}{\theta} \tag{9}$$

In this work, using the approximate model of TRMS, after many iterations, θ is found to be 0.001.

The estimator that solves this problem is given in (10).

$$\begin{aligned} P_0 &= 0 \\ \hat{x} &= 0 \\ P &= P_0 \\ \dot{P} &= AP + PA^T + Q - K_h CP + \theta P L^T S L P \\ K_h &= PC^T(CPC^T + R)^{-1} \\ \dot{\hat{x}} &= A\hat{x} + Bu + K_h(y - C\hat{x}) \\ \hat{z} &= L\hat{x}, \end{aligned} \tag{10}$$

Where K_h is the H_∞ observer gain, Q is the covariance of process noise, w_1 and R is the covariance of measurement noise, v_1. P is the solution for the differential Riccati equation shown in (10), which is positive definite matrix. Initial values of x and $\hat{x}$ are assumed to be zero. For choosing the Q matrix, a trial and error method is adopted where the response of the states are simulated and the value of the diagonal element of Q is increased so that it affects the value of K_h more or less. The value of R is also selected similarly and it affects all states equally. So an increase in the value of R will change the response of all the states. S is kept at 1 because good response is achieved by varying Q and R. It is observed that if Q is high and R is low, the observer performs well with process noise that is plant uncertainty but is affected by measurement noise. When Q is low and R is high, observer is less susceptible to measurement noise but is affected by process noise or plant uncertainty. So there must be a compromise between Q and R according to the specific situation. For different Q and R the state estimation results using H_∞ observer are mentioned in [7].

4. Results

The Kalman observer and H_∞observer are programmed and simulated in MATLAB separately[15]. Both Kalman observer and H_∞observer gains are dynamic and they come from the differential Riccati equations (6) and (10). The final Kalman observer gain, K_k and H_∞ observer gain, K_h are shown in (11) and (12). The Pitch output and Yaw output in case of Kalman observer are shown in Figure 3 and Figure 5. The Pitch output and Yaw output in case of H_∞observer are shown in Figure 4 and Figure 6.

$$K_k = \begin{bmatrix} -0.9786 & 0 \\ 0.0516 & 0 \\ 0.9377 & 0 \\ 0 & 0.1514 \\ 0 & -0.0526 \\ -0.2007 & 0 \\ 0.6527 & 0 \\ 0 & -0.6552 \\ 0 & 0.3442 \\ 0 & 1.2026 \end{bmatrix} \tag{11}$$

$$K_h = \begin{bmatrix} -0.0078 & 0 \\ -0.0016 & 0 \\ 0.0069 & 0 \\ 0 & 0.0010 \\ 0 & 0 \\ -0.0017 & 0 \\ 0.0043 & 0 \\ 0 & -0.0102 \\ 0 & -0.0008 \\ 0 & 0.0170 \end{bmatrix} \tag{12}$$

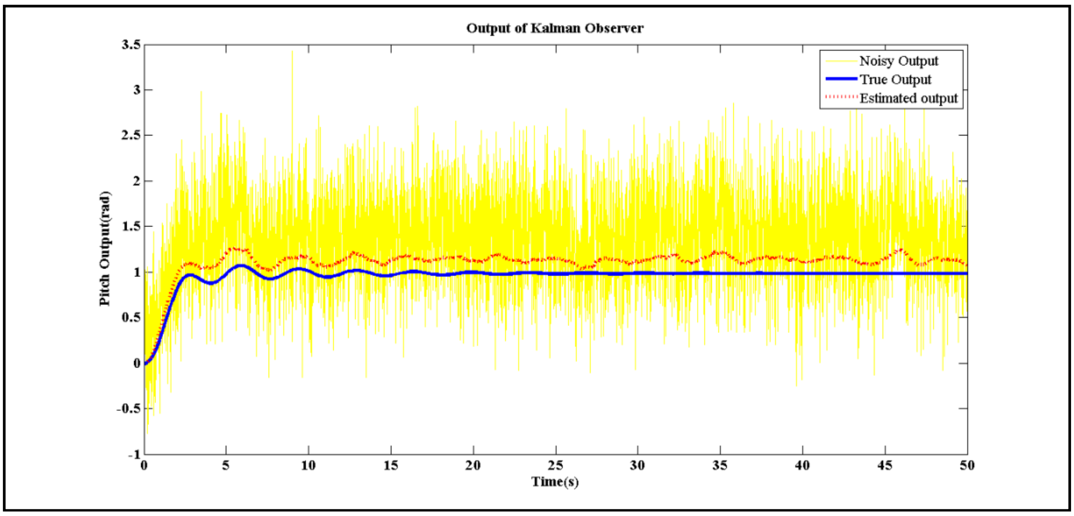

Figure 3. Pitch Output of TRMS (when Kalman Observer is used)

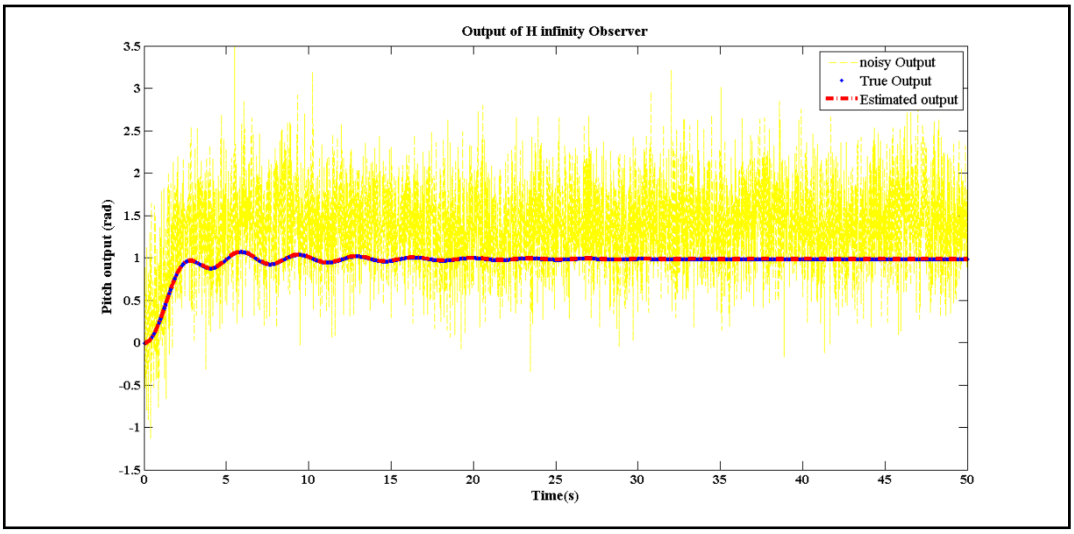

Figure 4. Pitch Output of TRMS (when H_∞ Observer is used)

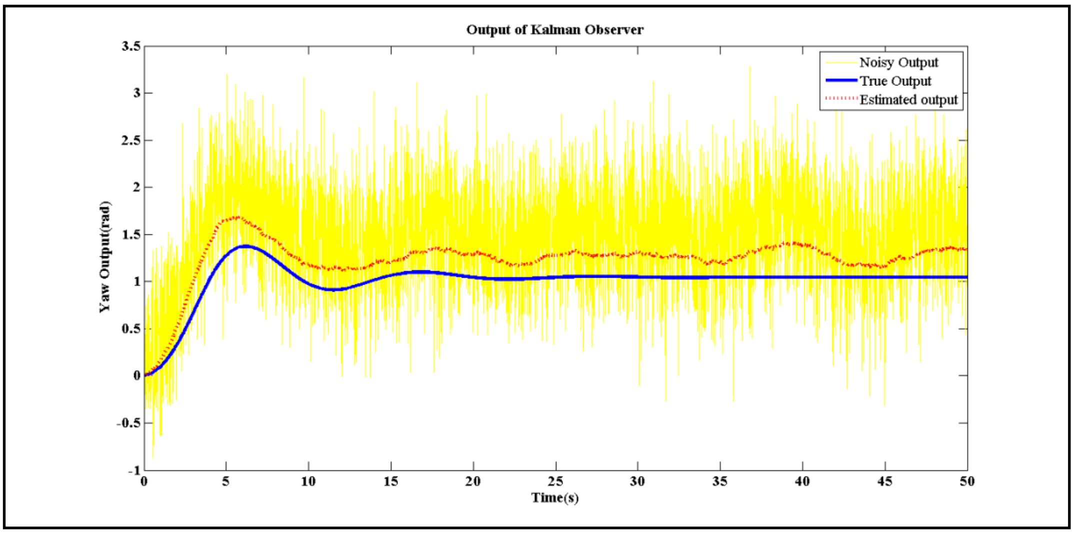

Figure 5. Yaw Output of TRMS (when Kalman Observer is used)

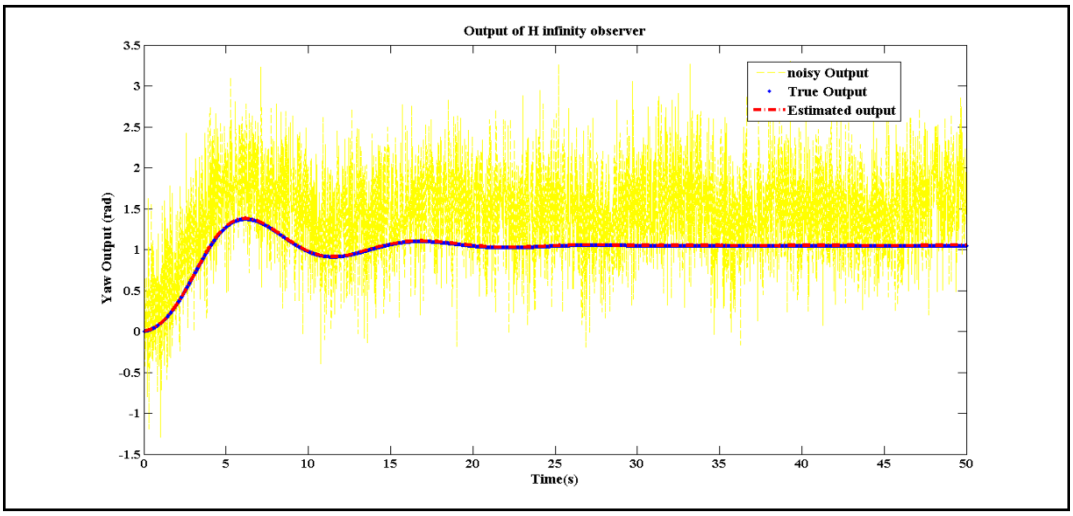

Figure 6. Yaw Output of TRMS (when H_∞ Observer is used)

All ten estimated states of TRMS are compared with true states using both Kalman observer and H_∞ observer. As seen from Figure 7 to Figure 26 all the estimated states in case of H_∞ observer is exactly same as the respective true states of TRMS. But in Kalman observer estimated and true states are different. This is mainly due to the selection of design parameters, covariances of process noise and measurement noise q, Q, r, R, selection of initial value for solution of Riccatti equation (P_0) and initial value of estimated state $\hat{x}(0)$. In H_∞ observer, designer can choose any value for covariances by trial and error method but in Kalman observer there is a restriction to choose the covariances, P_0 and $\hat{x}(0)$ which is shown in (6) and (10). Advantage of estimating states perfectly coinciding with true states would make further control effective which could be achieved using H_∞ observer.

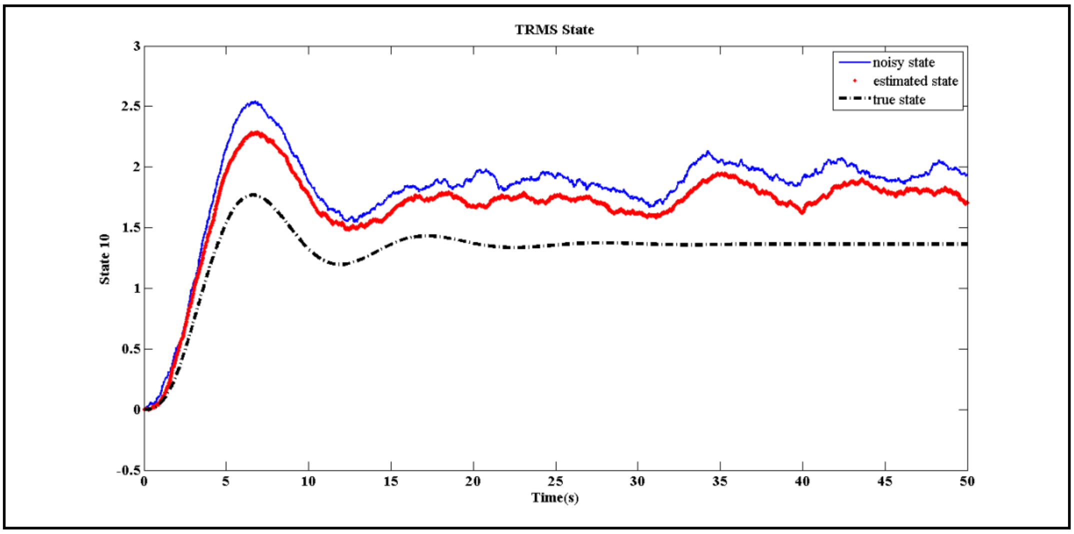

Figure 7. 10th State of TRMS When Kalman Observer is used

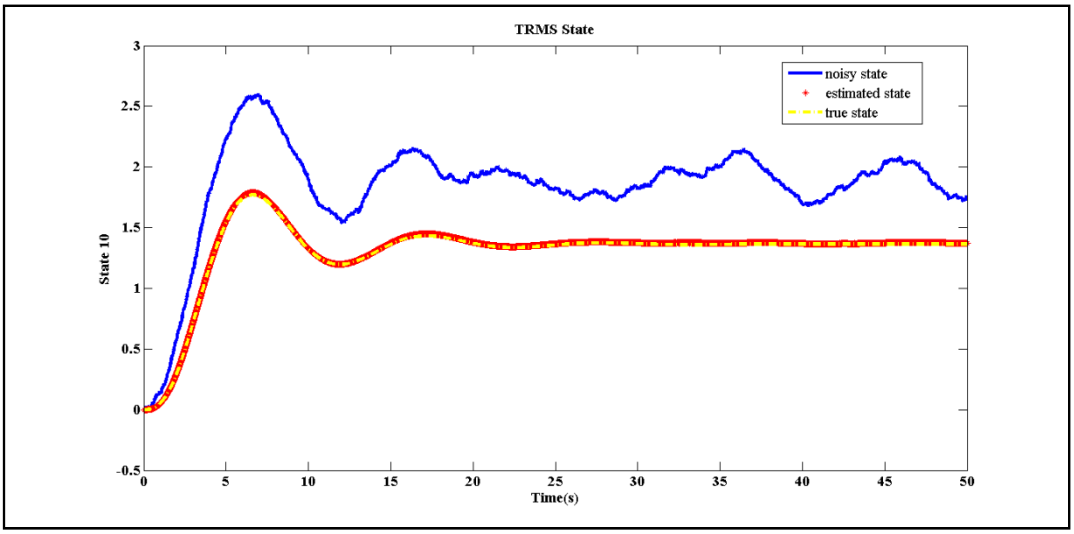

Figure 8. 10th State of TRMS When H_∞ Observer is used

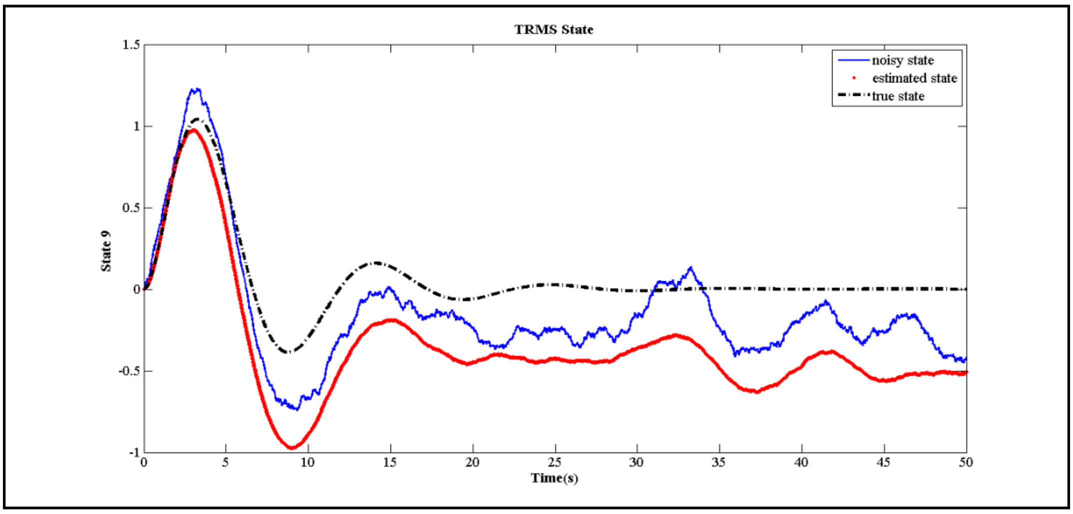

Figure 9. 9th State of TRMS When Kalman Observer is used

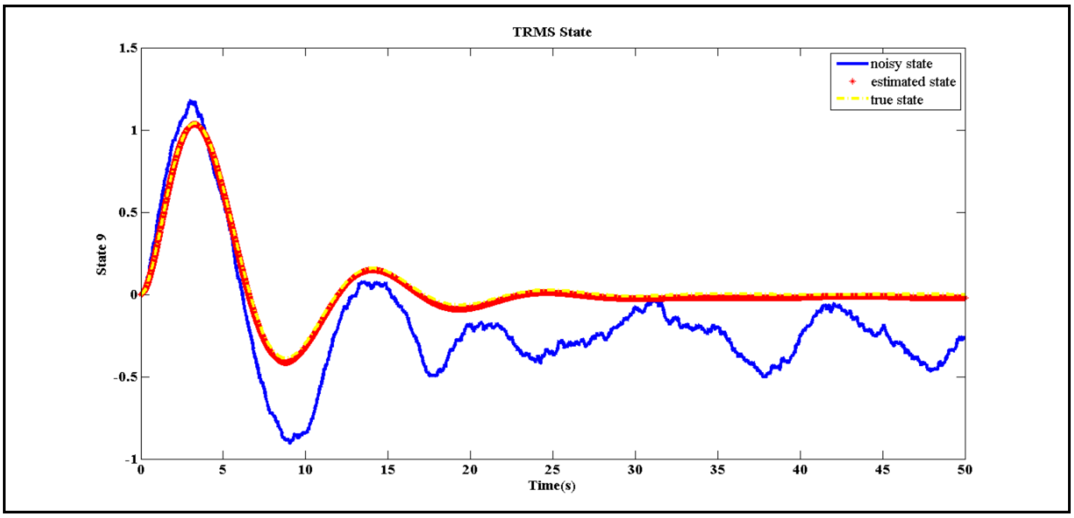

Figure 10. 9th State of TRMS When H_∞ Observer is used

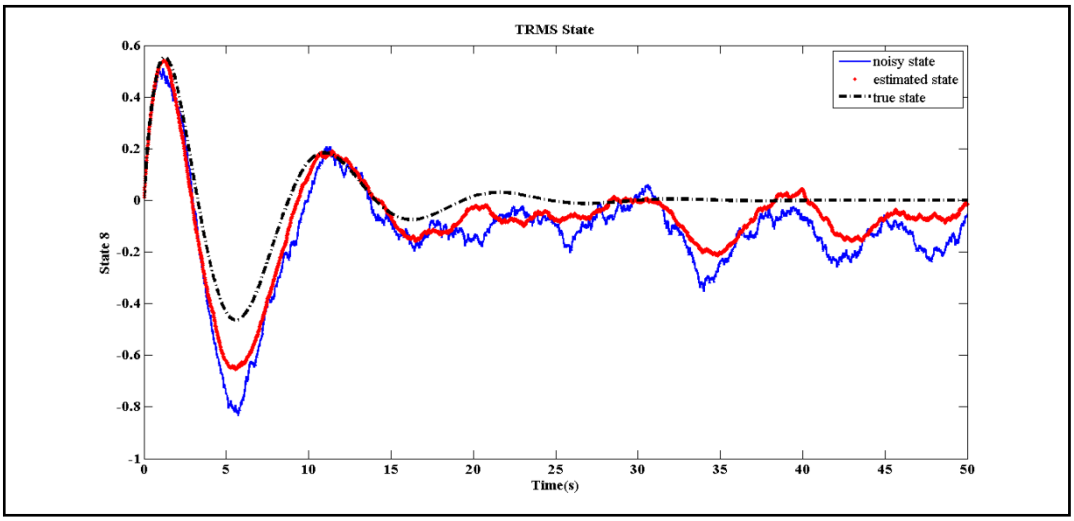

Figure 11. 8th State of TRMS When Kalman Observer is used

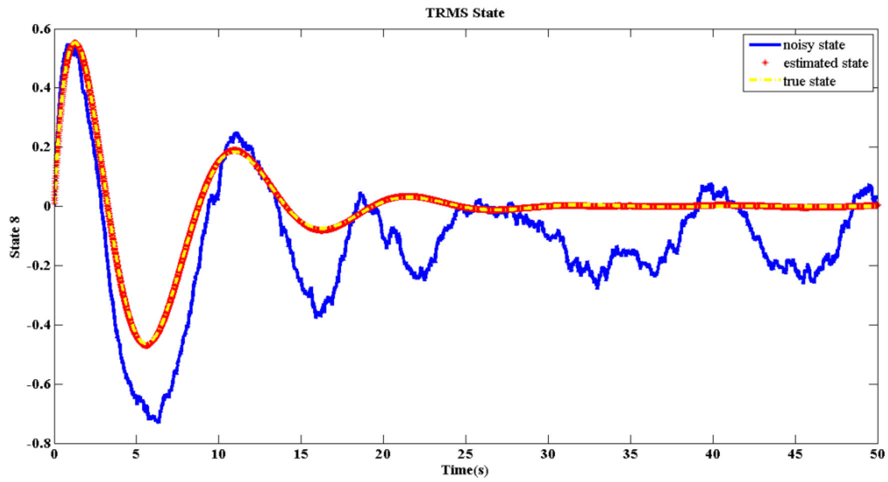

Figure 12. 8th State of TRMS When H_∞ Observer is used

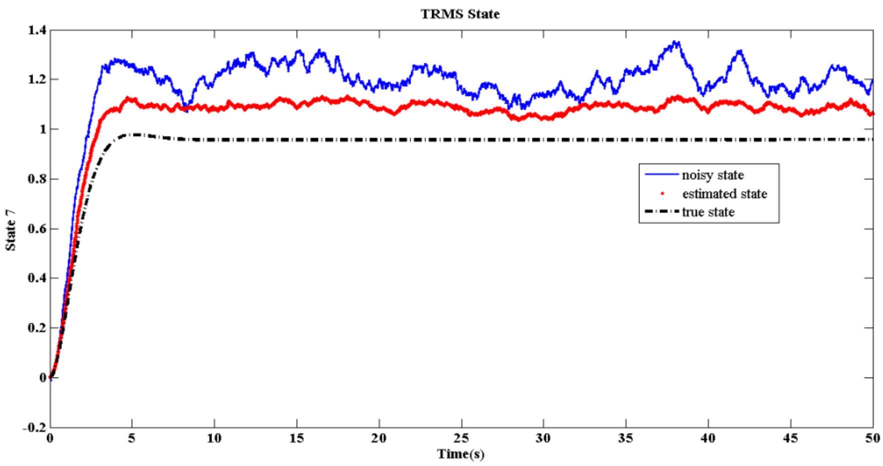

Figure 13. 7th State of TRMS When Kalman Observer is used

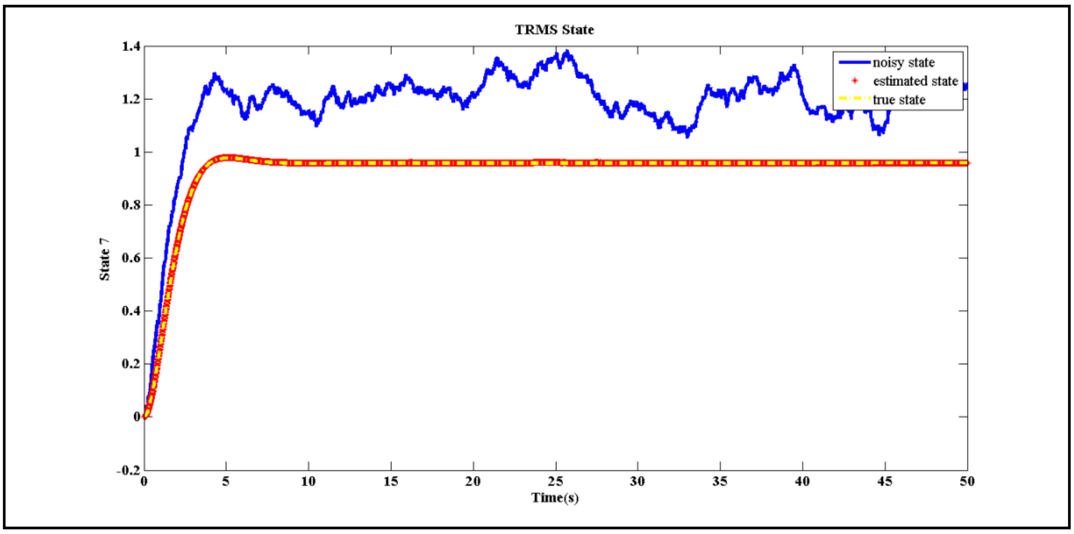

Figure 14. 7th State of TRMS When H_∞ Observer is used

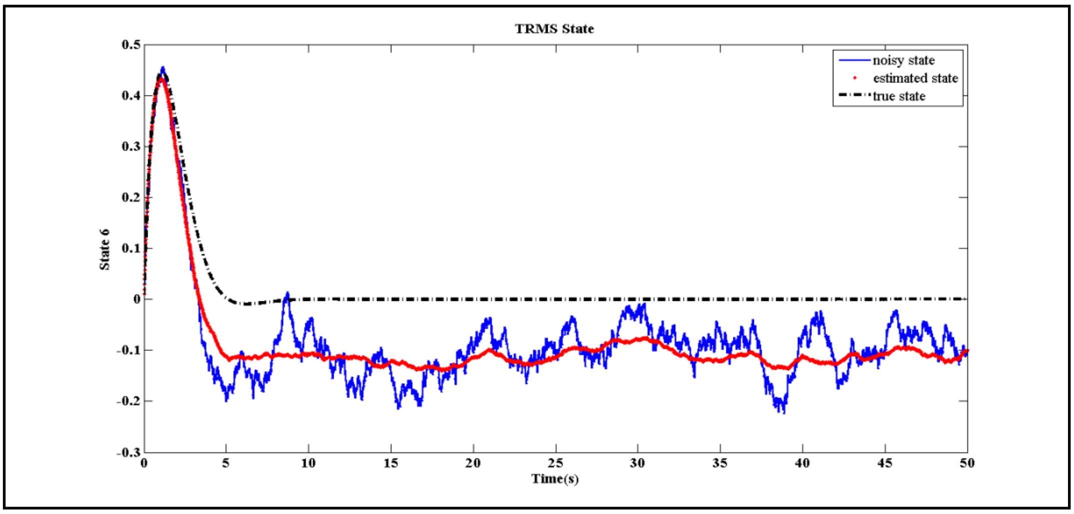

Figure 15. 6th State of TRMS When Kalman Observer is used

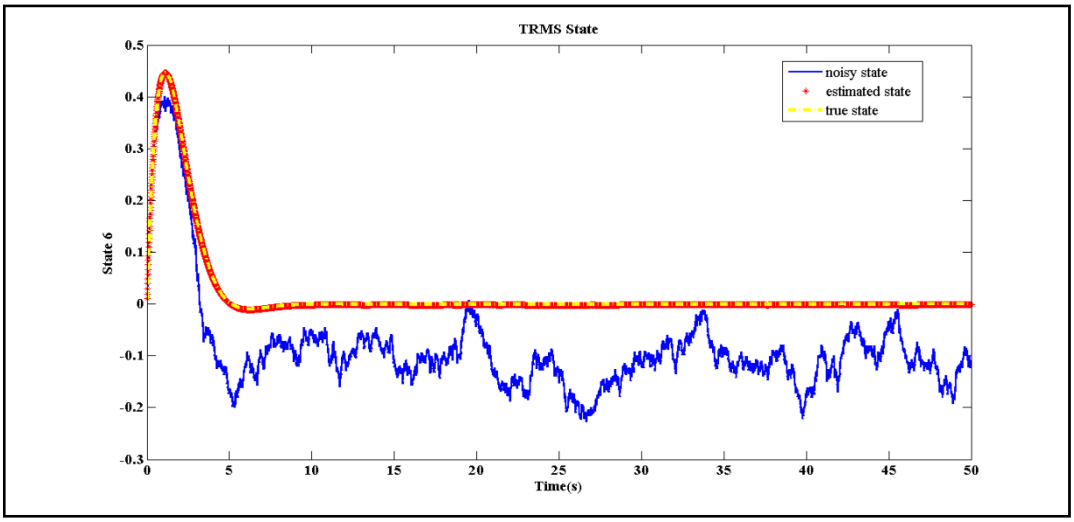

Figure 16. 6th State of TRMS When H_∞ Observer is used

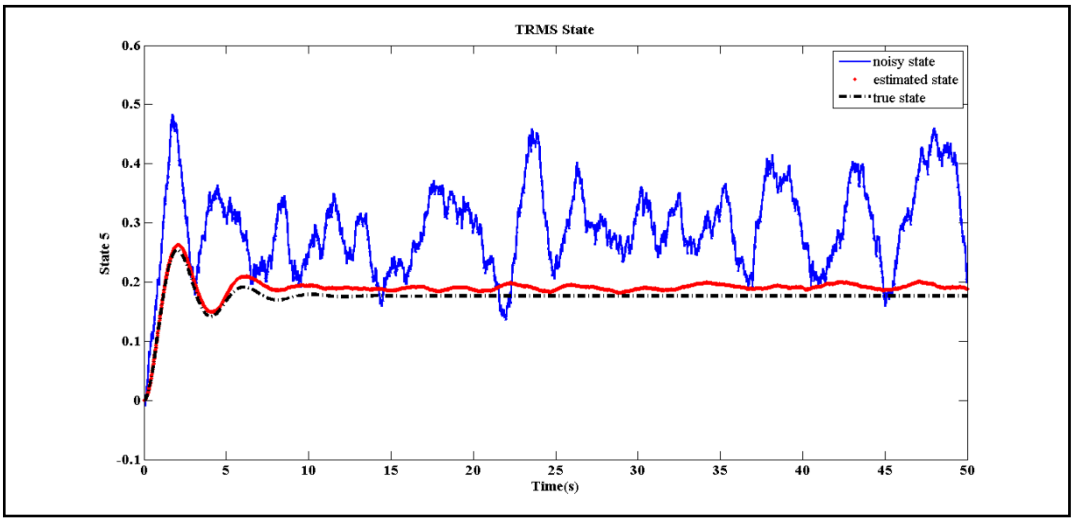

Figure 17. 5th State of TRMS When Kalman Observer is used

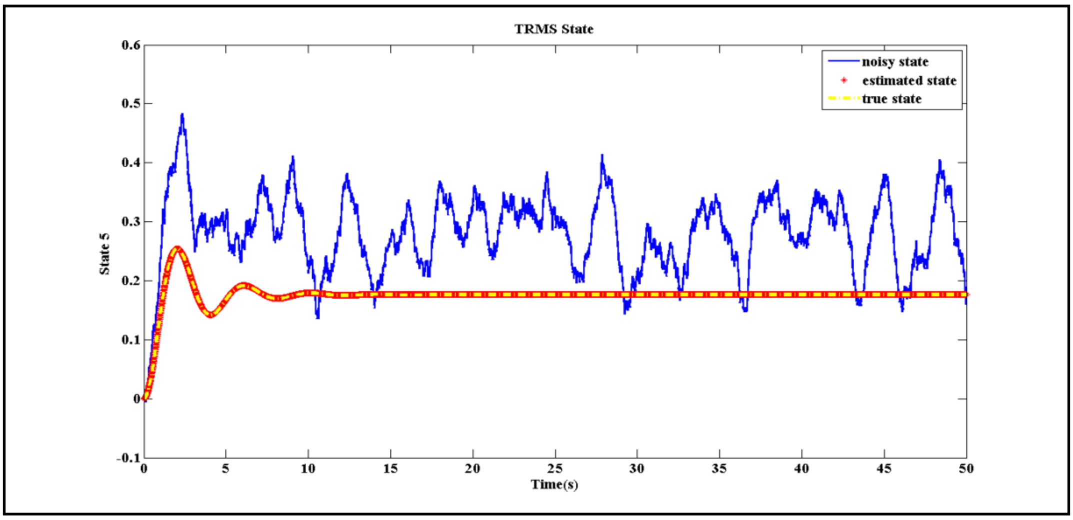

Figure 18. 5th State of TRMS When H_∞ Observer is used

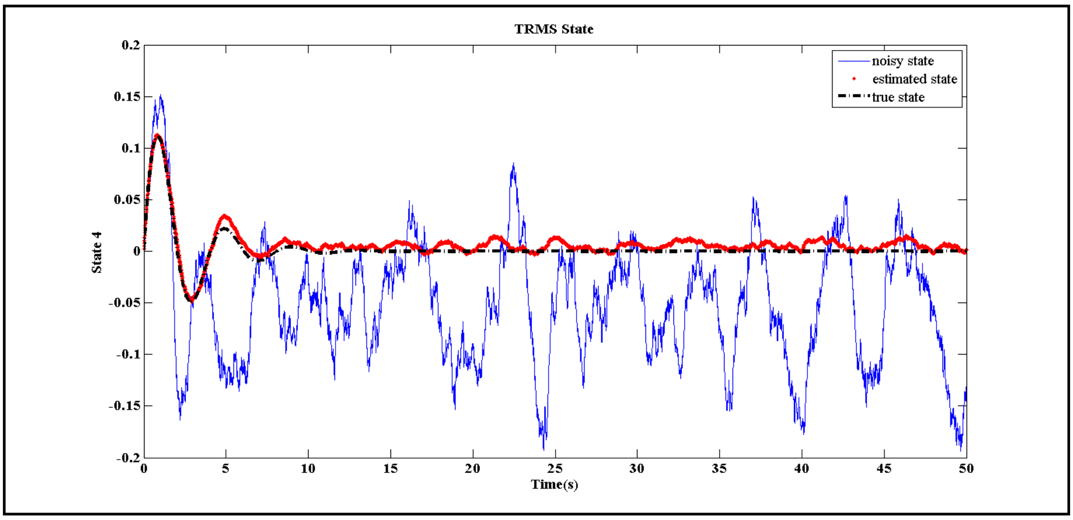

Figure 19. 4th State of TRMS When Kalman Observer is used

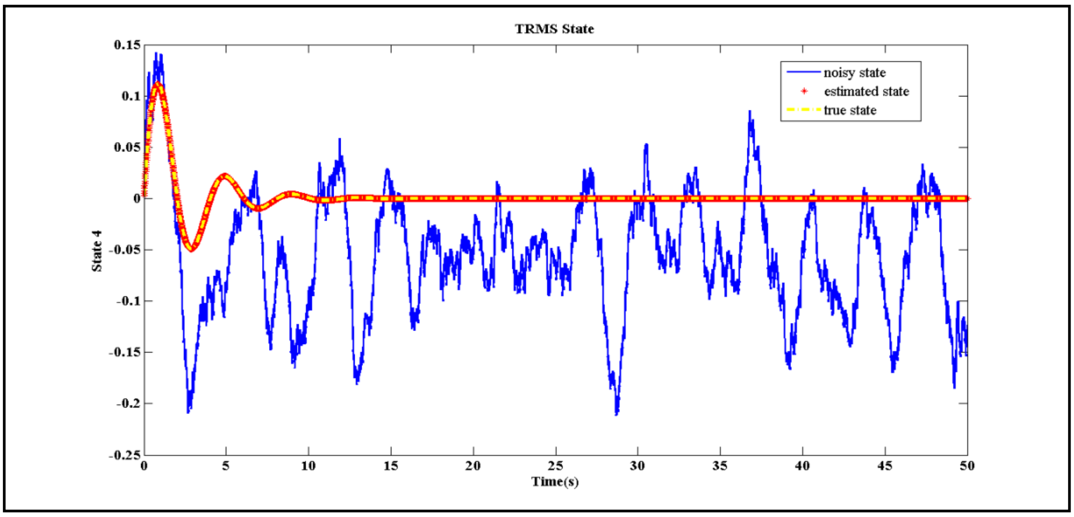

Figure 20. 4th State of TRMS When H_∞ Observer is used

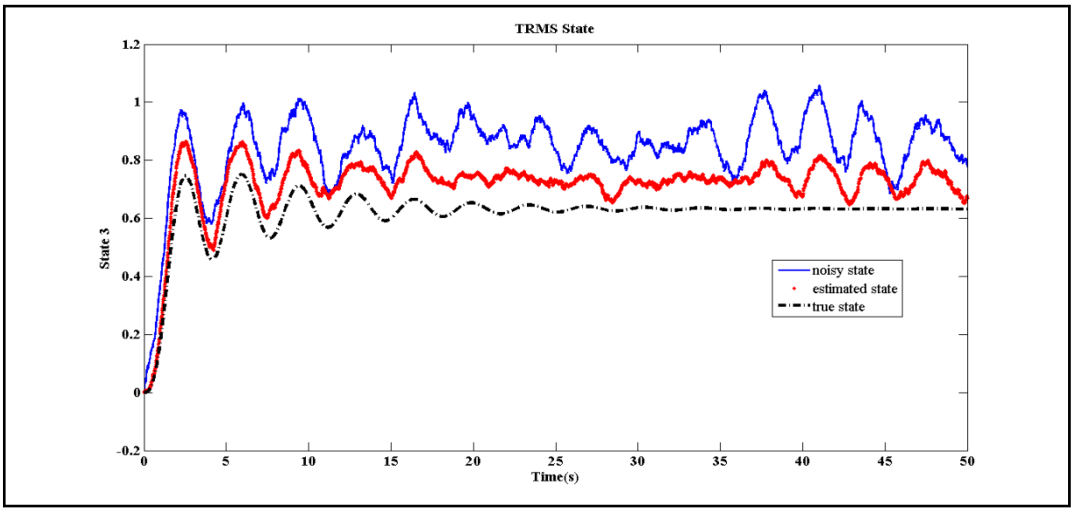

Figure 21. 3rd State of TRMS When Kalman Observer is used

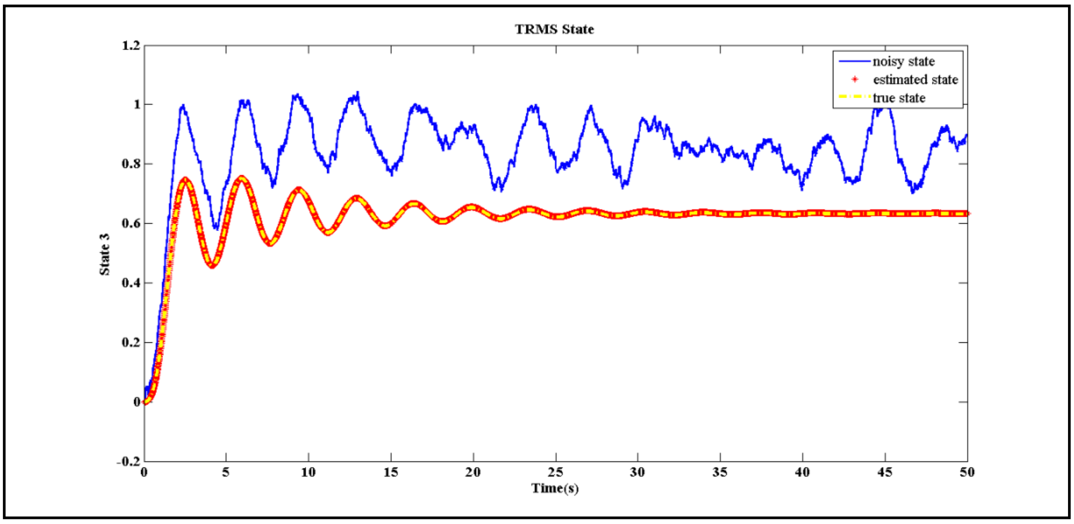

Figure 22. 3rd State of TRMS When H_∞ Observer is used

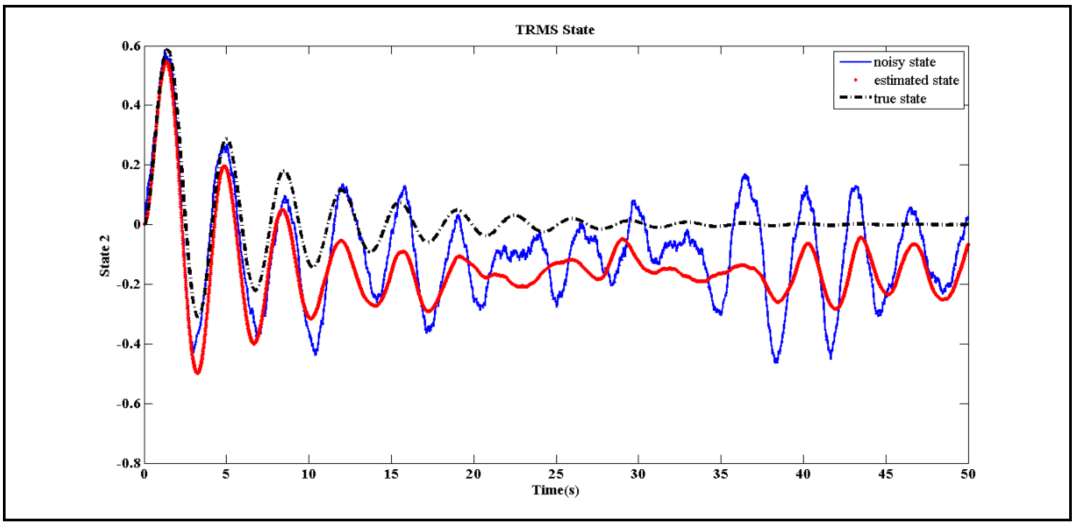

Figure 23. 2nd State of TRMS When Kalman Observer is used

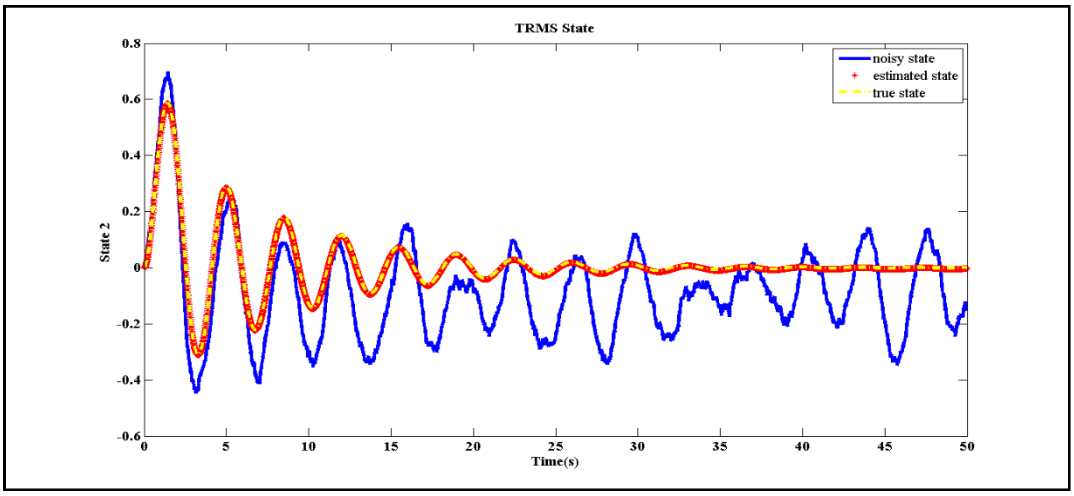

Figure 24. 2nd State of TRMS When H_∞ Observer is used

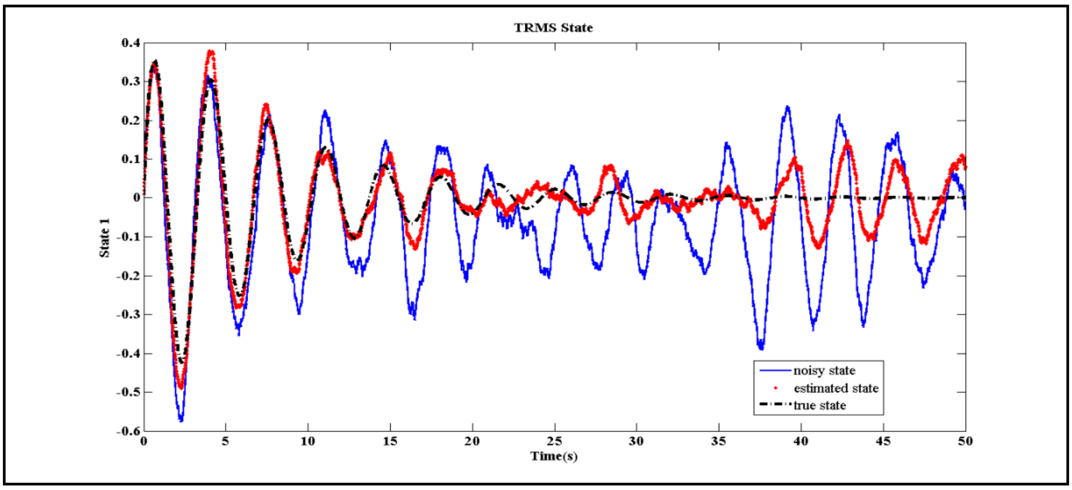

Figure 25. 1st State of TRMS When Kalman Observer is used

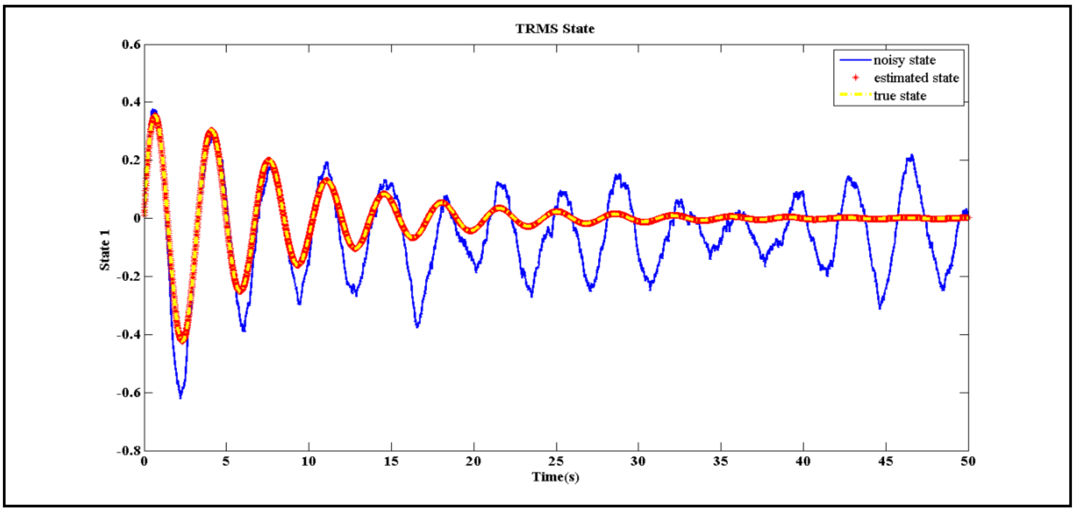

Figure 26. 1st State of TRMS When H_∞ Observer is used

5. Conclusion and Future work

The results of Kalman observer and H_∞ observer show that, for TRMS, in presence of worst case noise statistics with uncertainties, the H_∞ observer performs better than the Kalman observer. When any noise of unknown statistics impact on TRMS all estimated states in case of H_∞ observer are same as that of its true states. Whereas in case of Kalman observer the estimated states of TRMS deviate very much from the true states. This is also true for pitch output and yaw output of TRMS. So, it is better to use H_∞ observer than the Kalman observer if worst case noise with unknown statistics impacts on the uncertain system. Future work is to take the estimated states from H_∞ observer and feed it to the feedback H_∞ controller. Also to test the H_∞ observer based controller in real time with sensor, actuator failure for TRMS.

Appendix

Nomenclature

TRMS	Twin Rotor Multiple Input Multiple Output System.
x	State vector of TRMS.
A, B, C, D	State model of TRMS.
y	Output of TRMS.
u	Controlled Input to TRMS
w_1	Worst case process noise(with unknown statistics)
v_1	Worst case measurement noise(with unknown statistics)
q	Covariance of Process noise w_1, for Kalman observer design
r	Covariance of Process noise w_1, for Kalman observer design
Q	Covariance of Process noise w_1.
R	Covariance of Measurement noise v_1.
$\hat{x}$	Estimated state of TRMS.
z	Vector to be estimated.
P	Solution for the Riccati equation.
P_0	Initial value chosen for P
L	Positive definite matrices chosen by the designer.
K_k	Kalman observer gain.
K_h	H_∞ observer gain.
J	Cost function to be minimised.
θ	Performance bound.

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