Original Article

Estimation of Sensor Bias Fault in Adaptive Control of Power System

Sergey Brindred[1]| Minoo Akhtarian Zand[2*]

[1]*Department of Environmental Engineering-Water and Wastewater Engineering, Moscow University, Russia*
[2]*Department of Environmental Engineering-Water and Wastewater Engineering, Qatar University, Qatar*

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ABSTRACT

Based on the simulation results, steady-state tracking faults are improved. Control of indeterminate systems, despite the actuator and sensor bias, has been a major challenge. Sensor fault can cause process fault. Among the cases where sensor bias is common, air velocity measurements and gyroscope rates can be mentioned. Although considerable research efforts have previously focused on adapting the fault, the bias correction of the sensor appears to be relatively limited. However, the cause of several crashes was the sensor fault, due to radio altimeter fault, angle of attack sensor fault, airspeed speed sensor fault. Also, finding a way to fix the sensor bias problem is of the utmost importance. The direct model reference adaptive control (MRAC) method is used to control uncertain systems using controllers that are adapted to achieve a performance close to a reference model. However, these controllers maintain system stability and provide close tracking of the reference model response. In this study, we intend to address the problem of unknown fault bias matching by adjusting the direct reference model adaptive control for state-feedback for state-tracking (SFST). Also, to obtain an asymptotic stable bias fault estimator, we use the Kalman filter to estimate the bias sensor fault. Based on the simulation results, steady-state tracking faults are improved.

Introduction

Sensor bias matching schemes are usually investigated by the SFST-MRAC method and the problem of bias matching of unknown sensors in controlling uncertain systems is considered.

Such errors may cause serious damage to the stability and performance of the closed loop. Therefore, the model reference adaptive control (MRAC) law is modified to estimate sensor bias with gain matching and to form asymptotic tracking and signal limiting [1-2].

Also, the discussion of the adaptive control [3–8], despite the driving error and sensor error in the process, is aimed at the simultaneous matching of the sensor and bias sensor errors

***Corresponding Author:** *Minoo Akhtarian Zand (minoo.akhzand1983@gmail.com)*

with the help of MRAC control law. Therefore, the MRAC method is proposed, which is a driver error, without the need for error detection, identification and reconfiguration. Although the results presented are for cases with a single reference input, they can be extended to systems with multiple stimuli and multiple reference inputs. The FTFC scheme is proposed which includes both the outer ring controller and the inner ring [9-12]. After introducing a leader-follower control mechanism by integrating a collision avoidance mechanism as an outer ring control, designed to guarantee the UAV to prevent collisions with impediments, an FTC strategy, as a controller of the inner ring, is designed to counteract stimulus errors as well as to prevent saturation of healthy stimuli. Although they are practically applicable and especially attractive in terms of elegance and simplicity, there are drawbacks to the method of avoiding collision. Therefore, the research path can be directed towards updating the mechanism of avoidance of dealing with smart and adaptive capabilities. Bias estimations for multi-sensor systems are discussed [12–15], which are important in some practical areas, such as target tracking, integrated navigation, transmission network, fault tolerance, and so on. In fact, studies focus on the state matching problem for a type of dynamic system with multiple asynchronous sensors, where observations from different sensors are accidentally missing. Here, optimum state matching is achieved by using the multipurpose system theory and the modified Kalman filter. In addition, the problem of point-setting tracking is discussed by sensor bias and actuator offset [15-18]. For example, we consider a process that may be the trigger input of an unmodulated offset, while sensor measurements may also be corrupted by an unmodulated bias, which is probably due to incomplete calibration. So the question arises whether it is possible to achieve a constant zero-state error in the presence of both unknown states, stimulus offset and unknown sensor bias. In SISO systems, while there are both offset and bias sensor offsets, a servo-loop architecture with forward and reverse controllers cannot be used to track the position of the set point. Although the results in these promising method for maintaining stability and controllability in the event of papers are limited to SISO transfer functions, generalizations about MIMO based on state space models are also being investigated. For the case of both operator and sensor disturbances, both of which are measured, set point tracking using feed control is provided. MRAC schemes are designed by output feedback for output tracking in sensor error display [19-22]. And [23-26] have been expanded, and in fact the sensor uncertainty compensation problem has been addressed for the adaptive control of the multi-system reference model, two output feedback-based MRAC schemes for dynamically recognized MIMO systems. Sensor uncertainty as an indefinite function is a parameter adjustable and a compensator designed to be able to adapt. Therefore, for unknown dynamical systems, a new feedback control structure is created, by matching, so it will be able to detect uncertainties in both types of measurements. The results of effective offsets, system and sensor, of the simulation show that the proposed MRAC scheme for unknown dynamic systems can significantly improve tracking performance despite sensor uncertainty [27].

Kalman Filter

The Kalman filter is an efficient recursive filter that estimates the state variables of a dynamic system utilizing a set of indirect and distorted noise measurements. The original Kalman filter format is based on a white noise linear system, which is why it is guaranteed only under the assumptions of linearity of the system as well as white and system noise independent and Kalman filter optimality. Therefore, to use the Kalman filter, accurate information on the nature of the noise, including mean, variance, and standard deviation, must be available, which is sometimes difficult or impossible. The purpose of the Kalman filter is to estimate system state variables based on measurements with noise and random variables. The Kalman filter is a powerful and general tool for combining information in uncertain and dynamic environments. In most cases, the information extracted by this filter is very accurate. Before dealing with the Kalman filter, processes are briefly adressed.

Testing Performance of the Control Rules Provided

To test the efficiency of the different control rules presented in this study, in the presence of unknown sensor bias, the following two simulations are performed. In each of these cases an unknown bias is assumed to occur at t = 0.

Theory 1 (MRAC Feedback Bias Estimation)

The state variables for the longitudinal dynamic model are the four state variables: Actual velocity (s/m), angle of attack α (Degree), ground angle θ (Degree) and ground velocity q (Degree/second). Elevator and throttle inlet are the control inputs, denoted by u_e (in degrees) and u_t, respectively. Input u_e shows the elevator position (in degrees) and the input. The u_t valve shows the coefficient of strength by a fixed operating scale, so no unit is used for u_t [1]. The units of measurement of the β components that represent biases are, respectively, m/s, degrees, degrees, degrees per second. By measuring bias values, the standard MRAC control law is implemented, which applies, by conventionally or optionally, $\widehat{K}_1(t)$ and $\widehat{K}_2(t)$ at half their actual value. Initializing and matching interests are selected on a contractual or optional basis.

(1)

$$A = \begin{bmatrix} -0.0062 & -0.0815 & -0.1709 & -0.0026 \\ -0.0344 & -0.5717 & 0 & 1.0050 \\ 0 & 0 & 0 & 1.0000 \\ 0.0115 & -1.0490 & 0 & -0.6803 \end{bmatrix}$$

(2) $$B = \begin{bmatrix} 0 & 1.3287 \\ -11.4027 & -0.0401 \\ 0 & 0 \\ -44.5192 & 0.8824 \end{bmatrix}$$

(3) $$x(t) = [v \quad \alpha \quad \theta \quad q]^T$$

(4) $$u(t) = [u_e \quad u_t]^T$$

(5) $$A_m = A + Bk_1^T$$

(6) $$B_m = BK_2$$

Here K_1 is the LQR gain designed for optimal closed-loop performance. Interest $K_2=L_2$, such that $B_m=B$. In the simulation, K_2 is chosen to provide the appropriate scale *r(t)* (reference input). The unknown constant bias, in the case measurement, is either optionally or optionally selected as follows:

(7) $$\beta = [5 \quad 2 \quad -1 \quad 10]$$

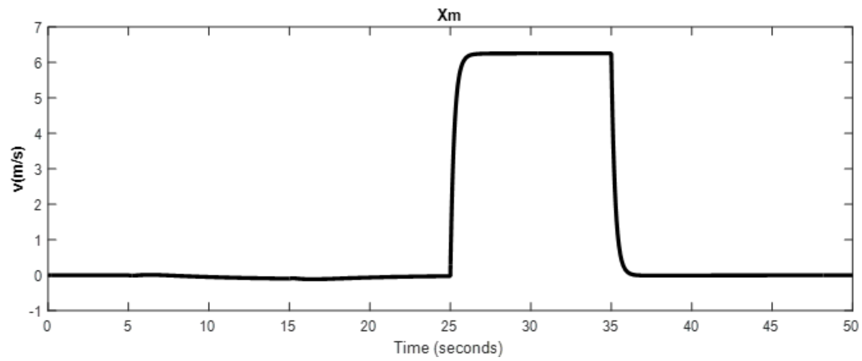
$$\widehat{K}_1(t) = 0.5K_1$$

$$\widehat{K}_2(t) = 0.5K_2$$

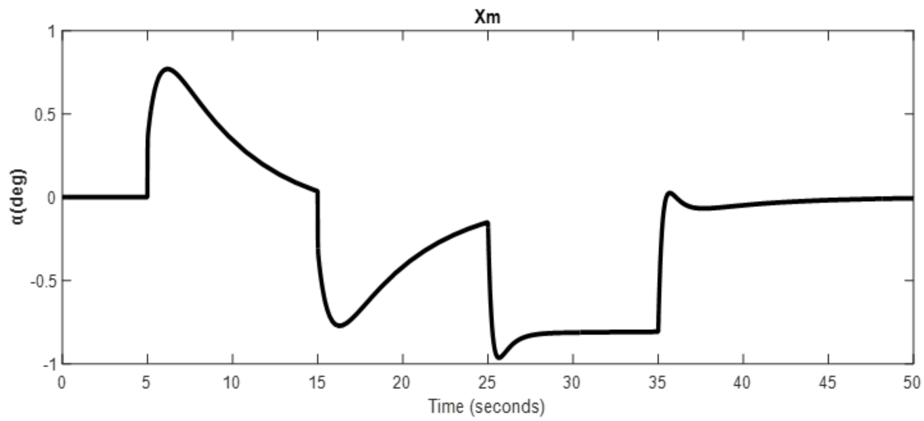
(8) $$\Gamma_1 = 0.005I_4$$

$$\Gamma_2 = 0.005I_2$$

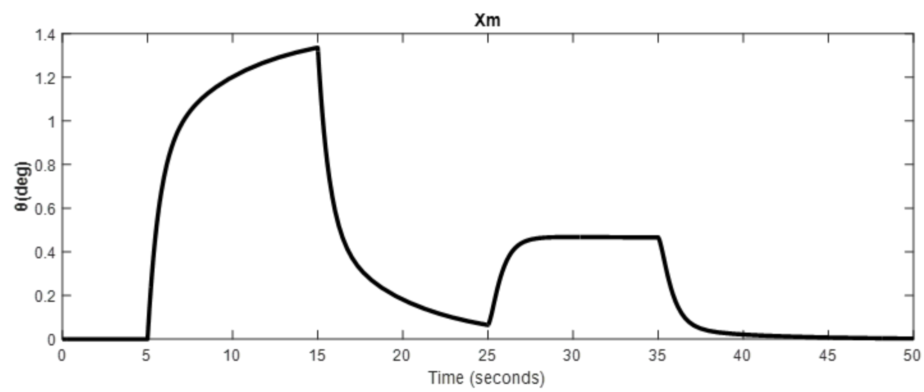
Figure (1) and Figure (2) show that by examining the simulation results, we reach the law of comparative control in Theory 1, the stability (limited signal) and the limitation of the tracking error (which is zero). It ensures that the states are slow, but by comparing x_m and $\bar{x}$, we find that our parameters do not converge with the main parameters in the system. Therefore, the limitation of the closed-loop signal or the limitation of the tracking error cannot be proved. However, in this example, the tracking error appears to be close to some constant non-zero values. So we need to have a correct estimate of β.



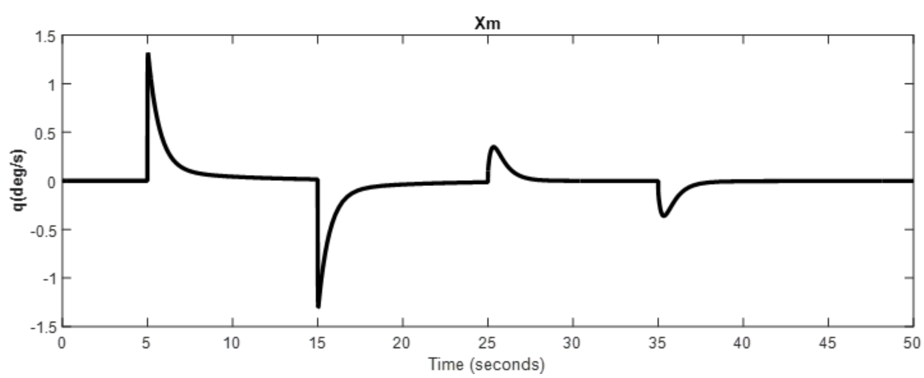
A. Parameter v



B. Parameter α

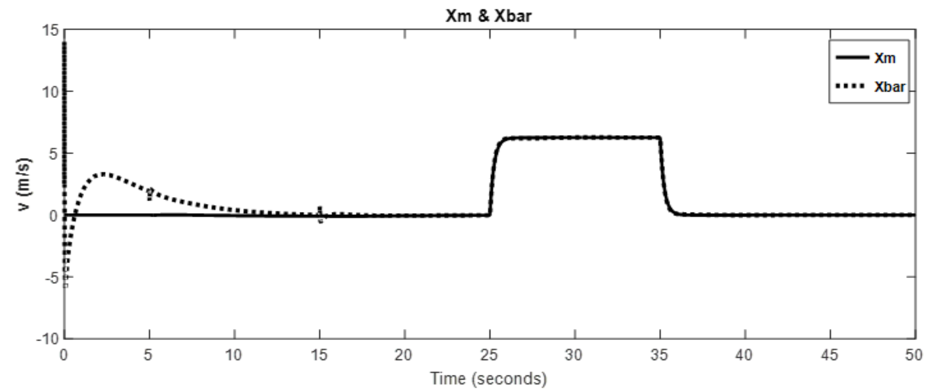


C. Parameter ɵ

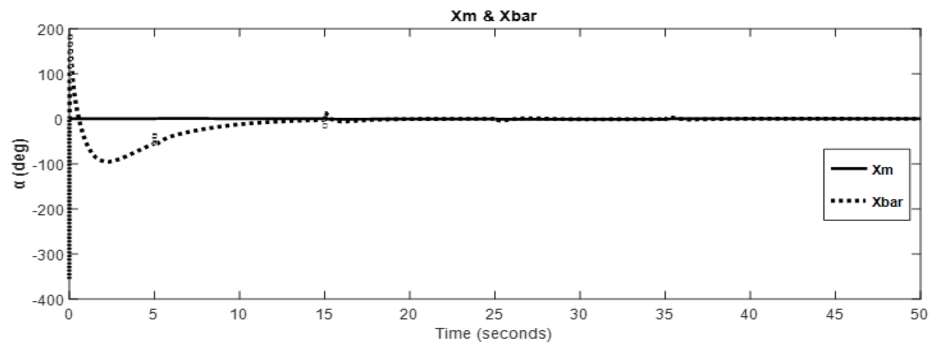


D. Parameter q

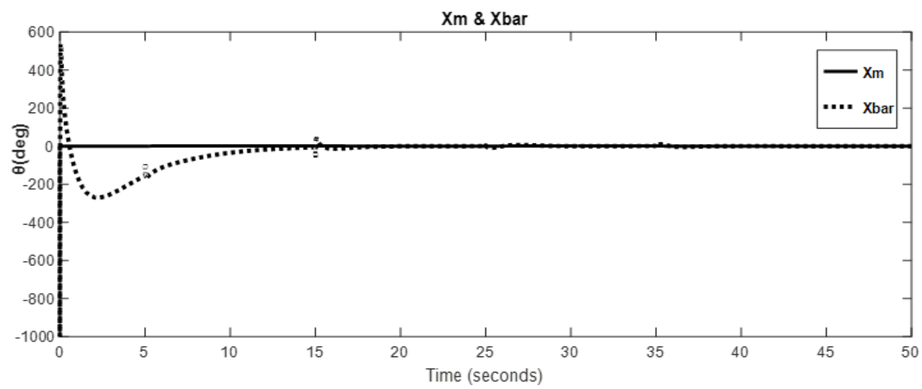
Figure 1. Show model reference modes (x_m) of theory 1



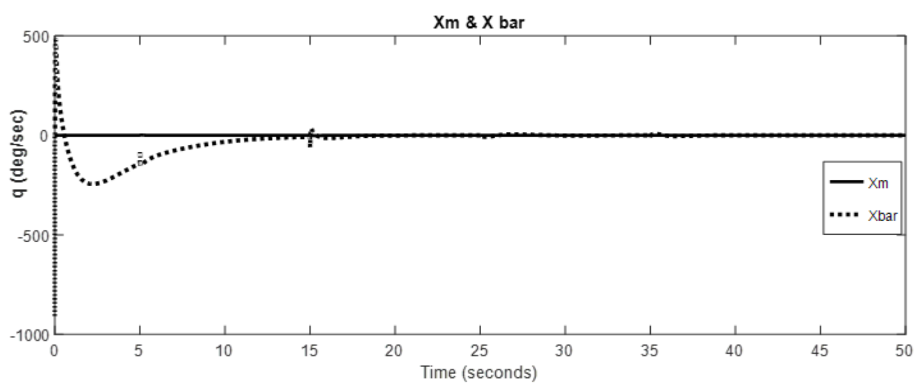
A. Parameter comparison v



B. Parameter comparison α



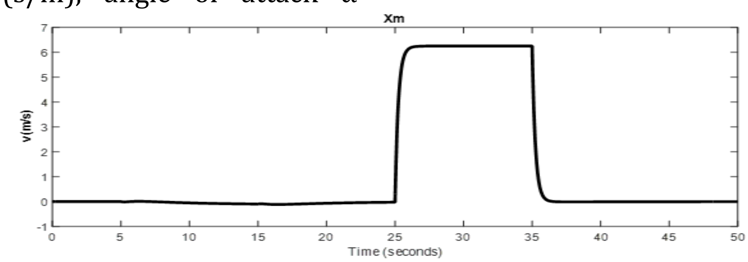
C. Parameter comparison β



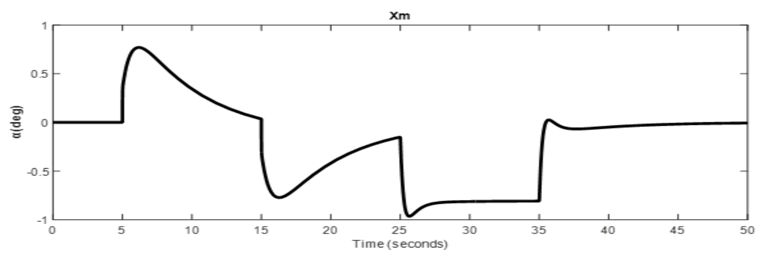
D. Parameter Comparison q

Figure 2. Comparison of the parameter (x_m) and ($\bar{x}$) of Theory 1

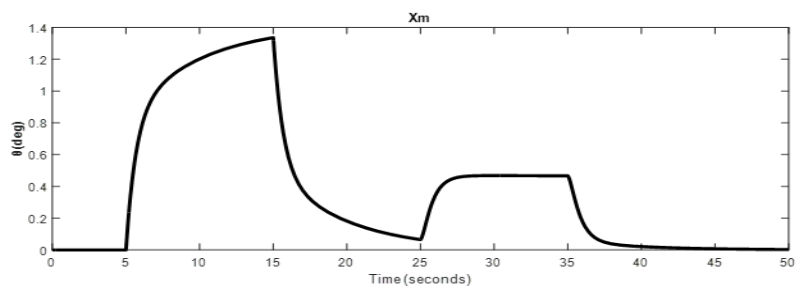
Theory 2, using asymptotic bias estimator by MRAC: In theory 2, asymptotic bias estimator, almost all the parameters are fully corrected and their values are closely converged to the reference model. Therefore, the more accurate the $\hat{\beta}$ estimate is, the better x can be measured and the closer to $\bar{x}$. The figures below show the accuracy of the material. Figures (3) and (4) show the correctness of the use of the Kalman filter to accurately estimate β. In Theory 1, by adding the feedback bias estimation based on the MRAC control law, the actual velocity parameters are v(s/m), angle of attack α (degrees), ground angle θ (degrees) and ground velocity q (degrees/seconds), to some extent. It is modified, but because it is a direct adaptive method, the device's parameters do not converge with the main parameters in the system. In theory 2, Asymptotic Bias Estimator, almost all parameters are completely corrected and their values are close and convergent to the reference model. So, the more accurate the estimate (β), the more accurate the ($\hat{\beta}$). As a result, the measurable $\bar{x}$ will improve and get closer to x_m.



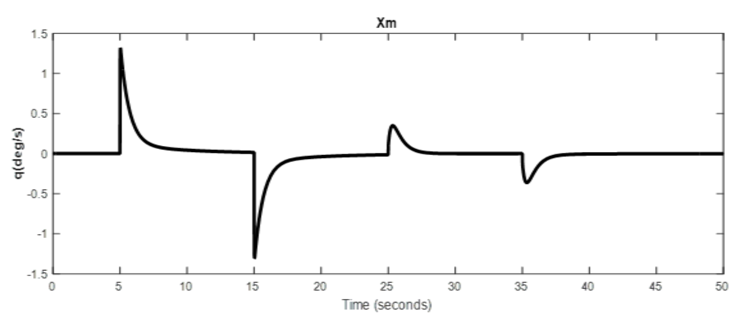
A. Parameter v



B. Parameter α

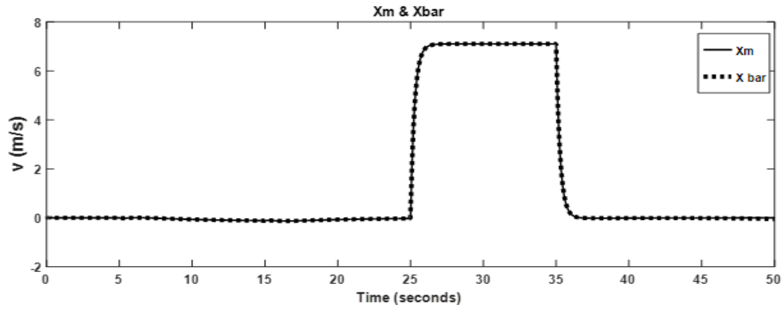


C. Parameter θ

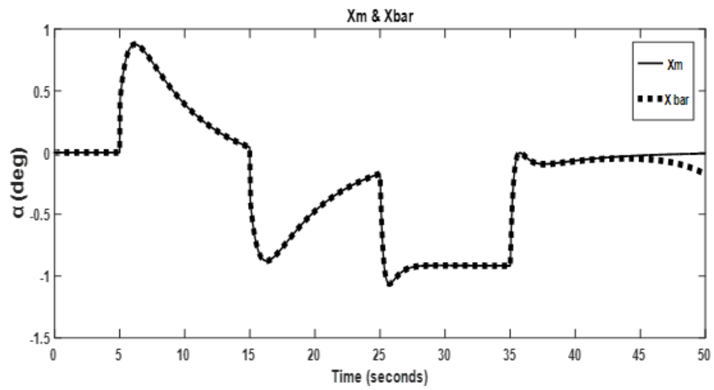


D. Parameter q

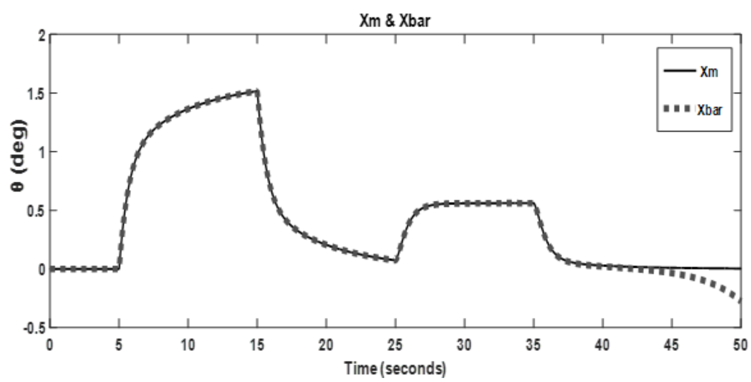
Figure 3. Representation of model reference states (x_m) of Theory 2



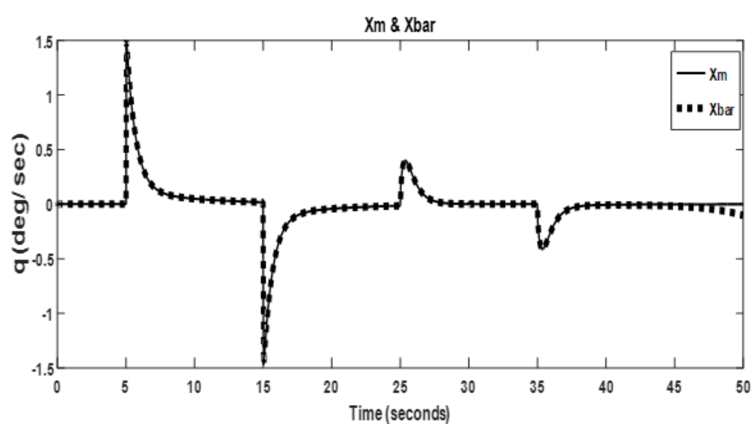
A. Parameter comparison v



B. Parameter comparison α



C. Parameter comparison β



D. Parameter Comparison q

Figure 4. Comparison of the parameters ($\bar{x}$) and (x_m) of theory 2

Conclusion

This study shows that bias can be estimated and used by MRAC to guarantee asymptotic state tracking and closed loop stability. For accurate estimation of β (bias), we used Kalman filter. The purpose of the Kalman filter is to estimate system state variables based on measurements with noise and random variables. Based on the simulation results, steady-state tracking errors are improved. In fact, the tracking error tends to zero. In Theory 1, by adding the feedback bias based on the MRAC control law, the actual velocity parameters are v(m/s), angle of attack α (degree), ground angle θ (degree) and ground velocity q (degree/second), partly. It is modified, but since it is a straightforward comparative method, the parameters of the device do not converge to the main parameters in the system. In Theory 2 (Asymptotic Bias Estimator), we obtain an accurate estimate of the bias using the Kalman filter, as a result, almost all parameters are fully corrected and their values are closely converged to the reference model.

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