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FIXED-WING UAVs CONTROL WITH MODEL UNCERTAINTIES

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Abstract

One of the major issues to deal with UAV technology is controlling the vehicle dynamics as proposed. Use of drones in multipurpose operations such as cargo delivery, disaster aid, food delivery etc. a controller needed robust against weight change, so the model uncertainties. Linear Controllers have been studied well and implemented successfully. Since the main strategy builds around linearizing the model at a trim condition, the model change affects performance. To get over this problem, nonlinear dynamics-based control algorithms have been developed. Since even the nonlinear approach depends on a defined model, model changes affect that too. A newly developing definition of the dynamics can be the answer to this problem.

Keywords: UAV, control, model, fixed-wing, filter

1. Introduction

In recent years, a serious amount of study has been made about fully autonomous UAV systems. Through the development of technology, various designs can find a place in the application. In a limited environment, it is being able to support or even replace different robotic systems with UAVs. The fixed-wing UAV type takes a step forward with the capability to carry higher volume payloads and long endurance capacity through wide operating conditions.

Maneuvering a system with changing model dynamics is a very competitive task. Model uncertainties can bring uncertainties and uncontrolled attitudes. One of the common concerns of these missions is that payload weight is about to change for every delivery. Another possible issue is the subject payload can be a liquid which would be able to slosh, in this case, flight safety becomes an even more serious concern. Due to described conditions, designing a controller that provides stability and robustness against model uncertainties is a vital request. Which is, can be satisfied with a proper control algorithm solution [1].

When the topic comes to Unmanned Aerial Vehicles, due to their small size, UAVs have the most vulnerable structure to disturbances among all aircraft designs. Especially the systems with a wider operation range need robust algorithms against modelling errors[2]. Such as; cargo delivery[3], rescue missions[4], pesticide spraying [5], medical supplies [6] etc. To address the modelling uncertainties many different control approaches has proposed in the literature[7].

In the literature, many different control strategies have been published for modelling uncertainties. Some researchers use linear gain scheduling feedback controllers, while others nonlinear and model-based control methods. Most of the studies have aimed to improve the performance with different strategies such as command filtering, differentiation strategy, cascaded control, fuzzy logic, machine learning, adaptive strategy etc. Since linear and nonlinear has their strong sides, both have found a place in different studies. Enhances of the nonlinear control approach date back to the late nineties and began with activities relating to Implicit Dynamic Inversion for Dynamic Inversion based control. Nonlinear controllers have been built around different methodologies, such as Sliding Mode controller, Backstepping controller, and Nonlinear Dynamic Inversion controller [8]. Among them, the

Backstepping algorithm has become the most widely used algorithm with its flexible design.

Throughout the given discussion, this paper proposes a comparison of various controlling methods. The study aims to achieve stabilization and the tracking performance of the Unmanned Aerial Vehicle (UAV) against modelling uncertainties in terms of weight change. The paper outline is as follows: Section II. defines a 6DoF fixed-wing UAV (Aerosonde UAV) which has been modelled in a MATLAB environment. Section III. targeted competitive controlling algorithms and used filters are discussed. Proposed controlling algorithms encompassing Integrator Backstepping, Linear Quadratic Integrator and Linear Quadratic Controller with Disturbance Observer control designs were compared. Section IV. Described controllers' performance comparisons are made through various scenarios. Finally in Section V. conclusion of the study has been presented.

2. UAV Model

The fixed-wing UAV model used in the study is known as Aerosonde UAV. Aerosonde's autopilot was studied by many researchers with different control techniques [9]. Aerosonde UAV's design and control surfaces are shown in Figure 1.

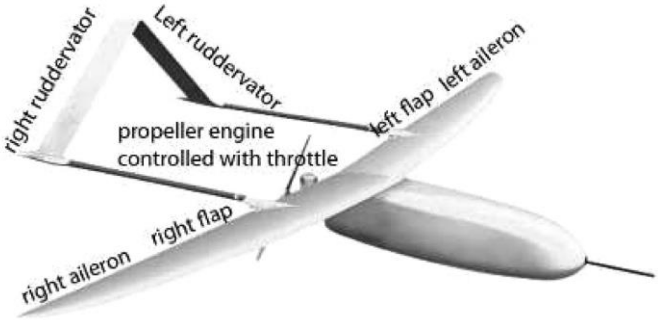


Figure 1 – Aerosonde UAV's design and control surfaces [10]

The mathematical model of the system represents the physical phenomena of UAV dynamics. Although, aerodynamic and structural coefficients of the system are achieved by measurements from sensors and approximations from calculations [10]. However, it is very possible to have some modelling errors in a project. Yet, these errors should be derived with minimum tolerance, since controllers mostly depend on the UAV model [11].

The 6 Degree of Freedom (6 DoF) nonlinear mathematical model off UAV consists of 12 state variables: inertial states (p_n, p_e, p_d), body frame velocities (u, v, w), Euler angles (ϕ, θ, ψ) angular velocities (p, q, r).

To achieve 12 state mathematical model of the UAV, firstly equations of motion (EoM) equation should be derived:

$$F_x = m(\dot{U} + qW - Vr) \tag{1}$$

$$F_y = m(\dot{V} + pW - Ur) \tag{2}$$

$$F_z = m(\dot{W} + pV - Uq) \tag{3}$$

$$M_x = I_{xx}\dot{p} - I_{xz}(\dot{r} + pq) + \left(I_{zz} - I_{yy}\right)qr \tag{4}$$

$$M_y = I_{yy}\dot{q} - I_{xz}(p^2 + r^2) + (I_{xx} - I_{yy})pr \tag{5}$$

$$M_z = I_{zz}\dot{r} - I_{xz}\dot{p} + pq\left(I_{yy} - I_{xx}\right) + I_{xz}qr \tag{6}$$

Where F_x, F_y, F_z are forces and M_x, M_y, M_z are moments and I_{xx}, I_{yy} and I_{zz} product of inertia.
After EoM, 12 state of the system can be described as below:

$$\begin{pmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{pmatrix} = \begin{pmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \frac{\sin\phi}{\cos\theta} & \frac{\cos\phi}{\cos\theta} \end{pmatrix} + \begin{pmatrix} p \\ q \\ r \end{pmatrix} \tag{7}$$

$$\begin{pmatrix} \dot{p} \\ \dot{q} \\ \dot{r} \end{pmatrix} = \begin{pmatrix} \Gamma_1 qr \ - \Gamma_2 qr \\ \Gamma_5 pr \ - \Gamma_6 (p^2 - r^2) \\ \Gamma_7 pq \ - \Gamma_1 qr \end{pmatrix} + \begin{pmatrix} \Gamma_3 l + \ \Gamma_4 n \\ \frac{1}{J_y} m \\ \Gamma_4 \ l \ + \Gamma_8 n \end{pmatrix} \tag{8}$$

Where $\Gamma_1 \Gamma_2, \ldots\ldots, \Gamma_8$ are inertia functions and J_y product of inertia.

$$\begin{pmatrix} \dot{p_n} \\ \dot{p_e} \\ \dot{p_d} \end{pmatrix} = (R_v^b(\phi, \theta, \psi))^T \begin{pmatrix} u \\ v \\ w \end{pmatrix} \tag{9}$$

Where $R_v^b(\phi, \theta, \psi)$is rotation matrix.

$$\begin{pmatrix} \dot{u} \\ \dot{v} \\ \dot{w} \end{pmatrix} = \begin{pmatrix} rv - qw \\ pw - ru \\ qu - pv \end{pmatrix} + \frac{1}{m} \begin{pmatrix} F_x \\ F_y \\ F_z \end{pmatrix} \tag{10}$$

The mathematical model of the Aerosonde UAV, designed on the MATLAB platform.

3. Control Algorithms

In this study, controllers can divide into two groups linear-nonlinear controllers or Linear Quadratic based-Backstepping based controlling algorithms. Linear controllers and nonlinear controllers respectively; Linear Quadratic Integrator (LQI), Linear Quadratic Regulator with Disturbance Observer (LQRDO), Integrator Backstepping (IBS and Incremental Backstepping (IKBS). For fixed-wing UAV control, a single layer controller approach is preferred.

The system is controlled through four states which are: X, Y positions, altitude, and airspeed. Simulation conditions are chosen as the continuous time to catch the closest results as real-life conditions. Closed-loop dynamics stability of the designed systems validated by the Lyapunov theory [12].

3.1 Linear Quadratic Regulator Algorithm

The Linear Quadratic Regulator(LQR) controlling algorithm has a very strong place in literature with its excellent performance and robustness through the plant [13]. Capability of the complex system dynamics and handle multiple actuators makes this methodology very suitable for multi-input multi-output (MIMO) systems [14]. Since LQR is a cost function-based methodology, the input signal has been defined as the cost. In this way, the optimum value for the control signal achieved [15]. Also, the stability of the designed system has been verified By the Lyapunov Theory. Finally, the optimal controller has been designed with 4 states controlling through the track the desired coordinates. The proposed controller's block diagram shown in Figure 2.

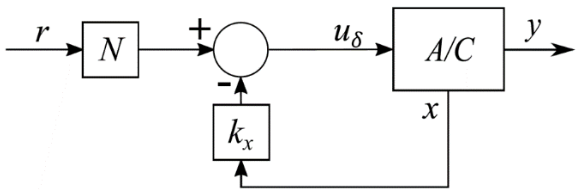


Figure 2 – Block diagram of the LQR controller

Firstly, a standard model of the system can be presented as below in state-space representation:

$$\dot{x} = Ax + Bu \tag{11}$$

$$y = Cx + Du \tag{12}$$

Secondly, the cost function of the Linear Quadratic Regulator can define as below:

$$J(x,u) = \frac{1}{2}\int_0^\infty (x^T(t)Qx(t) + u^T Ru(t))dt \tag{13}$$

Thirdly, the LQR gain k_x, calculated as given below:

$$k_x A + A^T k_x - k_x B R^{-1} B^T k_x + Q = 0 \tag{14}$$

And in the last step DC gain N calculated as given below

$$N = [-C(A - Bk_x)^{-1}B]^{-1} \tag{15}$$

3.2 Linear Quadratic Integrator Algorithm

Linear Quadratic Integrator is a very robust design which enhanced from Linear Quadratic controller with an Integrator component. In this way, the controller has gained more robust behavior against modelling uncertainties. Linear Quadratic Regulator with Disturbance Observer is a controller that combines Linear Quadratic algorithm with Disturbance Observer algorithm. Not only do both approaches depend on a predefined UAV model but also both algorithms use a linear method.

$$J = \frac{1}{2}\int_0^\infty ({x_i}^T H^T Q_i H x_i + 2r^T M^T Q_i H x_i + r^T M^T Q_i M r + u^T R u)dt \tag{16}$$

Block diagram of the Linear Quadratic Integrator controller shown in the Figure 3.

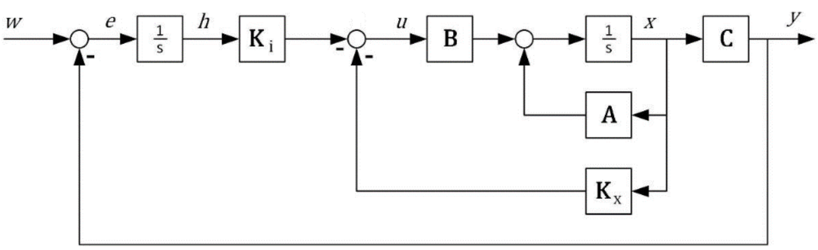


Figure 3 – Block diagram of the Linear Quadratic Integrator controller

3.3 Linear Quadratic Regulator with Disturbance Observer Algorithm

With its simplicity, efficiency and flexibility disturbance observer is one of the most common robust control methodologies. This algorithm uses previously defined dynamics variables with the current states of the system. In this way, detects and rejects the disturbances immediately [16]. With a globally stabilized approach, the methodology represents a very robust behavior. Another advantage of the system, disturbance rejection gains are able to tune independently and this brings remarkably flexibility to the controller design [17]. The disturbance observer compensation gain (k_{dx}) calculated as given below:

$$k_{dx} = (-C(A - Bk_x)^{-1}B_d) * (C(A - Bk_x)^{-1}B)^{-1} \tag{17}$$

General scheme block diagram of the LQRDO and Integrator Backstepping algorithms given Fig. 4.

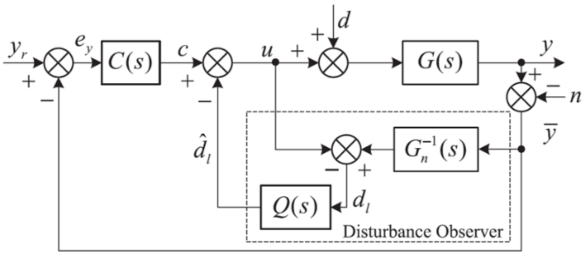


Figure 4 – Disturbance Observer diagram

3.4 Backstepping Algorithm

Backstepping control methodology is one of the most successful and widely employed nonlinear flight control strategies. The general idea of the linear controllers cancelling some of the nonlinear aspects of dynamics of the system and derive controller gains. Cancelling some of the dynamics brings some drawbacks to the controller performance. Yet, linear controllers have been applied to many different operations successfully. On the other hand, nonlinear controllers do not have this kind of defect. However, since conventional Backstepping algorithm depends on the accurate system model, modelling uncertainties reduce the feasibility of the design [18]. In this study, the Integrator Backstepping and Incremental Backstepping methods were used as the nonlinear controllers for the comparison. Both of the controllers' stability proven by Lyapunov functions [19].

3.4.1 Integrator Backstepping Algorithm

In terms of protecting global asymptotic stability (GAS), the backstepping algorithm can enhance with an integrator. In this way, a virtual input signal (ξ), can be designed through its desired value $\alpha(x)$. To achieve this, an error signal (z) should be designed and in this way, the controller approach will be an error neutralizing approach. Proposed modification can be shown as:

$$\dot{x} = Ax + B\xi \tag{18}$$

$$\dot{\xi} = u \tag{19}$$

$$z = \xi - \xi_{des} = \xi - \alpha(x) \tag{20}$$

Block diagram of the Integrator Backstepping controller shown in the Figure 5.

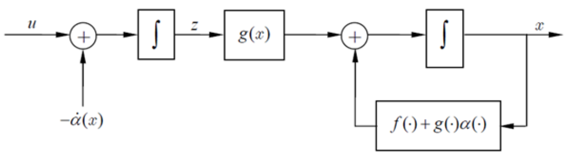


Figure 5 – Integrator Backstepping algorithm block diagram

3.5 Filters

The To avoid infeasible commands provided by the controller, a Command Filter (CF) is added to the controller. Commands filters are low pass filters which shape the command inputs to match the aircraft dynamics.[1] This technique has been used in backstepping strategies, constraining the pseudo-control in each step. Therefore, differentiation variables need to be estimated as a function of the measurements. To estimate signal derivatives, proposed filter also contains differentiator.[18]

$$\begin{bmatrix} x_c \\ \dot{x_c} \end{bmatrix} = \begin{bmatrix} q_1 \\ q_2 \end{bmatrix} \tag{21}$$

$$\begin{bmatrix} \dot{q_1} \\ \dot{q_2} \end{bmatrix} = \begin{bmatrix} q_2 \\ 2\zeta\omega_n \left(S_R \left\{ \frac{w_n^2}{2\zeta\omega_n} [S_M(x_d) - q_1] \right\} - q_2 \right) \end{bmatrix} \tag{22}$$

The architecture of the command filter used for the controller is shown in Figure. Each filter's output has been used in next part of cascaded algorithm.

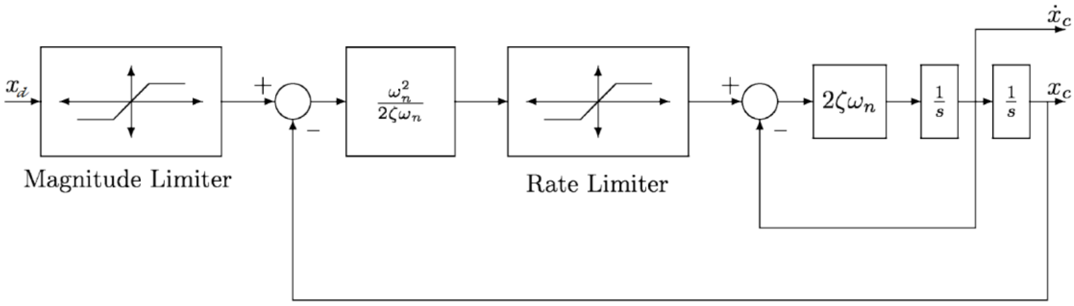


Figure 6 – Command Filter Block Diagram

The values of natural frequency and damping ratio of the command filters are selected such that it matches the aircraft dynamics without slowing down the system or asking for more performance than the aircraft can deliver. Chosen values given in Table–1.

Table–1. Command filter natural frequency values

	T	p	q	r	δ_e	δ_a	δ_r
ω_n	5	20	20	10	40	40	40

To avoid unachievable commands due to actuator constrains, first-order lag prefilters are also used to obtain reference signals:

$$H_{V,\alpha,\beta,p}(s) = \frac{\alpha_{ref}(s)}{\alpha_{autopilot}(s)} = \frac{1}{\sigma s+1} \tag{23}$$

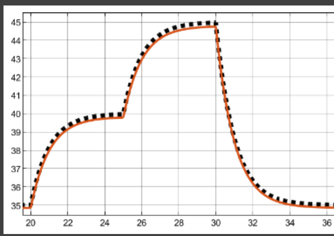
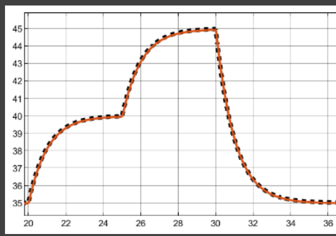
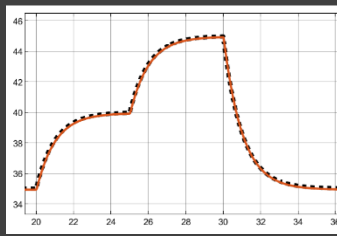
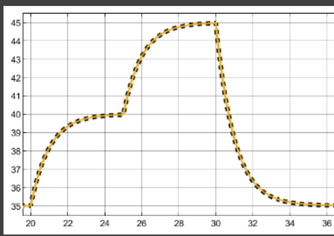
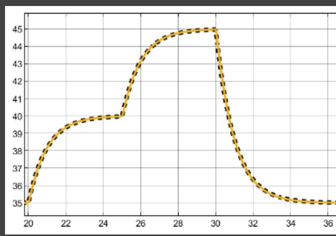
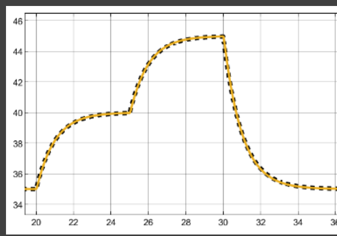
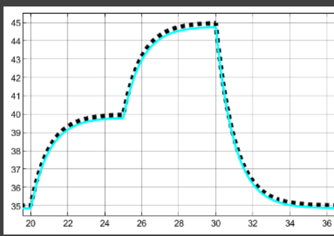
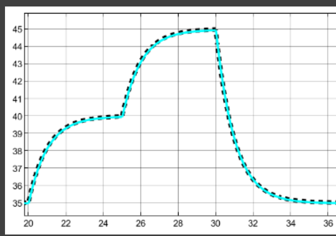
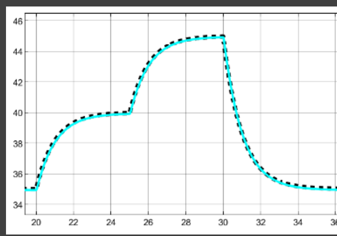
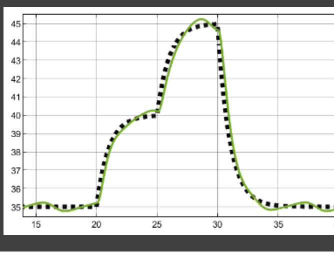
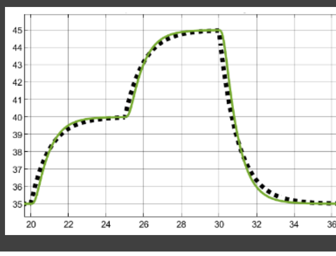
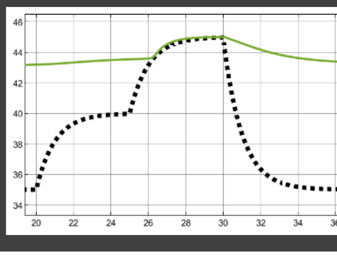
By given filter algorithms, reliable command signals and necessary derivative values has been calculated for the controller.

4. Simulations

Simulation has been made under airspeed command tracking under different weight conditions. The weights have been chosen especially extreme to represent more clearly unusual behaviours. In fact, original command signals have been given as step signals. Yet still, applied command filters showed a reliable performance and filtered the signals as the most achievable patterns. The achieved results are represented in Table 2. The command signal is represented as a black dotted line and controller outputs are given as straight lines.

Since the backstepping algorithm directly depend on UAV dynamics, it is not a surprise to achieve the most affected results. Backstepping algorithm loose stability with lower weight and presents overshoots. On the other hand, the Backstepping algorithm loses control under the heavyweight and presents almost uncontrolled dynamics.

Table 2: Speed Command tracking performance comparison under different weight conditions

	%10 Weight	%100 Weight	%200 Weight
LQR			
LQI			
LQR+DO			
Integrator Backstepping			

Surprisingly, Linear Quadratic Controller regardless of whether supported with Disturbance Observer or not, shows a similar undershoot profile. Even if it is a small amount, the Disturbance Observer signal has signs of rejecting the disturbance. Close inspection of the signals presented in the figure.

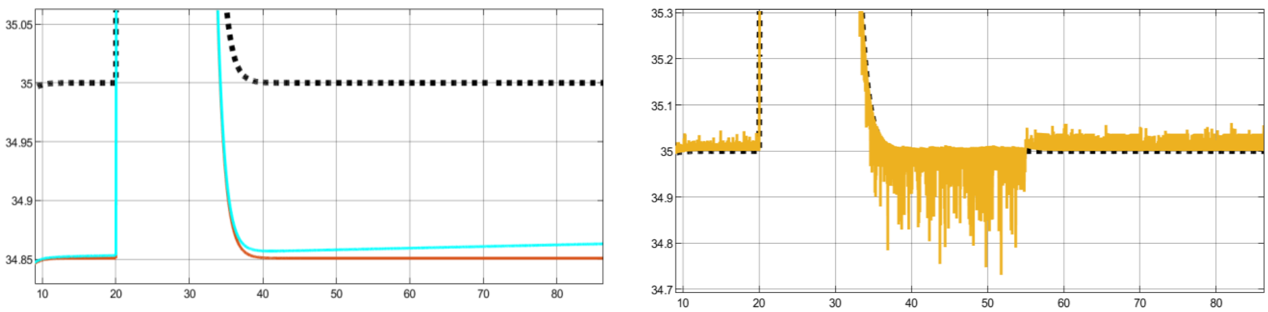


Figure - 7 LQR controller with-without Disturbance observer(left) and LQI controller signal disturbance (right)

However, even with the %200 of the weight, the Linear Quadratic Integrator controller does not show a noticeable error in terms of command tracking, only a small amount of lag occurs. When things come to being lightweight, the LQI controller faces instability issues. White noise like a disturbance on the LQI signal is represented in the figure.

5. Conclusion

The paper seeks to understand the dynamics of controllers against model uncertainties for fixed-wing UAVs. In terms of fixed-wing UAVs representation, Aerosonde UAV has been modelled. Which is a flight-proven fixed-wing UAV design. Throughout the achievement of different outcomes as much as possible, different controlling algorithms are designed. Which are; Integrator Backstepping, Linear Quadratic Regulator, Linear Quadratic Integrator and Linear Quadratic Controller with Disturbance Observer control designs were compared. To avoid windup and actuator issues prefilters and command filters has designed and implemented. For comparison, the airspeed state of the UAV has been investigated through different weight parameters.

Fixed-wing UAV structure has the capability of completing missions that need long endurance and high payload. With these advantages, it is possible to say that the fixed-wing has a promising future. Thus, robust algorithms development is a necessary issue and finding the most suitable controller can be possible by comparing different controllers. On the other hand, through the extending commercial use and expectations of UAVs, controlling methodologies need to be enhanced among users' demands direction.

The aim of this research is, to compare and find the most robust controller against model uncertainties. Through study, simulation comparisons have been made with different weight scenarios in terms of model uncertainty. Since all of the used methodologies in model-based designs, it is expected to suffer every disturbance on the model. To see these effects more clearly, it would be a wise idea to investigate body exes related states inspection in future. Since the Backstepping algorithm directly builds on system dynamics, having this kind of wind up is an expected issue. But flexibility and other advantages standstill. To this extent using a less model-dependent model with a Backstepping algorithm could give a satisfying outcome.

For future research, this study will be a base for future research researchers. Such as seeking a way to cover model dependency of given controllers or targeting a different methodology. Also considering the last user-based problems can give literature a more reliable direction. It is not possible to draw a one-way direction since every controlling algorithm has its advantages and disadvantages. This aspect makes different controlling algorithms suitable for different concepts. Investigating and classifying controlling algorithms in terms of targeting aspects would make the literature more comprehensible.

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7. Copyright Statement

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