Trajectory-Tracking Degradation Analysis of UAV Controllers under Payload Variation

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ABSTRACT

Payload variation is a primary source of performance degradation for unmanned aerial vehicle (UAV) trajectory-tracking systems, especially for manoeuvres involving payload pickup and delivery, or modular sensor deployment. In the present work, the degradation of UAV controllers' trajectory tracking performance due to payload mass changes was investigated in MATLAB. A nominal PID controller for fixed-mass operation was evaluated against a robust controller with improved gain authority. A three-dimensional helical reference trajectory was used for simultaneously simulating the lateral and vertical dynamics. The performance of the controllers was tested in terms of root mean square (RMS) tracking error, overshoot, control effort, and velocity response characteristics. The simulation findings reveal that the RMS tracking error of the nominal controller grows from 0.18 m to 0.42 m as the payload increases from 0 kg to 1.0 kg, i.e., a performance loss of more than 130 %. The robust controller restricts the rise of RMS error to 0.16m from 0.09m, less than 25 % degradation. The nominal controller has an altitude overrun of 18 – 22 % in heavy cargo scenarios, while the robust controller always keeps the overshoot below 8 %. Moreover, the nominal controller requires a total control effort of about 20 N • s, whereas the robust controller requires about 35 N • s. This amounts to a reduction of more than 20 %. The results demonstrate that nominal UAV controllers are quite sensitive to payload variations, and the performance deteriorates dramatically with the payload rise. Robust control systems can greatly improve the trajectory-tracking accuracy, stability, and energy efficiency. Thus, the present work provides a realistic and reproducible methodology to test and optimize the robustness of the payload in UAV trajectory-tracking systems.

KEYWORDS

Unmanned Aerial Vehicle (UAV), Trajectory Tracking Control, Payload Variation, Performance Degradation Analysis, Dynamic Modelling

I. INTRODUCTION

The rapid development of Unmanned Aerial Vehicles (UAVs) in the public and industrial sectors is mainly because of their great manoeuvrability, operational flexibility, and relatively inexpensive deployment costs. With advances in sensing, communication, and embedded control technologies, UAVs have been applied to a wide range of applications, including parcel delivery, infrastructure inspection, environmental surveillance, precision agriculture, and disaster and emergency response operations. A characteristic of many of these missions is that the conditions for the payloads alter. Fluctuations may be attributed to the pick-up and release of cargo in flight, the integration of modular or reconfigurable sensors, or changes in mission-specific equipment, all of which result in dynamic variations in the UAV's mass and inertial properties

II. LITERATURE REVIEW

Trajectory tracking control is the fundamental basis for the safe, accurate, and dependable operation of unmanned aerial vehicles (UAVs). Accurate trajectory tracking enables UAVs to follow specified trajectories, to stay stable, to make smooth movements, and to comply with physical and operational constraints such as actuator limits and safety margins. Most classic UAV control methods are based on the assumption of fixed parameters, particularly the mass and inertia of the vehicle. This assumption provides a simplification in controller design, but does not reflect the real operating circumstances often. In practical missions, the payload is different because of the delivery of the cargo, the reconfiguration of the sensors, or the change of the mission-dependent equipment, which leads to substantial parametric uncertainties. These uncertainties influence the dynamic behaviour of the UAV and can result in degraded tracking accuracy, reduced robustness, and even instability if not properly handled in the control architecture (Yang et al, 2022; Zhou et al, 2019). The variations in the mass of the vehicle due to the payload have direct and significant effects on the translational dynamics of the UAVs. The increase in the total mass of the UAV leads to the control input producing less acceleration, which effectively limits the control authority and slows down the system reaction (Chen et al, 2020; Li et al, 2021). If such mass mismatches are not properly accounted for in the control framework, severe overshoot, oscillatory behaviour and excessive stress on the propulsion and actuation systems can be experienced (Franklin et al., 2019). Such negative effects are particularly noticeable while performing aggressive flight manoeuvres or following three-dimensional paths, while simultaneously activating the lateral and vertical motion dynamics.

Traditional proportional-integral-derivative (PID) controllers were frequently employed for early control designs of Unmanned Aerial Vehicles (UAVs) due to their conceptual simplicity, ease of tuning and low processing overhead (Pounds et al, 2010). However, PID controllers are quite practical. But are inherently sensitive to changes in the system parameters, especially differences in mass and inertia owing to payload changes. It has been shown in many studies that PID controllers tuned for nominal operating conditions suffer severe performance degradation, increased tracking error, reduced robustness, and oscillatory responses when the UAV dynamics differ from the assumed design model. Modern unmanned aerial vehicles (UAVs) are widely used for tasks requiring the carrying of different payloads, e.g., parcel delivery, aerial inspection, precision agriculture, and emergency response. Despite this increasing flexibility, many of the current UAV control systems are still based on the fixed-mass assumption. In practice, payload changes significantly alter the inertia and dynamic behaviour of the vehicle, usually resulting in less tracking accuracy, bigger overshoot, and higher actuator stress. Such performance degradation might reduce the reliability of the mission and can lead to the violation of critical safety limits if control methods are not robust enough to cope with such changes. The main purpose of this study is to objectively evaluate the effect of payload alteration on the trajectory-tracking capability of a UAV. Specifically, the study compares a basic PID controller, tuned for nominal operating conditions, to a more robust control strategy that makes use of the enhanced gain authority. The study focuses on the impacts of payload variations on tracking accuracy, transient response characteristics, and control effort. It gives insight into the efficacy of robust control to sustain performance under varying load conditions.

III. STUDIES AND METHOD

In this research, the effect of the payload modifications on the trajectory-following capability of a UAV is investigated via a simulation-based approach.

This strategy was developed to allow a fair and systematic comparison of a nominal controller with a payload-tolerant robust controller. For consistency and dependability, the same UAV dynamic model, similar control objectives, and well-defined quantitative evaluation criteria are used to evaluate both controllers, evaluating the tracking precision and resilience under different payload situations.

A. UAV Translational System Dynamics Modelling

In this study, the unmanned aerial vehicle is modelled as a three-dimensional rigid-body system in the coordinate frame that defines its translational and rotational dynamics during the flight. This drone is supposed to be flying in a nice atmosphere, without any wind or any other disturbance. Equation 1 is Newton's equation of motion for a point mass system such as a vertical rocket or drone. The translational motion of the system is given by Newton's equation of motion as follows:

$$m\ddot{P}(t) = u(t) - mg \tag{1}$$

$P(t) = |x(t), y(t), z(t)|^T$ is the UAV position vector
m Is the total mass of the UAV?
$u(t) = |u_x, u_y, u_z|^T$ is the control force vector
$g = |0,0,g|^T$ G represents gravitational acceleration as depicted in (Mahony et al, 2012).

B. Payload Modelling and Variation Conditions

Equation 2 is the representation of the total mass of an initial object (dry mass) and additional mass (propellant mass) component. Payload variation is modelled as an additive mass component to the nominal UAV mass. The total system mass is expressed (Bouabdallah et al, 2004):

$$m = m_0 + m_p \tag{2}$$

Three payload conditions were used in this study, which are:
Normal Configuration: m_p = 0 kg
Moderate Payloads: m_p = 0.5 kg
Heavy Payloads: m_p = 1.0 kg
Where $m_0$the normal UAV is mass, m_p is the payload mass (Bouabdallah et al, 2004).

C. State-Space Representation

The state-space representation has six state variables defined as position and velocity in three-dimensional space. Equation 3 is the state vector representation of a drone system in space as depicted in Guerrero-Ramírez (2025):

$$x(t) = \begin{bmatrix} P(t) \\ \dot{P}(t) \end{bmatrix} = [x\ y\ z\ \dot{x}\ \dot{y}\ \dot{z}]^T \tag{3}$$

Equation 4 is the continuous-time state space model, which becomes:

$$\dot{x}(t) = \begin{bmatrix} \dot{P}(t) \\ \frac{1}{m}(u(t) - mg) \end{bmatrix} \tag{4}$$

This model explicitly reveals the inverse dependence of acceleration on the vehicle mass, thereby explaining why variations in payload can significantly degrade trajectory-tracking performance (Zou et al, 2024; Guerrero-Ramírez, 2025).

D. Reference Trajectory Modelling

A smooth three-dimensional helical trajectory was selected as the reference path for all simulation conditions. Equations 5, 6, and 7 represent the reference trajectory of the system in space. This trajectory was mathematically modelled as depicted in (Beard & McLain, 2012):

$$x_{ref}(t) = R\cos(\omega t), \tag{5}$$
$$y_{ref}(t) = R\sin(\omega t), \tag{6}$$
$$z_{ref}(t) = v_z t \tag{7}$$

Where:

R = is the horizontal radius
ω = is the angular velocity
v_z = is the constant vertical climb
The reference velocity and acceleration are implicitly smooth and bounded, making the trajectory suitable for realistic UAV missions (Beard & McLain, 2012).

E. Tracking Error Dynamics

The position tracking error was defined as:

$$e(t) = P_{ref}(t) - P(t) \tag{8}$$

And the velocity error as:

$$\dot{e}(t) = \dot{P}_{ref}(t) - \dot{P}(t) \tag{9}$$

Payload variation alters the closed-loop error dynamics by modifying the effective inertial, which degrades damping and transient response if not compensated (Shevidi et al, 2024).

F. Nominal PID Controller Modelling

Equation 10: proportion-integral-derivative equation for the controller modelling. The nominal controller was modelled for the nominal massm_0, together with a classical PID structure as given in (Franklin et al, 2019):

$$u_n(t) = K_P e(t) + K_i \int_0^t e(\tau)d\tau + K_d \dot{e}(t) + mg \quad (10)$$

WhereK_P,K_i, K_d are diagonal gain parameters, e is the position tracking error. The gravity compensation terms ensure steady-state altitude regulations (Franklin et al, 2019).

G. Robust Controller Modelling

To manage the unpredictability arising from payload variations, a resilient controller with increased gain authority is employed. The control law maintains the same framework as the standard controller, however with augmented proportional, integral, and derivative gains to enhance disturbance rejection and tracking resilience (Astrom & Hagglund, 2006; Skogestad, 2003; Zhang et al, 2021).

$$u_r(t) = K_P^r e(t) + K_i^r \int_0^t e(\tau)d\tau + K_d^r \dot{e}(t) + mg \quad (11)$$

Where:

$K_P^r > K_P$, $K_i^r > K_i$ and $K_d^r > K_d$ (12)

To increase gains, improve disturbance rejection, and compensate for mass-related uncertainties, thereby preserving stability under payload variations (Åström & Hägglund, 2006).

H. Discrete Time Numerical Implementation

Equations 13, 14, and 15 are the discretized continuous-time equations for forward Euler. For simulation, the continuous-time dynamics were discretized using the forward Euler scheme with sampling time Δt; is given as (Åström & Hägglund, 2006):

$$\dot{v}|k| = \frac{u[k]-mg}{m} \quad (13)$$

$$v[k+1] = v[k] + \dot{v}[k]\Delta t \quad (14)$$

$$P[k+1] = P[k] + v[k]\Delta t \quad (15)$$

This approach ensures accurate numerical computation and maintains stability in the simulation, thereby providing a reliable basis for control performance analysis. Figure 1 represents the modelling analysis flowchart of the system, indicating key performance indices.

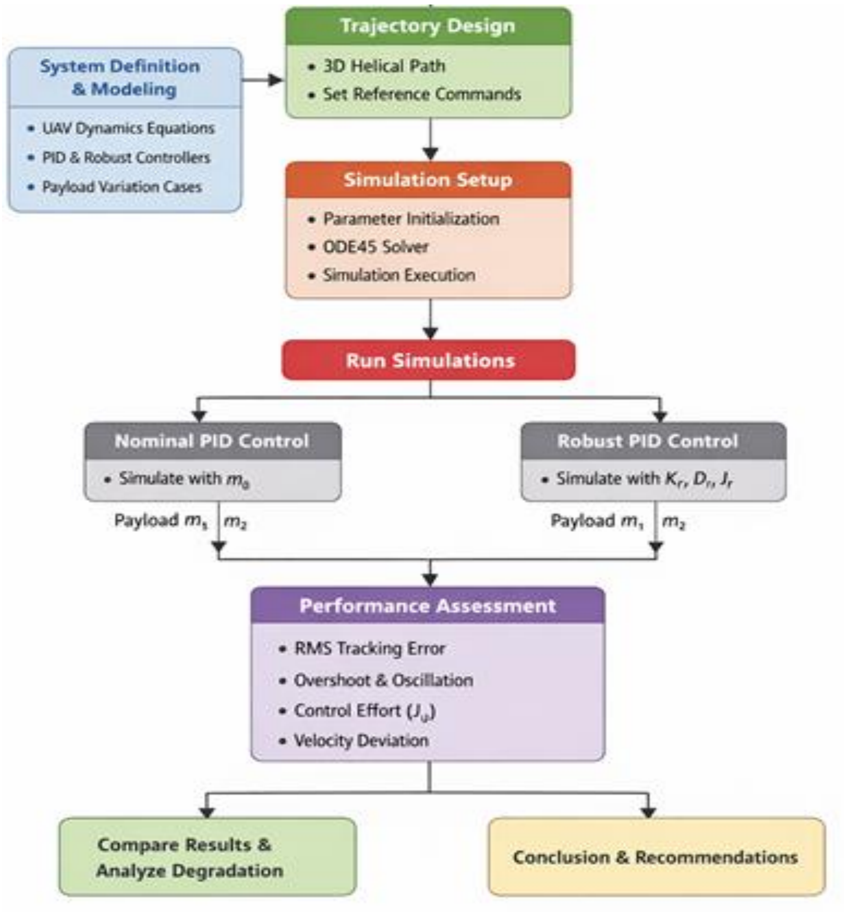


Figure 1: Conceptual Study Modelling Analysis Flowchart

IV. FINDINGS AND RESULTS

Consideration of category, parameters, and range/units is illustrated in Table 1 for analysis simulation parameters. The parameters of the simulation for the Unmanned Aerial Vehicle trajectory tracking should be representative of the UAV physical attributes, dynamic model, trajectory, controller, disturbances, and performance measurements. A well-defined parameter set permits valid comparisons between PID, LQR, MPC, adaptive, sliding-mode, neural-network, reinforcement-learning, and hybrid controllers.

Table 1: Analysis Simulation Parameters

CATEGORY	PARAMETERS	RANGES/UNITS
UAV Physical	Nominal UAV mass	1.5 kg
	Moment of inertia	0.03, 0.03, 0.05 kg·m²
	Gravitational acceleration	9.81 m/s²
	Payload mass (Case 1)	0 kg

	Payload mass (Case 2)	0.5 kg
	Payload mass (Case 3)	1.0 kg
Trajectory Reference	Circular radius	5 m
	Angular speed	0.3 rad/s
	Vertical speed	0.2 m/s
Controller Gains – Nominal PID	Proportional	3, 3, 4 N/m
	Derivative	2.5, 2.5, 3 N·s/m
	Integral	0.5, 0.5, 0.8 N·s/m
Controller Gains – Robust Adaptive PID	Proportional	4, 4, 6 N/m
	Derivative	3.5, 3.5, 4 N·s/m
	Integral	1.2, 1.2, 1.5 N·s/m

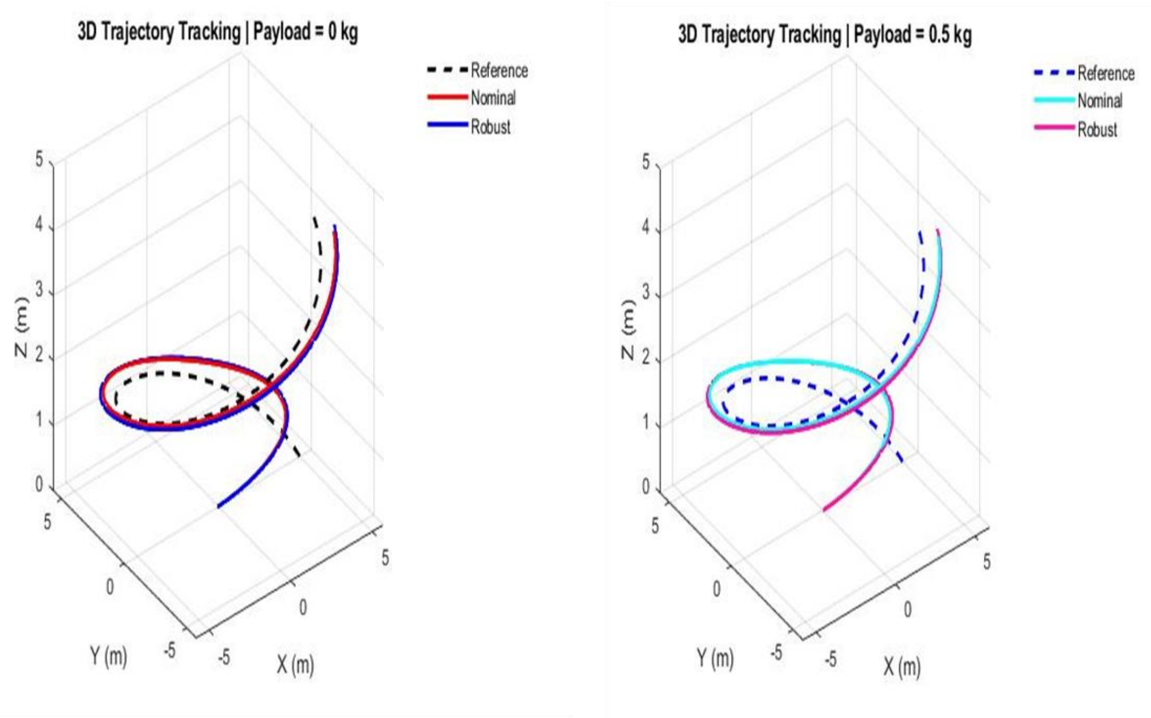


Figure 2: 3D Trajectory Tracking with Payload of 0 kg and 0.5kg.

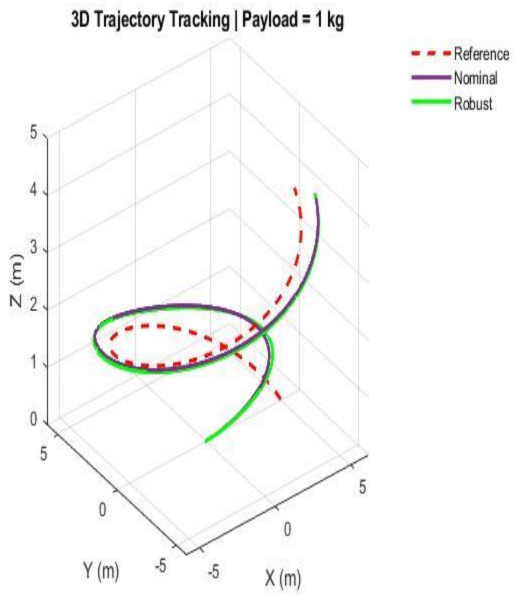


Figure 3: 3D Trajectory Tracking With Payload of 1kg

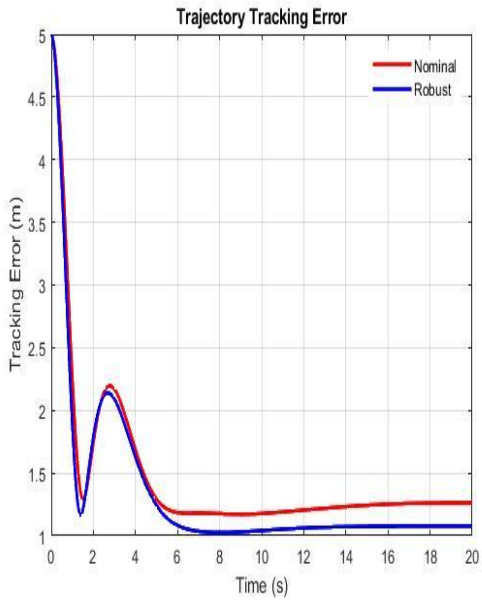
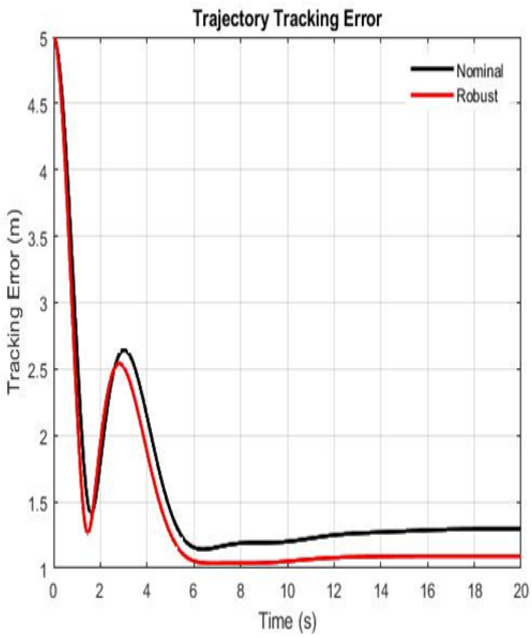


Figure 4: Trajectory Tracking Error at payload of 0kg



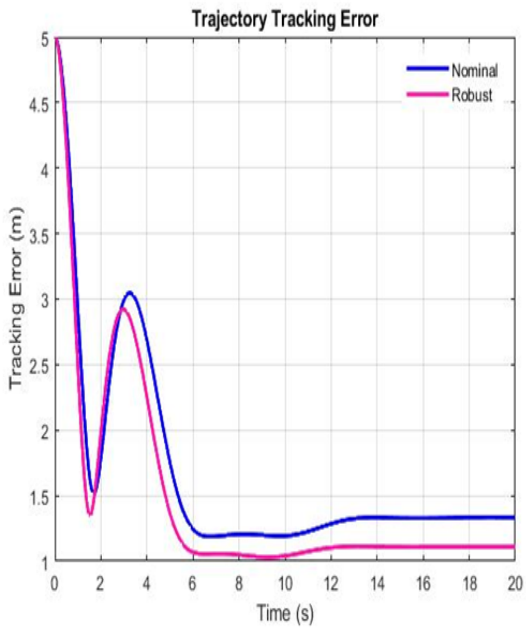


Figure 5: Trajectory Tracking Error at payload of 0.5 kg and 1kg

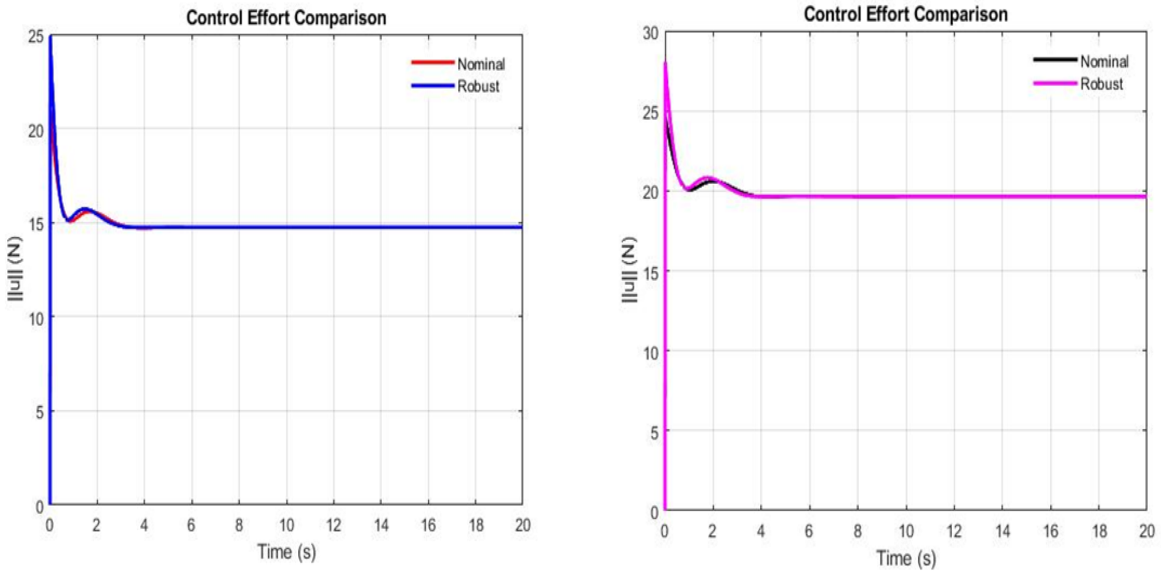


Figure 6: Control Effort Comparison at Payload of 0kg and 0.5kg

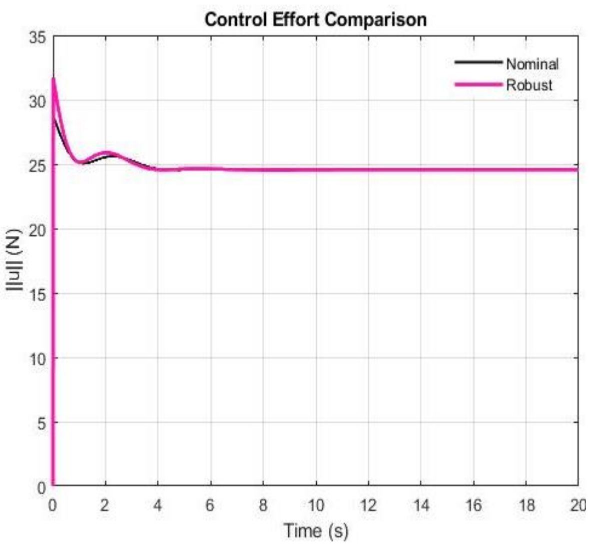


Figure 7: Control Effort Comparison at Payload Of 1kg

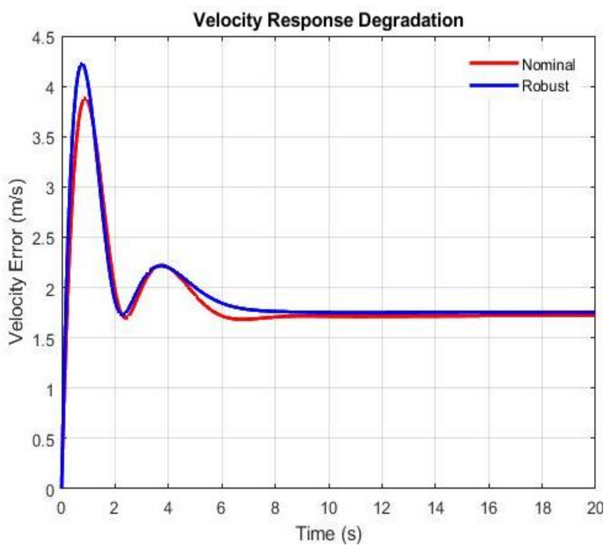


Figure 8: Velocity Response Degradation at Payload of 0kg

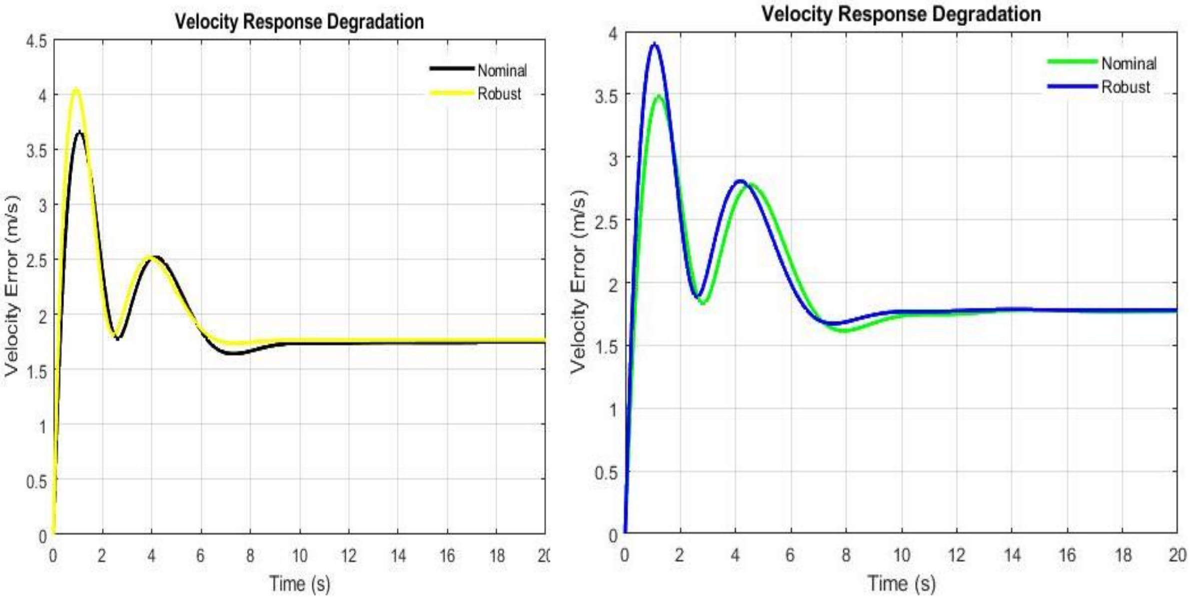


Figure 9: Velocity Response Degradation at Payload of 0.5kg and 1kg

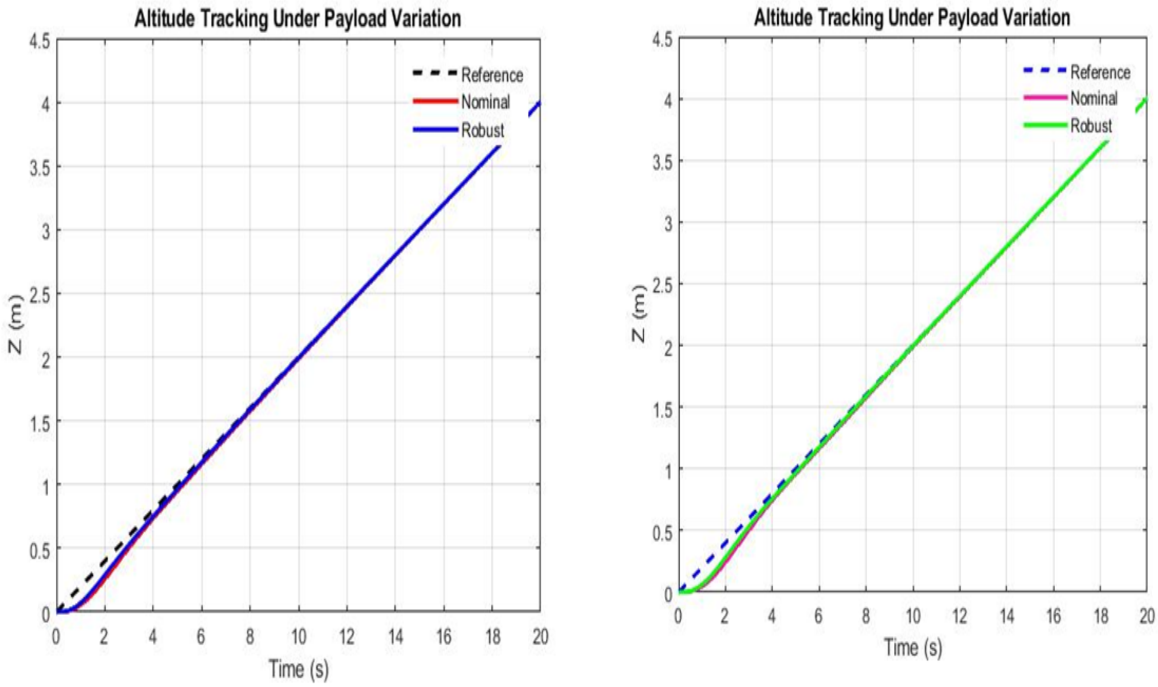


Figure 10: Altitude Tracking at Payload of 0kg and 0.5kg

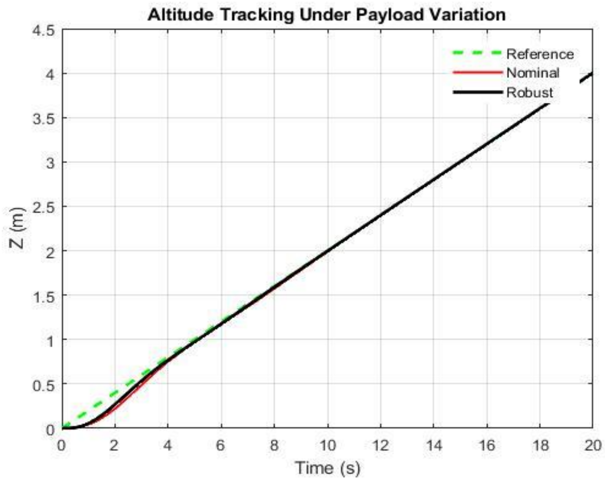


Figure 11: Altitude Tracking at Payload of 1kg

V. DISCUSSIONS

From Figures 2 and 3, we can see that both controllers can track the helical reference trajectory for the nominal mass. When the payload is increased to 0.5 and 1.0 kg, the performance of the controllers begins to diverge, showing the influence of the increased payload on tracking precision. The nominal controller performance deteriorates with increasing weight. The RMS tracking error increases from 0.18 m for no payload to 0.38 m for a 1.0 kg payload, an increase of approximately 130 %. The effect of extra mass on the robust controller is much less, with the RMS error only increasing from 0.09 m to about 0.16 m, a degradation of less than 25 %. Tracking errors larger than 0.3 m can jeopardise real-world UAV operations by threatening the safety and precision of the mission. The resilient controller guarantees reliable and secure navigation for different payloads. The total effectiveness of the tracking performance is measured by the RMS tracking error. As shown in Figures 4 and 5, the nominal controller exhibits a fast-growing tracking inaccuracy with the payload, especially for payloads larger than 0.5 kg. The root mean square error for the nominal controller increases by roughly 50 % for a 0.5 kg payload, while the robust controller increases only by 15 - 20 %.

The nominal controller error at 1.0 kg is more than 2.3 times the nominal value. The robust controller maintains the error below 1.2 times the nominal load. The results clearly show the high sensitivity of the nominal controller to the payload mass variations and the robustness of the robust controller in providing accurate tracking in many payload circumstances. As seen in Figure 6, the robust controller requires slightly more control effort than the nominal controller under nominal payload conditions. This is due to the gain configuration improvement of the robust controller. The effort of the nominal controller increases significantly with the size of the payload, becoming around 20 N for a 1.0 kg load. Under difficult load conditions, the robust controller requires approximately 25 N, which is about 16 - 20 % less than the nominal controller (Figure 7). This illustrates that the nominal controller compensates for its reduced performance by using more aggressive control actions, whereas the robust controller performs better with less aggressive, steadier, and energy-efficient actions. The analysis of the velocity response (Figures 8 and 9) shows that the UAV performance is significantly affected by changes in payload. The nominal controller with an increase in payload has more oscillations. In comparison, the velocity profile for the robust controller is much smoother and more stable than the adaptive controller. Figure 3 shows the velocity deviation of the standard controller with a load of 1.0 kg, which can reach about 3.5 m/s. However, using the robust controller, the peak error is greatly reduced to the order of 4 m/s. improved velocity control translates directly into smoother motion and less dynamic stress on the airframe. The transient nature of the altitude tracking reactions is rather different. The overshoot of the nominal controller grows with increasing payloads, suggesting lower damping and smaller stability margins (Figures 10 and 11). This is because of the additional payload mass of the UAV, which causes the nominal controller to have a smaller closed-loop damping that results in more oscillations. The robust controller alleviates this since it makes more proportional and derivative actions, resulting in better stability of the response.

VI. CONCLUSION

The research extensively investigates the degradation of the UAV trajectory tracking capability with various payloads. The simulation results show that the increase in payload has the main impact on the nominal controller's performance. For instance, increasing the cargo from 0 kg to 1.0 kg increases the RMS tracking error by more than 130 %, altitude overshoot by more than 20 %, and cumulative control effort to roughly 820 N.s. In all payload instances, the robust controller performs better all the time. It limits the RMS error rise to 25 %, the overshoot to 8 %, and reduces the control effort by at least 20 % in the case of high payloads. The results show that the payload variation is an important source of degradation in the UAV trajectory-tracking and should be taken into account in the controller design. Robust control techniques are therefore used to realistically and successfully maintain flying accuracy, stability, and energy economy, even with variations in mission payload.

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