



Offline Constrained PID Gain Tuning for Single-Axis UAV Roll Stabilization Under Disturbance Torque

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ABSTRACT

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Controlling the roll motion of a quadcopter under external disturbances remains challenging because of the nonlinear and under-actuated nature of the system. This paper presents an offline simulation study of constrained proportional-integral-derivative (PID) tuning for a small-angle, single-axis quadcopter roll model. The plant constructed uses $J_x = 0.020 \text{ kg} \cdot \text{m}^2$, viscous damping $b = 0.050 \text{ N} \cdot \text{m} \cdot \text{s}/\text{rad}$, and a 30° reference. The controller incorporates derivative filtering, $\pm 0.25 \text{ N} \cdot \text{m}$ torque saturation, a $3 \text{ N} \cdot \text{m}/\text{s}$ torque-rate limit, and back-calculation anti-windup. MATLAB `fmincon` with the Sequential Quadratic Programming algorithm is specified using deterministic multistart initialization. Condition-specific gains are computed for various disturbance torques from 0 to $0.12 \text{ N} \cdot \text{m}$ and compared with manual tuning and one fixed PID optimized jointly across the full range. At $0.10 \text{ N} \cdot \text{m}$, the joint fixed controller reduces Integral of Absolute Error from 0.6213 to 0.1976 rad·s and settling time from 3.63 to 1.00 s, with 0.434° overshoot. Gains tuned at $0.02 \text{ N} \cdot \text{m}$ produce 4.566° overshoot when transferred to $0.10 \text{ N} \cdot \text{m}$, whereas the joint-fixed controller remains consistent. During a $0.02\text{-}0.10\text{-}0.02 \text{ N} \cdot \text{m}$ switching sequence, it returns to within $\pm 0.6^\circ$ of the reference in 0.46-0.49 s after each torque change and remains bounded under pulse, sinusoidal, and stochastic torques. A nine-case $\pm 20\%$ inertia and damping sweep remains stable; its worst settling time and overshoot are 2.82 s and 2.91° . These results indicate that the optimization-based tuning approach provides improved stability, which makes it suitable for operating conditions that are uncertain and time-varying within a range.

1. INTRODUCTION

Quadrotors require fast attitude regulation despite aerodynamic loads, actuator limits, and the coupling present in the full vehicle dynamics. Foundational experimental and modeling studies established the principal roll, pitch, yaw, and translational interactions [1, 2]. Later surveys [3], large-platform experiments [4], and geometric tracking studies [5] show that the complete problem is nonlinear and under-actuated. The present work attempts to work on the small-angle roll axis so that the offline tuning and disturbance-transfer questions are examined transparently.

Proportional-integral-derivative (PID) control remains attractive because its structure is interpretable and inexpensive. Classical tuning rules [6] and modern PID design guidance [7] also make it clear that performance depends on the plant, operating envelope, actuator behavior, and chosen objective. Optimization can reduce manual trial and error, as fixed values of PID gains may not perform well all the time, and adjusting them based on the current conditions can give better results.

Recent work spans metaheuristic offline search [8], differential-evolution tuning [9], neural adaptation, fuzzy gain

adjustment, estimator-assisted updates, robust auto-tuning, constrained nonlinear control, and safety-critical design. These studies differ substantially in plant order, disturbance model, online update mechanism, and validation platform. Direct comparison of numerical error values is therefore inappropriate, but their design choices provide a useful context for identifying what the reconstructed study does and does not establish. The online and adaptive studies in Table 1 update controller or estimator states during operation [10-13], whereas the constrained and safety-oriented studies address richer dynamics or guarantees [14-17]. The present study instead asks a narrower reproducibility question: whether one fixed PID tuned over a specified disturbance range transfers more consistently than gains optimized at only one disturbance level.

The contributions are: (i) a fully specified, reproducible constrained tuning problem; (ii) seven constant-torque cases; (iii) cross-condition tests and a fixed PID jointly optimized across all levels; (iv) switching, pulse, sinusoidal, and bounded stochastic torques; and (v) explicit actuator saturation, torque-rate limits, anti-windup, control histories, and standard error indices.

Table 1. Position of the present study relative to representative work

Tuning Method	Model/Disturbance	Update	Validation Platform
NN-PID [10]	Quadrotor/wind	Online	Simulation
FPID-RNN [11]	Trajectory/nonlinear	Adaptive	Simulation
EKF-PID [12]	6-DOF/Gaussian	Online	Simulink
Auto-tuning [13]	Faults/parameter shift	Online	Simulation
Hybrid P-PID [14]	Uncertain nonlinear	Offline	Simulation
Implicit PID [15]	Time/state constraints	Fixed	Simulation
MOPSO-PID [16]	Roll-axis objectives	Offline	Simulation
Safety-critical [17]	Planar/event trigger	Online	Simulation
This study	Roll axis/5 torque profiles	Offline	MATLAB simulation

Note: NN-PID = Neural Networks PID; FPID-RNN = Fuzzy PID-Recurrent Neural Network; EKF-PID = Extended Kalman Filter-PID; MOPSO-PID = Multi-Objective Particle Swarm Optimization-PID.

2. ROLL-AXIS MODEL AND CONTROLLER

2.1 Reduced-order plant

For small roll angles and near-hover operation, pitch, yaw, translation, rotor dynamics, and inter-axis coupling are omitted. The roll dynamics equation is

$$J_x \ddot{\phi}(t) = u(t) + \tau_d(t) - b\dot{\phi}(t) \quad (1)$$

where, ϕ is roll angle (rad), $J_x = 0.020 \text{ kg} \cdot \text{m}^2$ is roll inertia, $b = 0.050 \text{ N} \cdot \text{m} \cdot \text{s}/\text{rad}$ is viscous damping, u is commanded roll torque, and τ_d is an externally applied roll torque in $\text{N} \cdot \text{m}$. A torque of $0.02 \text{ N} \cdot \text{m}$ corresponds to 1 rad/s^2 of uncompensated angular acceleration, while $0.10 \text{ N} \cdot \text{m}$ corresponds to 5 rad/s^2 for the selected inertia. These labels denote low and high test loads for the model considered. This deliberate reduction is consistent with extracting one attitude channel from established multirotor models [1-5], but it does not retain their translational or cross-axis coupling. Figure 1 shows the single-axis roll control model used.

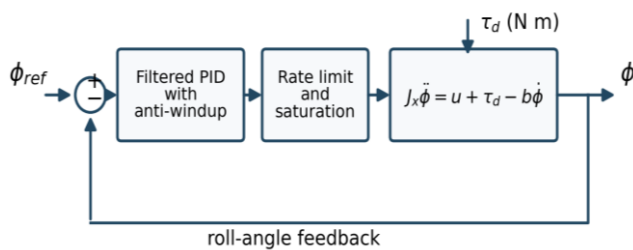


Figure 1. Single-axis roll control closed-loop architecture

2.2 Proportional-integral-derivative, filtering, and actuator constraints

$$u(t) = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt} \quad (2)$$

The input is represented as $u(t)$ and $e(t) = \phi_{ref}(t) - \phi(t)$ is the error. The gains K_p , K_i and K_d are the proportional, integral, and derivative gains. The demanded torque is rate-limited to $3 \text{ N} \cdot \text{m}/\text{s}$ and saturated to $\pm 0.25 \text{ N} \cdot \text{m}$. Back-calculation anti-windup with gain 10 s^{-1} feeds the difference between demanded and applied torque into the integrator. Therefore, the reported control histories include the same constraints used during optimization. Explicit saturation and anti-windup are essential because unconstrained optimization can otherwise select aggressive gains whose apparent benefit is created by a numerically unlimited actuator [7, 18].

3. OFFLINE OPTIMIZATION AND SIMULATION SETUP

3.1 Objective and gain bounds

The normalized condition-specific objective is

$$J = IAE/0.20 + 0.35ITAE/0.40 + 0.08E_u/0.05 + 0.25M_p/3 + 0.10up/0.25 + R(K) \quad (3)$$

where, Integral of Absolute error (IAE) = $\int |e| dt$, Integral of Time multiplied by Absolute Error (ITAE) = $\int t|e| dt$, $E_u = \int u^2 dt$, M_p is overshoot in degrees, up is peak absolute torque, and $R(K) = 0.05(K_p/5)^2 + 0.25(K_i/5)^2 + 0.05(K_d/1.5)^2$. The regularizer discourages an artificial optimum at a gain bound when saturation masks aggressive unsaturated demand. Gains are bounded by $0.05 \leq K_p \leq 5$, $0 \leq K_i \leq 6$, and $0 \leq K_d \leq 1.5$. The fixed robust baseline minimizes the mean of J over seven torque levels plus 0.20 times the worst-case J . The mixed objective penalizes tracking error, late error, control energy, overshoot, peak torque, and excessive gain magnitude rather than optimizing only a single transient statistic.

Table 2. Reproducible optimization and simulation settings

Item	Specified Value
Software	MATLAB R2025b; Optimization Toolbox
Optimizer/Numerical Solver	Fmincon, SQP, central differences
Starts	5 common + 1 retained regression start
Limits	160 iterations; 2000 evaluations
Tolerances	Optimality, function, step = $1e-8$
Step size, simulation duration	Fixed-step Euler; $dt = 0.005 \text{ s}$; $T = 8 \text{ s}$
Reference profile	0 to 30 deg step at $t = 1 \text{ s}$
Constant torque	Applied at $t = 2 \text{ s}$; $0-0.12 \text{ N} \cdot \text{m}$
Initial state	$\phi(0) = 0$; $\dot{\phi}(0) = 0$
Manual gains	$[K_p, K_i, K_d] = [1.20, 1.00, 0.20]$

Wall-clock optimization time is hardware-dependent. The code used records tic/toc time, iterations, and function evaluations for every run. Table 2 details the simulation settings used. The five starts used are [1.20, 1.00, 0.20, 0.60, 0.05, 0.12, 1.50, 0.50, 0.35, 2.50, 1.50, 0.60], and [4.00, 3.00, 1.00]. A sixth retained regression solution is added to each problem so reruns remain insensitive to small release-dependent differences in a local SQP search. This is a deterministic multistart procedure, not a global-optimality claim [19].

3.2 Reproducibility protocol

A single script defines the plant, controller, disturbance profiles, optimizer settings, metric definitions, and random seed. Each candidate gain vector is evaluated with the same fixed-step simulation and actuator model. The script writes the condition-specific gains, joint gains, optimization diagnostics, constant-disturbance metrics, cross-condition metrics, and dynamic-profile metrics to comma-separated files before generating the figures. The stochastic profile uses a fixed twister seed and a bounded low-pass sequence, so every reported sample path is repeatable. This separation between offline search and online execution also distinguishes the method from controllers with an embedded autotuning function [20].

3.3 Disturbance profiles and metrics

Seven constant torques, 0, 0.02, ..., 0.12 N·m, are used for gain trends. Robustness tests keep one controller active while torque switches 0.02 N·m at 2 s, 0.10 N·m at 4 s, and 0.02 N·m at 6 s. Further profiles are a 0.10 N·m pulse from 3.0 to 3.5 s, a 0.06 sin (2 π 0.6(t-2)) N·m torque, and seeded low-pass stochastic torque with 0.03 N·m RMS clipped to ± 0.08 N·m. Reported metrics are 2% settling time, overshoot, final 0.5-s mean signed error, IAE, control energy, peak torque, and saturation fraction.

3.4 Metric definitions

All integral indices are evaluated from the reference step at $t_0 = 1$ s to the final simulation time $T = 8$ s.

Rise time is the interval between the first 10% and 90% crossings of the 30 deg command. Settling time is the earliest time after which the roll error remains within $\pm 2\%$ of the command for the rest of the record. Overshoot is the maximum positive excursion above the command, final error is the signed mean over the last 0.5 s, and saturation fraction is the proportion of samples at the ± 0.25 N·m torque limit. For persistent sinusoidal forcing, settling time is left undefined if the trajectory does not remain permanently inside the band.

4. RESULTS AND DISCUSSION

4.1 Seven-level gain study

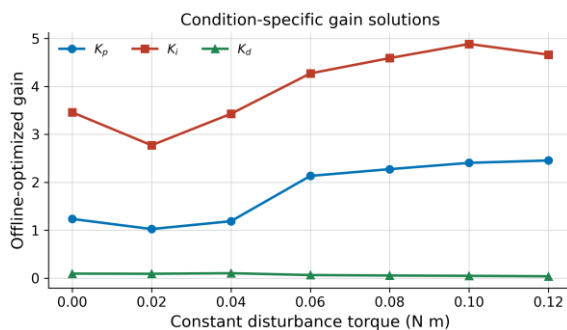


Figure 2. Condition-specific offline gain solutions for seven constant torques

Figure 2 shows that the local solutions do not justify a simple monotonic gain schedule. K_i falls from 3.4604 at 0 N·m to 2.7725 at 0.02 N·m, then rises to 4.8866 at 0.10 N·m before

decreasing at 0.12 N·m.

Table 3 confirms that all seven local solutions remain inside the specified gain bounds. Settling time improves markedly relative to manual tuning, but no single gain varies monotonically with torque over the full range. The result is therefore evidence for the selected finite set of constrained optima.

Table 3. Seven-level condition-specific gain and performance results

τ_d (N·m)	K_p	K_i	K_d	T_s (s)	IAE
0.00	1.2360	3.4604	0.0953	1.240	0.1726
0.02	1.0245	2.7725	0.0917	1.595	0.1879
0.04	1.1886	3.4288	0.1036	1.625	0.1842
0.06	2.1336	4.2715	0.0654	1.510	0.1991
0.08	2.2744	4.5910	0.0559	1.010	0.1957
0.10	2.4057	4.8866	0.0490	0.955	0.1904
0.12	2.4551	4.6623	0.0397	0.945	0.1918

4.2 Baseline and cross-condition tests

The joint fixed PID lowers IAE by 68.2% relative to the manual gains at 0.10 N·m and settles 2.63 s sooner, while remaining close to the condition-specific optimum. Table 4 summarizes the performance of the controller.

Figure 3 shows the cross-condition test response of roll angle and torque. It is observed that torque reaches the peak value of 0.25 N·m, but the integral state remains bounded because back-calculation is active.

Table 4. Performance at constant torque $\tau_d = 0.10$ N·m

Controller	$K_p/K_i/K_d$	T_s (s)	M_p (deg)	IAE
Manual	1.20/1.00/0.20	3.630	0.000	0.6213
0.10-tuned	2.406/4.887/0.049	0.955	0.010	0.1904
Joint fixed	2.286/4.527/0.052	1.000	0.434	0.1976

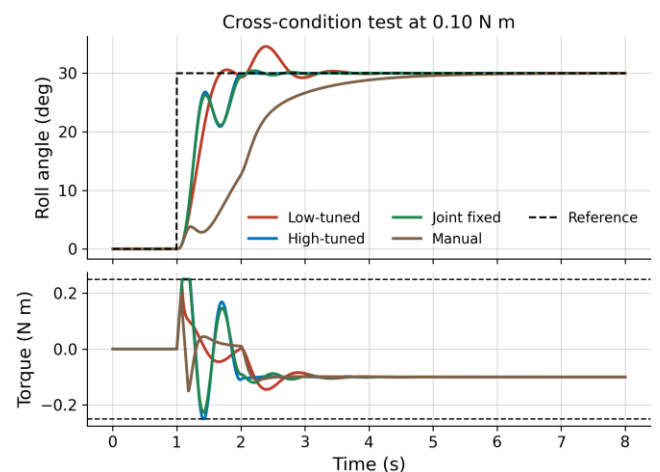


Figure 3. Cross-condition roll angle and applied torque at 0.10 N·m

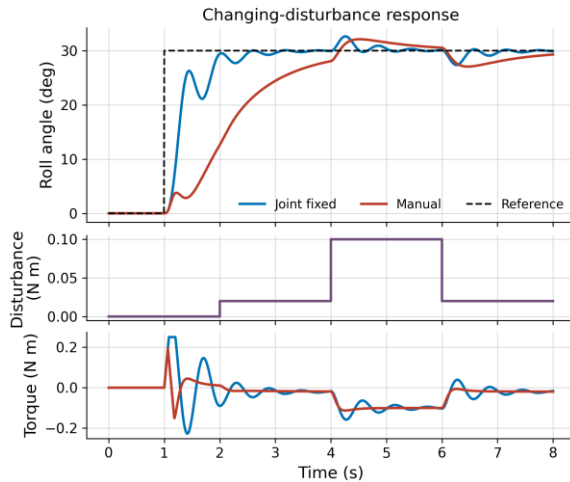
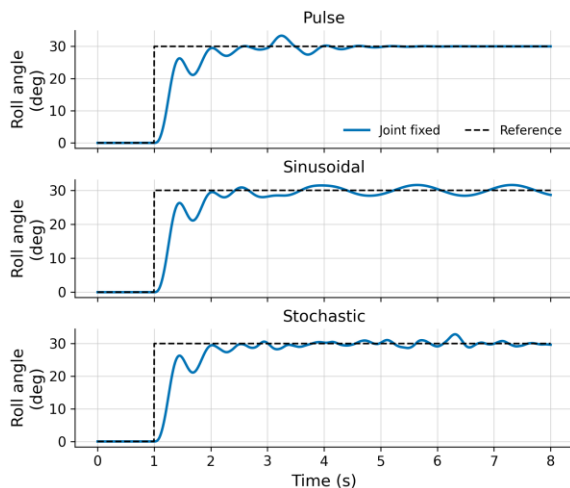
Summary in Table 5 shows that the low-level gains are acceptable at 0.02 N·m but overshoot by 4.566 deg when tested at 0.10 N·m. The high-level gains and joint fixed gains remain stable at both conditions. Thus, the experiments show that a fixed controller should be tuned over the intended operating envelope for optimal results.

Table 5. Cross-condition robustness summary

Gains Used	Test Torque	T_s (s)	M_p (deg)	IAE
0.02-tuned	0.02	1.595	0.660	0.1879
0.02-tuned	0.10	2.060	4.566	0.2192
0.10-tuned	0.02	1.940	0.251	0.2095
0.10-tuned	0.10	0.955	0.010	0.1904
Joint fixed	0.02	1.960	0.081	0.2116
Joint fixed	0.10	1.000	0.434	0.1976

4.3 Changing and nonconstant disturbances

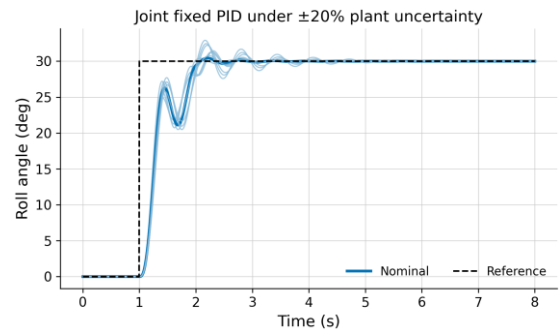
Figure 4 shows the response of the controller to switching disturbances. With no gain updates during the run, the joint fixed PID returns to within ± 0.6 deg of the 30 deg command in 0.485 s after the first 0.02 N·m step. The manual controller has not reached the same recovery band before the next event. Figure 5 shows roll angle variations of the joint-fixed PID controller to various input conditions and the results are summarized in Table 6. Across pulse, sinusoidal, and bounded stochastic tests, the joint controller remains bounded; IAE is 0.2370, 0.2911, and 0.2581 rad·s, respectively. A single settling-time value is not reported for the persistent sinusoid because the disturbance prevents permanent entry into a 2% band.

**Figure 4.** Response of one fixed controller to a 0.02-0.10-0.02 N·m torque sequence**Figure 5.** Joint fixed-proportional-integral-derivative (PID) responses under pulse, sinusoidal, and stochastic torque**Table 6.** Dynamic-profile performance of the joint fixed controller

Profile	IAE	M_p (deg)	Final Error (deg)	E_u ($N^2 \cdot m^2 \cdot s$)
Switching	0.2491	2.633	0.0364	0.0470
Pulse	0.2476	3.320	0.0001	0.0319
Sinusoidal	0.3027	1.581	0.0971	0.0370
Stochastic	0.2669	2.832	0.1685	0.0305

4.4 Plant-parameter sensitivity

To test whether the fixed gains depend critically on the nominal coefficients, roll inertia J_x and viscous damping b are varied independently by $\pm 20\%$, producing a 3×3 grid of nine plants. The controller gains, 0.10 N·m constant disturbance, actuator limits, integration step, and all metric definitions remain unchanged. This is a local parametric sensitivity test; it is not a substitute for identifying a physical airframe. Figure 6 shows the joint fixed PID controller sensitivity to inertia and damping and results are summarized in Table 7.

**Figure 6.** Roll response envelope for nine inertia-damping combinations at 0.10 N·m**Table 7.** Joint fixed-proportional-integral-derivative (PID) sensitivity to inertia and damping

$J_x/\text{Nominal}$	$b/\text{Nominal}$	T_s (s)	M_p (deg)	IAE
0.8	0.8	1.620	1.449	0.1895
0.8	1.0	1.565	1.319	0.1936
0.8	1.2	1.380	1.269	0.1964
1.0	0.8	0.950	0.405	0.1940
1.0	1.0	1.000	0.434	0.1976
1.0	1.2	1.305	0.769	0.2021
1.2	0.8	2.820	2.907	0.2431
1.2	1.0	2.235	2.442	0.2335
1.2	1.2	2.215	2.216	0.2279

All nine responses remain bounded and converge to the reference. The slowest case occurs at 1.2 J_x and 0.8 b , where settling time rises to 2.82 s, overshoot to 2.907 deg, and IAE to 0.2431 rad·s. Lower inertia produces faster responses but approximately 1.27-1.45 deg overshoot. The nominally tuned fixed controller is therefore locally robust to the tested coefficient changes, although performance degrades as expected for larger inertia combined with weaker damping.

4.5 Aggregate performance and actuator use

A controller selected for an operating envelope should be judged across that envelope rather than at its best single point. Table 8 therefore aggregates the seven constant-torque tests.

Relative to manual tuning, the joint fixed controller reduces mean settling time from 3.871 to 1.462 s and mean IAE from 0.6612 to 0.2048 rad·s. Its worst IAE is 0.2165 rad·s, which is only 8.7% above the worst condition-specific value of 0.1991 rad·s. The small loss relative to seven separate optima is the price of retaining one implementable gain vector.

The joint controller uses more control energy than the manual gains because it corrects the step and load changes more rapidly: mean E_u rises from 0.0340 to 0.0539 N²·m²·s.

Table 8. Aggregate results over seven constant-torque tests

Controller	Mean T_s	Worst T_s	Mean IAE	Worst IAE	Max Sat. (%)
Manual	3.871	4.205	0.6612	0.7211	0.000
Condition-specific	1.269	1.625	0.1888	0.1991	2.436
Joint fixed	1.462	1.990	0.2048	0.2165	1.499

4.6 Local linear stability check

A simple analytical check complements the time-domain simulations. If derivative filtering, saturation, rate limiting, and anti-windup are temporarily neglected, the ideal PID and reduced plant yield the characteristic polynomial

$$J_x s^3 + (b + K_d) s^2 + K_p s + K_i = 0 \quad (4)$$

For positive coefficients, the third-order Routh-Hurwitz condition is $(b + K_d) K_p > J_x K_i$. Define the normalized margin $\rho = (b + K_d) K_p / (J_x K_i)$, for which $\rho > 1$ indicates local asymptotic stability in this idealized model. The joint fixed gains give $\rho = 2.576$. Across the seven condition-specific solutions, ρ ranges from 2.362 to 2.883. Thus, every reported gain vector passes the same local check with a finite margin.

This calculation is deliberately limited: it neither proves stability of the constrained nonlinear implementation nor establishes robustness beyond the tested plant set. The filtered derivative adds a state, while saturation, torque-rate limiting, and anti-windup make the closed loop piecewise nonlinear. The bounded disturbance tests, nine-plant parameter sweep, and step-size refinement therefore remain the primary numerical evidence.

4.7 Numerical and assumption audit

Table 9 records the status and role of every parameter that materially affects the reported response. These values define a reproducible benchmark.

A step-size refinement check is also performed, as shown in Table 10 at the 0.10 N·m test using the joint fixed gains. Halving the nominal step from 0.005 to 0.0025 s changes IAE from 0.19762 to 0.19891 rad·s (0.65%) and overshoot from 0.434 to 0.411 deg. Doubling the step to 0.010 s gives the same 1.00 s settling time.

4.8 Interpretation relative to prior work

The simulations conducted support that tuning at one load can transfer poorly, while one fixed controller optimized over the intended envelope can remain consistent for the tested reduced-order plant than adaptive, estimator-based, or nonlinear quadrotor studies [10-17]. The main methodological contribution is consequently reproducibility.

Table 9. Status of constructed model and controller parameters

Quantity	Specified Value	Status/Role
Roll inertia J_x	0.020 kg·m ²	constructed plant assumption
Damping b	0.050 N·m·s/rad	constructed plant assumption
Reference	300 at 1 s	Benchmark command
Torque limit	±0.25 N·m	Actuator constraint assumption
Torque-rate limit	3 N·m/s	Actuator constraint assumption
Derivative filter	30 rad/s	Controller implementation choice
Anti-windup gain	10 s ⁻¹	Controller implementation choice
Integration step	0.005 s	Numerical setting
Simulation time	8 s	Numerical setting
Torque range	0-0.12 N·m	Defined test envelope

Table 10. Fixed-step refinement at 0.10 N·m

dt (s)	T_s (s)	M_p (deg)	IAE	E_u (N ² ·m ² ·s)
0.0100	1.0000	0.4842	0.19514	0.08182
0.0050	1.0000	0.4339	0.19762	0.08247
0.0025	0.9975	0.4114	0.19891	0.08279

4.9 Limitations and interpretation

This is a simulation-based control study with a focus on single axis stabilization with ± independent 20% variations of inertia and damping being tested and correlated. Pitch, yaw and other variations will be studied further and communicated in future articles.

5. CONCLUSION

A reproducible offline constrained PID study was constructed for a reduced single-axis UAV roll model. Seven constant torques show that condition-specific optima vary non-monotonically. Cross-condition tests reveal poor transfer of the 0.02 N·m gains to 0.10 N·m, while one PID jointly optimized across the full range provides consistent performance. At 0.10 N·m, it reduces IAE from 0.6213 to 0.1976 rad·s relative to manual tuning and settles in 1.00 s with 0.434 deg overshoot. The same fixed gains recover within 0.46-0.49 s after switching torque changes and remain bounded under pulse, sinusoidal, and stochastic inputs. The same gains remain stable across a nine-case ±20% inertia-damping sweep, with a worst settling time of 2.82 s. Halving the integration step changes IAE by only 0.65%. Future work should identify parameters from a physical platform, extend the model to 6-DOF dynamics and motor delay, quantify uncertainty, and validate through SIL/PIL/HIL before flight testing as mentioned in Table 11.

5.1 Data and code availability

No external experimental dataset is used. The companion MATLAB script defines the plant, gain bounds, objective function, disturbance cases, uncertainty grid, numerical settings, and plotting commands needed to regenerate the

reported tables and figures. It also exports machine-readable CSV files for the torque sweep, transfer matrix, dynamic-disturbance tests, uncertainty study, and integration-step refinement.

Table 11. Minimum staged validation before flight

Stage	Added Evidence	Required Check
SIL	6-DOF plant and allocation	Repeat envelope and uncertainty tests
PIL	Compiled controller on target	Timing, discretization, and numeric parity
HIL	Sensors, motors, delay, noise	Limits, anti-windup, and fault response
Tethered test	Identified physical airframe	Predefined safety and tracking thresholds

5.2 Recommended validation sequence

The optimized signal in this study is an idealized roll-axis torque. A physical implementation must first map that torque through a control allocator to individual motor commands and verify the assumed ± 0.25 N·m magnitude and 3 N·m/s rate limits against measured propulsion data. Roll inertia, damping, motor lag, sensor noise, computation delay, and battery-dependent thrust should then replace the constructed values. The 0.005 s integration step is a numerical setting, not evidence that a 200 Hz embedded implementation is adequate.

At each stage, the same gain vector should be frozen before testing so that any performance change can be attributed to the added plant realism rather than retuning. Acceptance criteria should be declared in advance for settling time, IAE, peak error, actuator saturation, and recovery after a torque change. Only after the fixed-gain baseline passes these checks would a comparison with an online adaptive or estimator-based controller support a defensible claim of added complexity versus measurable benefit.

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NOMENCLATURE

b Viscous roll damping, $N \cdot m \cdot s / rad$

e(t)	Roll-angle tracking error, rad
Eu	Control-energy index, $N^2 \cdot m^2 \cdot s$
IAE	Integral of absolute error, $rad \cdot s$
ISE	Integral of squared error, $rad^2 \cdot s$
ITAE	Integral of time-weighted absolute error, $rad \cdot s^2$
J_x	Roll-axis moment of inertia, $kg \cdot m^2$
K_p, K_i, K_d	Proportional, integral, and derivative gains
M_p	Peak overshoot, deg
τd	Applied disturbance torque, $N \cdot m$
u	Applied roll-control torque, $N \cdot m$
φ	Roll angle, rad