

EXPERIMENTAL FLIGHT VALIDATION OF A ROCKET-ASSISTED REUSABLE UAV PLATFORM

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ABSTRACT

Reusable high-altitude atmospheric observation platforms are attracting increasing attention because conventional sounding rockets are expendable and observation balloons have limited manoeuvrability and recovery capability. This paper presents the preliminary validation of a rocket-assisted reusable unmanned aerial vehicle (UAV) for future high-altitude observation missions. The proposed system consists of a rocket-powered lower stage and a foldable-wing UAV that separates after ascent and autonomously recovers. A six-degree-of-freedom nonlinear dynamic model incorporating propulsion, variable mass, aerodynamics, actuator dynamics, and gimbal backlash is developed. A nonlinear model predictive controller (NMPC) integrated with an extended Kalman filter (EKF) is evaluated using experimentally identified parameters and high-fidelity nonlinear simulations. Simulation results demonstrate improved robustness against actuator mismatch while maintaining real-time computational feasibility. The proposed framework provides a practical foundation for future rocket-assisted separation experiments and reusable high-altitude UAV flight demonstrations.

Keywords: Rocket-assisted UAV, Reusable UAV, High-altitude observation, Nonlinear model predictive control, Extended Kalman filter

1. INTRODUCTION

High-altitude atmospheric observations are essential for improving numerical weather prediction, environmental monitoring, climate research, and atmospheric science. Accurate in-situ measurements obtained in the upper troposphere and lower stratosphere are increasingly important for validating satellite observations and improving atmospheric prediction models. However, existing observation platforms exhibit inherent limitations in terms of operational flexibility, cost, and measurement capability [1].

As illustrated in Tab. 1, Observation balloons provide long-duration measurements but have limited manoeuvrability and poor recovery accuracy because their trajectories are primarily determined by atmospheric winds. Conventional sounding rockets rapidly reach high altitudes but are generally expendable, making repeated scientific missions expensive and operationally inefficient. Consequently, there is growing interest in reusable high-altitude platforms that combine the rapid ascent capability of rockets with the operational flexibility of unmanned aerial vehicles [2].

To address these limitations, this study investigates a rocket-assisted reusable unmanned aerial vehicle (UAV) platform capable of vertical launch, powered ascent, stage separation, autonomous atmospheric observation, and controlled recovery. Unlike conventional sounding rockets, the proposed concept enables repeated operation of the upper-stage UAV while maintaining rapid access to the lower stratosphere. The overall mission concept is illustrated in Fig. 1, where a rocket-assisted launch vehicle transports a foldable-wing UAV to high altitude before separation and autonomous flight. The platform aims to provide a reusable and cost-effective solution for future atmospheric observation missions [5, 6].

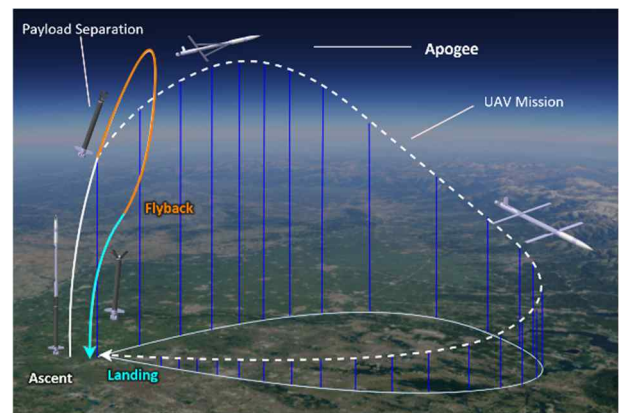


Figure 1. Mission concept and flight profile

Table 1. Comparison of atmospheric observation platforms

Platform	Observation Aircraft	Observation Balloon	Expendable Sounding Rocket	Reusable Sounding Rocket	Proposed Method
Appearance					
Reusability	Yes	Limited	No	Yes	Yes
Operational Altitude	< 37.7 km	< 53 km	> 50 km	> 50 km	> 30 km
Station-Keeping	Yes	Limited	No	No	Yes
Precision Recovery	Yes	No	No	Yes	Yes

Although the complete mission profile has not yet been experimentally demonstrated, preliminary flight experiments have been conducted to reduce technical risk and validate the proposed control architecture. Rather than presenting a fully mature flight system, this paper focuses on constructing a reliable simulation framework based on experimentally identified system parameters. A nonlinear six-degree-of-freedom dynamic model, including propulsion dynamics, actuator nonlinearities, and variable mass properties, is developed to represent the vehicle behaviour with improved fidelity. Furthermore, a nonlinear model predictive controller combined with an extended Kalman filter is evaluated under various actuator mismatch conditions to investigate controller robustness during the recovery phase.

The main contributions of this paper are summarized as follows:

1. Development of a high-fidelity nonlinear simulation framework for a rocket-assisted reusable UAV platform.
2. Experimental parameter identification of propulsion and actuator dynamics for simulation-based validation.
3. Design of a flight control architecture integrating nonlinear model predictive control (NMPC) and an extended Kalman filter (EKF).
4. Comparative simulation studies demonstrating the effects of controller tuning and model mismatch on recovery performance.

The validated simulation framework presented in this work will serve as the basis for upcoming rocket-assisted separation flight experiments and future high-altitude flight demonstrations.

2. SYSTEM OVERVIEW

2.1. Mission Concept

Conventional atmospheric observation platforms suffer from significant operational limitations. Observation balloons provide long-duration

measurements but cannot accurately control flight trajectories or recovery locations. Sounding rockets rapidly reach the upper atmosphere but are generally expendable and therefore unsuitable for repeated scientific missions. To overcome these limitations, this study proposes a reusable rocket-assisted UAV platform capable of rapid stratospheric access and autonomous recovery.

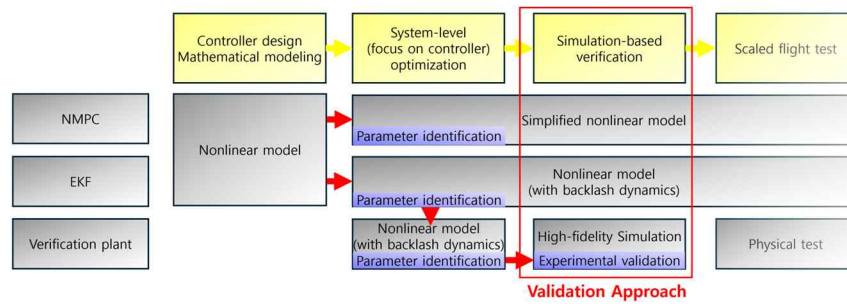
The overall mission profile is illustrated in Fig. 1. The system consists of a reusable rocket-assisted launch vehicle and a foldable-wing UAV. After vertical launch, the rocket accelerates the vehicle through the dense lower atmosphere to the target altitude. At the designated separation point, the UAV deploys its folding wings and transitions to autonomous fixed-wing flight for atmospheric observation. Upon mission completion, the UAV returns to the recovery site while the launch vehicle independently performs powered recovery for reuse.

Compared with conventional sounding rockets, the proposed concept significantly improves operational efficiency by enabling repeated use of the flight hardware while reducing mission cost. Furthermore, compared with observation balloons, the platform provides substantially improved manoeuvrability, controllability, and recovery accuracy.

The proposed mission consists of the following operational phases:

1. Vertical launch using rocket propulsion.
2. Powered ascent to the designated separation altitude.
3. Stage separation and wing deployment.
4. Autonomous atmospheric observation mission.
5. Return flight and precision recovery of the UAV.
6. Independent recovery of the launch vehicle.

This architecture combines the rapid ascent capability of sounding rockets with the flexibility and reusability of unmanned aerial vehicles, providing an attractive solution for future atmospheric observation missions.

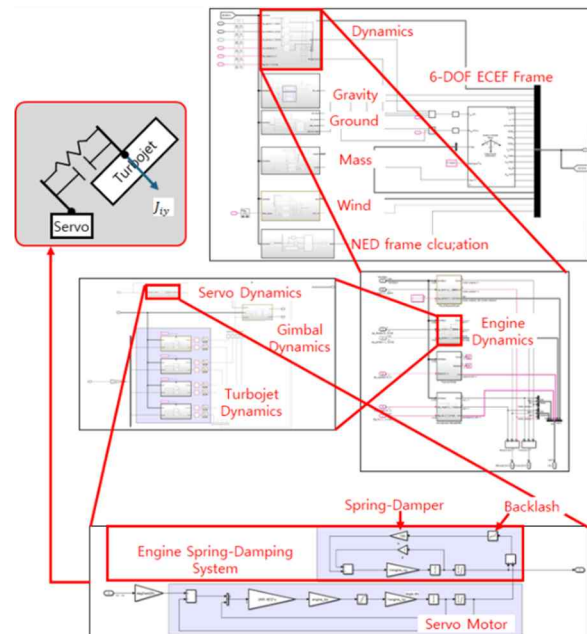


2.2. Validation Strategy

The validation process is summarized in Fig. 2. First, a nonlinear mathematical model of the complete vehicle is established based on rigid-body dynamics, propulsion characteristics, and actuator dynamics. Experimental system identification is then performed to estimate unknown parameters, including propulsion performance, gimbal dynamics, and actuator nonlinearities. The identified parameters are incorporated into a high-fidelity nonlinear simulation environment, which serves as the primary verification platform for controller evaluation.

This stepwise validation methodology minimizes development risk by verifying individual subsystems before conducting full-scale high-altitude flight demonstrations.

A high-fidelity nonlinear simulation environment, as shown in Fig. 3, is developed to accurately represent the dynamics of the proposed reusable UAV platform.



freedom rigid-body dynamics together with detailed propulsion, actuator, and environmental models.

1. Earth-Centered Earth-Fixed (ECEF) coordinate transformation
2. Six-degree-of-freedom nonlinear rigid-body dynamics
3. Variable mass properties and center-of-gravity movement due to fuel consumption
4. Nonlinear turbojet propulsion model
5. Gimbal thrust vector control (TVC) dynamics
6. Aerodynamic force and moment models
7. Atmospheric density variation with altitude
8. Wind disturbance models
9. Gimbal backlash and dead-zone dynamics
10. Sensor noise and state-estimation uncertainty

are identified through experiments and incorporated into the simulation to reproduce realistic flight behaviour. Consequently, the simulator provides a reliable platform for evaluating controller robustness under practical operating conditions.

The resulting simulation environment establishes a direct connection between experimentally identified hardware characteristics and subsequent controller performance evaluation, thereby improving the credibility of the simulation results presented in this study.

3. MATHEMATICAL MODEL

3.1. Six-Degree-of-Freedom Dynamic Model

To accurately predict the flight behaviour of the proposed reusable UAV platform, a nonlinear six-degree-of-freedom (6-DOF) rigid-body dynamic model is developed, as shown in Fig. 4. The model simultaneously describes the translational and rotational motion of the vehicle while accounting for the effects of propulsion, gravity, and aerodynamic forces.

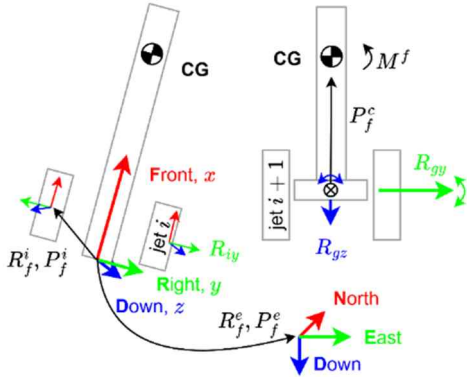


Figure 4. Six-degree-of-freedom dynamic model of the reusable UAV

The translational motion of the vehicle is expressed as

$$m\dot{v}_B = F_T + F_A + F_G - m(\omega \times v_B) \quad (1)$$

where m denotes the vehicle mass, v_B is the body-frame velocity vector, F_T is the propulsion force, F_A represents the aerodynamic force, and F_G denotes the gravitational force expressed in the body frame.

The rotational dynamics are described by Euler's rotational equation

$$J\dot{\omega} = M - \omega \times (J\omega) \quad (2)$$

where J denotes the inertia matrix, ω is the body angular velocity vector, and M represents the total

external moment generated by thrust vector control and aerodynamic effects.

Vehicle attitude is represented using unit quaternions to eliminate the singularities associated with Euler-angle parameterization during aggressive flight manoeuvres.

Since the propulsion system continuously consumes fuel during flight, both the vehicle mass and inertia properties vary with time. These time-varying characteristics are incorporated into the simulation model to improve prediction accuracy throughout the mission.

3.2. Propulsion Model

The proposed platform employs turbojet engines equipped with TVC mechanisms, as shown in Fig. 5. The generated thrust depends on the throttle command as well as atmospheric operating conditions.

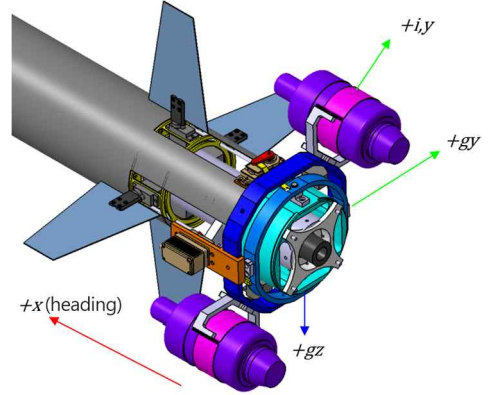


Figure 5. Gimbal thrust vector control model and actuator dynamics

The engine thrust is modelled as

$$T = T_{max}\delta_T \quad (3)$$

where T_{max} denotes the maximum available thrust and δ_T is the normalized throttle command.

To represent practical engine behaviour, the maximum thrust is modelled as a nonlinear function of

1. air density,
2. flight altitude,
3. Mach number, and
4. engine operating characteristics.

Fuel consumption is simultaneously calculated during the simulation, resulting in continuously varying vehicle mass and center-of-gravity location.

Unlike simplified constant-thrust models, this nonlinear propulsion model enables more realistic prediction of vehicle performance during both ascent and recovery phases.

3.3. Gimbal Dynamics

The propulsion system utilizes thrust vector control through servo-driven gimbal mechanisms. The gimbal rotates each turbojet nozzle to generate control moments required for vehicle attitude stabilization.

The gimbal dynamics are modelled as a second-order system

$$J_g \ddot{\theta} + K_d \dot{\theta} + K_p \theta = u \quad (4)$$

where J_g is the gimbal rotational inertia, K_p is the proportional servo gain, K_d is the derivative servo gain, and u denotes the commanded gimbal angle.

This simplified actuator model adequately represents the servo dynamics required for controller evaluation.

However, physical flight hardware exhibits additional nonlinearities that are not represented by the nominal controller model. These nonlinearities include

1. backlash,
2. dead-zone,
3. rate saturation,
4. servo delay.

To evaluate controller robustness, these nonlinear effects are incorporated into the high-fidelity verification simulator while maintaining a simplified prediction model inside the NMPC algorithm [3].

3.4. Aerodynamic Model

Aerodynamic forces and moments are computed using the conventional rigid-body aerodynamic formulation.

The aerodynamic force is expressed as

$$F_A = qSC \quad (5)$$

where q is the dynamic pressure, S is the reference area, and C denotes the aerodynamic force coefficient.

Similarly, aerodynamic moments are obtained using experimentally estimated moment coefficients.

Atmospheric density is calculated as a function of altitude based on the standard atmosphere model. Consequently, both aerodynamic forces and propulsion performance vary continuously during the ascent and descent phases.

3.5. Simulation Assumptions

The developed nonlinear simulation includes the following practical characteristics:

1. Variable vehicle mass due to fuel consumption
2. Time-varying inertia tensor
3. Center-of-gravity movement
4. Nonlinear turbojet performance
5. Aerodynamic force and moment models
6. Wind disturbance
7. Sensor noise
8. Gimbal backlash
9. Servo dead-zone
10. Actuator rate limitation
11. ECEF coordinate transformation

These components significantly improve the realism of the simulation compared with conventional controller-oriented models and provide a suitable platform for evaluating control performance prior to full-scale flight experiments.

4. NONLINEAR MODEL PREDICTIVE CONTROL AND STATE ESTIMATION

4.1. Nonlinear Model Predictive Control

The recovery phase of the proposed reusable UAV requires accurate attitude stabilization while satisfying actuator and propulsion constraints. Conventional PID controllers are computationally efficient but exhibit degraded performance when actuator nonlinearities such as backlash, dead-zone, and rate limitations become significant. To improve robustness under these conditions, a nonlinear model predictive controller (NMPC) is adopted (Fig. 6) [3].

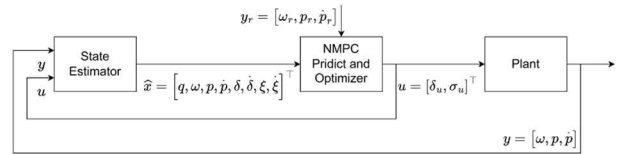


Figure 6. Structure of the nonlinear model predictive controller (NMPC)

Unlike conventional feedback controllers, NMPC predicts the future system response over a finite prediction horizon and computes an optimal control sequence by minimizing a constrained cost function. At each control update, only the first control input is applied, and the optimization is repeated using

newly estimated system states.

The optimization problem is formulated as

$$\min_u \sum_{k=0}^{N_p} \left[(x_k - x_{ref})^T Q (x_k - x_{ref}) + u_k^T R u_k \right] \quad (6)$$

subject to

1. nonlinear vehicle dynamics,
2. actuator dynamics,
3. thrust limits,
4. gimbal angle limits,
5. gimbal rate constraints,
6. throttle limits.

Here, Q and R denote the state and control weighting matrices, respectively, while N_p represents the prediction horizon.

To satisfy real-time implementation requirements, the prediction horizon was selected to maintain a controller update rate of approximately 10 Hz. The controller parameters were subsequently optimized using Sequential Quadratic Programming (SQP).

4.2. State Estimation Using Extended Kalman Filter

Reliable state estimation is essential for predictive control, particularly when nonlinear actuator behaviour and sensor uncertainties are present. An EKF is therefore employed to estimate the complete vehicle state.

The EKF estimates

1. vehicle position,
2. velocity,
3. attitude,
4. angular velocity,
5. gimbal states,
6. propulsion states.

The prediction step utilizes the nonlinear dynamic model, while the measurement update incorporates onboard sensor information including inertial measurements and navigation data.

The EKF recursively computes

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1}, u_k) \quad (7)$$

followed by the measurement correction

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k (z_k - h(\hat{x}_{k|k-1})) \quad (8)$$

where K_k is the Kalman gain, z_k is the

measurement vector, $h(\cdot)$ denotes the nonlinear measurement model.

The EKF enables robust state estimation even under sensor noise and moderate model uncertainty, thereby improving controller performance during recovery.

4.3. Model Mismatch

Although the NMPC prediction model assumes ideal actuator behaviour to reduce computational complexity, the actual hardware exhibits significant nonlinear characteristics, as shown in Fig. 7.

Among these nonlinearities, actuator backlash introduces dead-zone behaviour that degrades tracking performance. The backlash model is expressed as

$$d > 0 \quad (9)$$

where d represents the experimentally identified dead-zone angle.

Directly incorporating this nonlinear backlash model into the NMPC prediction model considerably increases computational complexity and may violate the real-time execution requirement.

Therefore, two different dynamic models are employed.

The NMPC prediction model neglects backlash

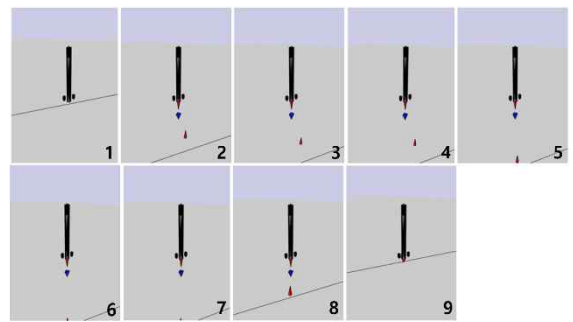
$$d = 0 \quad (10)$$

to reduce computational burden, whereas the EKF utilizes the experimentally identified actuator model

$$d > 0 \quad (11)$$

to improve state estimation accuracy.

This dual-model strategy provides a practical compromise between computational efficiency and model fidelity.



(a)

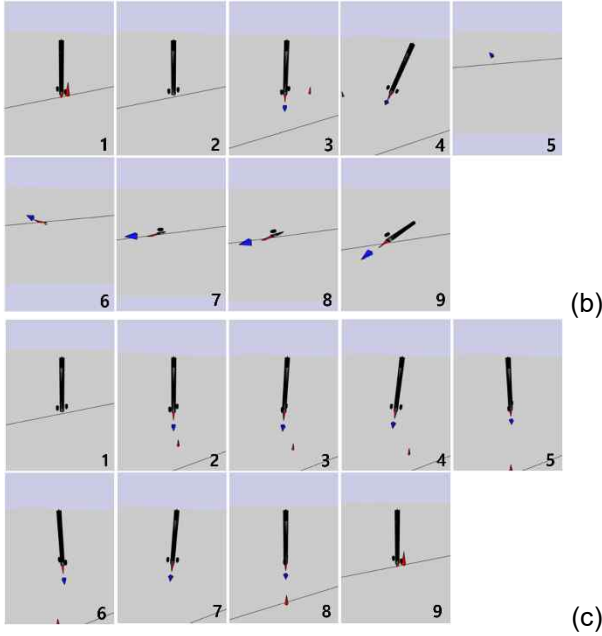


Figure 7. *Ideal and mismatched gimbal actuator models:*

- (a) ideal model (MPC and EKF),
(b) mismatched actuator model in MPC and EKF,
(c) mismatched actuator model in MPC only

4.4. Parameter Identification

The accuracy of the simulation environment strongly depends on the fidelity of the identified model parameters. Therefore, key propulsion and actuator parameters were experimentally identified prior to controller evaluation (Tab. 2).

The identified parameter groups include

1. vehicle mass,
2. center of gravity,
3. inertia tensor,
4. maximum engine thrust,
5. turbojet coefficients,
6. gimbal inertia,

7. servo gains,
8. dead-zone width,
9. backlash characteristics.

These parameters were incorporated into the nonlinear verification simulator to reproduce realistic hardware behaviour.

Compared with purely analytical models, experimentally identified parameters significantly improve the consistency between simulation and future flight-test observations.

4.5. Simulation Scenarios

To evaluate the effects of controller tuning and actuator mismatch, four simulation scenarios were considered (Tab. 3).

Scenario I: Ideal actuator model with manually tuned controller parameters. This scenario serves as the nominal baseline.

Scenario II: Actuator mismatch introduced while maintaining the original controller parameters. This case evaluates the degradation caused by model uncertainty.

Scenario III: Actuator mismatch with controller weights optimized using SQP. The objective is to investigate whether controller optimization can recover the performance loss caused by actuator mismatch.

Scenario IV: Ideal actuator model with optimized controller weights. This scenario represents the best achievable performance under ideal modelling assumptions and serves as the upper performance bound.

These four scenarios enable systematic evaluation of the influence of actuator mismatch and controller tuning on recovery performance.

Table 2. *Experimentally identified model parameters*

Group	Terms	Model Role
Rigid Body	m, CG, J_B	6-DOF state dynamics
TVC / Gimbal	J_g, K_p, K_d	Gimbal actuator dynamics
Propulsion	T_{max}, δ_T, ξ	Thrust and fuel-consumption model
Actuator Mismatch	d, J_g, K_p and K_d errors	Actuator mismatch model
Integrated Simulation	identified parameter set	High-fidelity plant / EKF model

Table 3. *Definition of simulation scenarios*

Scenario	Plant Model	Controller Weights	Purpose	Interpretation
I	Nominal	Initial	Ideal baseline	Ideal Case
II	Degraded	Initial	HW mismatch	Loss by HW mismatch
III	Degraded	SQP Optimized	Retuned mismatch	Recovery by optimized
IV	Ideal	SQP Optimized	Best case	Optimized nominal case

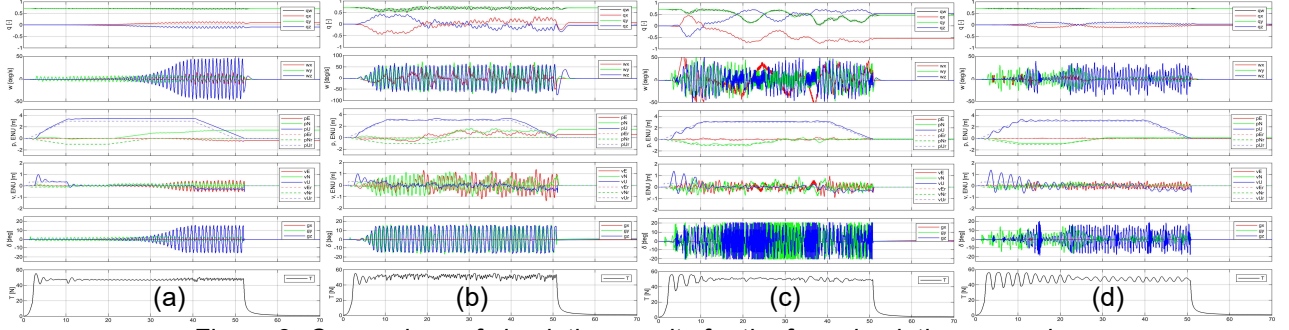


Figure 8. Comparison of simulation results for the four simulation scenarios:
(a) Scenario I (ideal actuator model with initial controller weights),
(b) Scenario II (actuator mismatch with initial controller weights),
(c) Scenario III (actuator mismatch with SQP-optimized controller weights),
(d) Scenario IV (ideal actuator model with SQP-optimized controller weights)

Table 4. Quantitative comparison of recovery performance under the four simulation scenarios

Scenario	e_{RMS} [m]	e_{land}^{xy} [m]	ϕ_{t_∞} [kg]
I	5.6062e-1 (+00.00%)	2.2193e-0 (+00.00%)	1.6951e-1 (+0.00%)
II	6.2011e-1 (+10.61%)	1.2814e-0 (-42.26%)	1.7786e-1 (+4.93%)
III	1.4430e-1 (-74.26%)	2.5789e-2 (-98.84%)	1.7355e-1 (+2.38%)
IV	1.2440e-1 (-77.81%)	1.7344e-2 (-99.22%)	1.6644e-1 (-1.81%)

Note: Values in parentheses denote relative change versus Scenario I: $\Delta[\%] = 100(m_s - m_I)/m_I$

5. SIMULATION RESULTS AND DISCUSSION

The proposed NMPC-EKF framework was evaluated under four simulation scenarios representing ideal and mismatched actuator conditions. Fig. 8 compares the recovery responses, while Tab. 4 summarizes the corresponding performance metrics.

Compared with the nominal controller (Scenario I), actuator mismatch (Scenario II) increased both the RMS tracking error and landing error. After SQP-based controller optimization (Scenario III), the RMS error was reduced by 74.26% and the landing error by 98.84%, despite the actuator mismatch. Scenario IV achieved the best overall performance under ideal actuator assumptions, reducing the RMS and landing errors by 77.81% and 99.22%, respectively.

These results demonstrate that the proposed NMPC-EKF framework effectively mitigates actuator mismatch and substantially improves recovery performance while maintaining real-time computational feasibility.

6. CONCLUSIONS

This paper presented a simulation-based validation framework for a rocket-assisted reusable UAV platform using experimentally identified system parameters and a high-fidelity nonlinear simulation environment. The proposed NMPC-EKF controller demonstrated improved robustness against

actuator mismatch, reducing the RMS tracking error by up to 77.81% and the landing error by up to 99.22%.

Future work will focus on rocket-assisted separation experiments and flight validation of the complete reusable platform using measured flight data.

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