Real-Flight Validation of a Two-Stage RLS for Quadcopter Mass and Actuator Fault Estimation

Mohamed Ahsan Mafaz[1], Nadjim Horri[2], Qian Lu[3] and Matthew England[1]

***Abstract*—Parameter and fault estimation methods for quadcopter UAVs are commonly validated in simulation, with performance under real flight conditions and autopilot implementation constraints less explored. This paper presents a practical validation of a two-stage recursive least-squares estimator for identifying UAV mass and actuator loss of effectiveness using real-flight data. Building on prior simulation-based work, the estimator is evaluated through real flights with controlled payload variations that induce known parameter changes. The results demonstrate consistent convergence to the true vehicle mass across multiple payload configurations and reliable identification of nominal actuator effectiveness. The study highlights practical aspects influencing estimator performance, including filtering requirements and interactions with onboard state-estimation pipelines. We demonstrate the feasibility of extracting reliable parameter and health information from standard autopilot data, providing a reproducible step toward integrating online estimation into future adaptive and fault-tolerant UAV control systems.**

***Index Terms*—quadcopter UAV, recursive least squares, parameter estimation, adaptive control, real-flight validation**

I. Introduction

Reliable operation of quadcopter UAVs in practical missions requires awareness of changes in vehicle parameters and actuator performance. A two-stage recursive least-squares (TSRLS) estimation framework capable of simultaneously identifying actuator loss of effectiveness (LoE), mass, and inertia has been proposed by the authors and validated in simulation [1]. This demonstrated the potential of the approach for adaptive and fault-tolerant control, but its behaviour under realistic measurement noise, filtering, and autopilot implementation constraints remains unexplored. Bridging this gap is necessary before integrated into UAV control architectures. Hence we focus now on the experimental validation of the TSRLS estimator using real-flight data. The aim is to assess whether the estimator can recover key parameters from realistic flight logs and to identify factors that influence its practical performance.

II. Methodology

The quadcopter model follows the formulation presented in [1], where the dynamics are derived using the Newton–Euler formalism. Although the experiments are conducted on a real UAV platform, this model provides the parametric structure required for the TSRLS estimation framework. The flight controller under study follows the commercial PX4 firmware running on the PX4 Vision Autonomy Development Kit [2]. It is based on a hierarchical control architecture common in UAV control research, e.g. [3]. It consists of a cascaded PID loop, where attitude control is performed in an inner-loop and the outer-loop is the position controller. The inner-loop usually works at a higher frequency and stabilizes the attitude of the quadcopter, while the outer-loop generates the thrust required to maintain the altitude and position of the quadcopter. The default PID gains provided by the PX4 firmware were used and kept constant across all flight experiments to ensure consistent and repeatable evaluation conditions.

[1] Centre for Computational Science and Mathematical Modelling, Coventry University (e-mail: mohamedmam@uni.coventry.ac.uk, Matthew.England@coventry.ac.uk). [2] School of Engineering, University of Leicester (e-mail: nmh22@leicester.ac.uk). [3] Centre for Future Transport and Cities, Coventry University (e-mail: ad5271@coventry.ac.uk).

Fig. 1: Flight testing at Skyfarer HQ, United Kingdom

The TSRLS estimator presented in [1] is combined with a Butterworth filter to estimate actuator loss of effectiveness in the first stage, $\Theta_1 = \begin{bmatrix} k_1 & k_2 & k_3 & k_4 \end{bmatrix}^T$, and quadcopter mass and inertia in the second stage, $\Theta_2 = \begin{bmatrix} m & I_{xx} & I_{yy} & I_{zz} \end{bmatrix}^T$, using measured flight data and control inputs, under realistic measurement noise and other practical constraints. These are estimated at each time step by minimizing the weighted least-squares cost function:

$$J_i = \sum_{t=1}^{n} \lambda_i^{n-t} \Big(Y_i(t) - X_i(t)\Theta_i(t-1) \Big)^2, i = 1, 2.$$

Here i is the stage index and n, λ_i, Y_i, X_i and Θ_i respectively denote the number of samples, forgetting factor, output observation vector, information matrix and the parameters to be estimated. The TSRLS forgetting factors were 0.9 and 0.5 for the first and second stages respectively. The estimator outputs are not used for online controller adaptation, as the focus is on validating its ability to estimate UAV parameters.

III. Experimental Flight Validation and Results

Flight experiments were conducted at at Skyfarer HQ to evaluate the TSRLS estimator using real quadcopter data (Figure 1). A waypoint mission was generated in QGroundControl consisting of autonomous takeoff, followed by a pentagonal

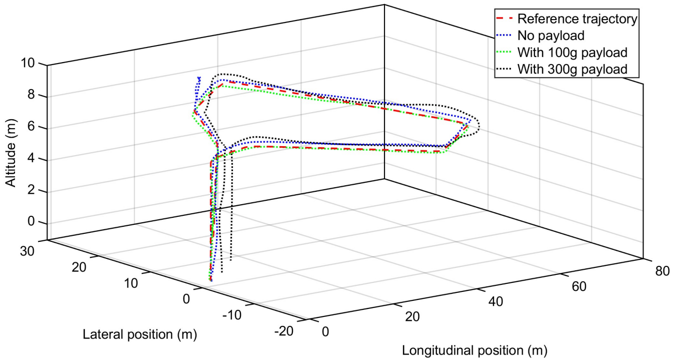
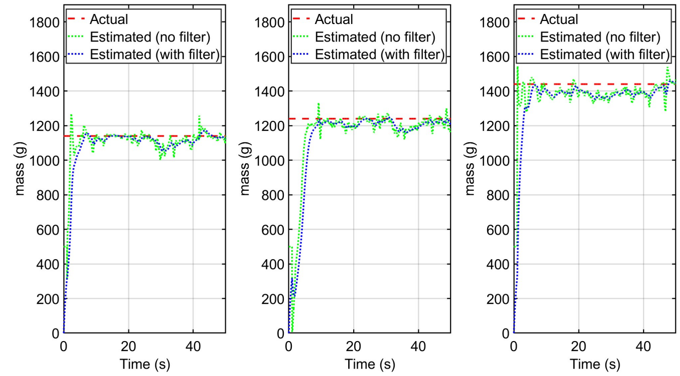


Fig. 2: Trajectory tracking for different payload masses

route at 8m altitude, and concluding with an autonomous landing. To introduce controlled parameter variations, additional payloads were mounted onto the UAV to modify its total mass. Flights were performed with three configurations: no payload, 100g payload, and 300g payload. Mass variation was selected as a safe and repeatable method to induce known parameter changes while preserving actuator functionality. Flight logs from each experiment were recorded using the onboard PX4 firmware and processed offline using the TSRLS framework.

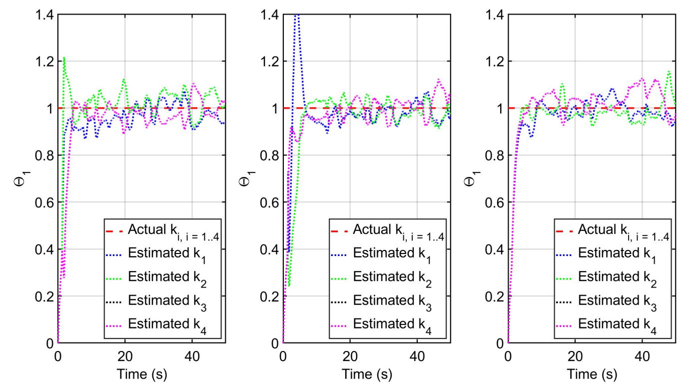
Figure 2 provides the trajectory tracking comparisons for different payload masses in 3D view for the flight. The results are presented in Figure 3 and Figure 4, which shows the actual and estimated values for mass and actuator LoE for the three payload cases. The TSRLS algorithm successfully converged to the actual mass across all three test cases, demonstrating its capability to accurately identify parameter variations induced by payload changes. In addition, the estimator consistently predicted full actuator health, validating its ability to provide reliable online estimates under nominal conditions. Although the payloads were mounted near the UAV's centre of mass to primarily affect mass, they were not perfectly centred, which likely introduced unintended variations in the moments of inertia. As a result, the inertia estimates could not be conclusively validated, and this misalignment may have contributed to residual estimation variability observed in the results.

To use the TSRLS with real flight data, it was necessary to apply a low-pass filter to the raw estimates to smooth out high frequency noise and improve the estimation for both mass and actuator LoE. A first-order Butterworth filter was implemented with a passband edge frequency of 1 rad/s. Though filtering significantly improved the estimation accuracy, noticeable fluctuations still remained, which can be attributed to residual sensor noise and possibly the lack of precise tuning of the onboard extended Kalman filter (EKF) within the PX4 firmware. These observations highlight practical constraints that influence estimator deployment. Future efforts should therefore explore methods to enhance estimator robustness through better filter design or develop procedures for tuning the EKF in a safe and systematic manner. Overall, the offline analysis demonstrated strong estimator performance, supporting the feasibility of integrating TSRLS into real-time adaptive control frameworks.



(a) (b) (c)

Fig. 3: Actual and estimated mass of quadcopter UAV (a) no payload (b) 100g payload (c) 300g payload



(a) (b) (c)

Fig. 4: Actual and estimated actuator LoE (with filter) (a) no payload (b) 100g payload (c) 300g payload

IV. Conclusion

We presented an experimental validation of the TSRLS parameter estimation framework [1] using real quadcopter flight data. The results demonstrate that the estimator can reliably identify vehicle mass variations and correctly infer actuator health from standard autopilot logs despite sensing noise and implementation constraints. Future work will focus on integrating the estimator into online adaptive and fault-tolerant control loops for real-time UAV operation.

Acknowledgments: We thank Skyfarer Ltd., whose facilities, assistance, and support were instrumental in facilitating our flight testing activities.

References

[1] M. Mafaz, N. Horri, Q. Lu, and M. England, "Robust auto-tuning control of a delivery quadcopter with motor faults, mass and inertia estimation," *IFAC-PapersOnLine*, vol. 58, no. 28, pp. 744–749, 2024. [Online]. Available: https://doi.org/10.1016/j.ifacol.2025.01.055

[2] PX4, "PX4 vision autonomy development kit," 2026. [Online]. Available: https://docs.px4.io/main/en/complete_vehicles_mc/px4_vision_kit

[3] R. Mahony, V. Kumar, and P. Corke, "Multirotor aerial vehicles: Modeling, estimation, and control of quadrotor," *IEEE Robotics and Automation Magazine*, vol. 19, no. 3, pp. 20–32, 2012. [Online]. Available: https://doi.org/10.1109/MRA.2012.2206474